Can Migration Mitigate Weather Damages?*

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Abstract

Extreme weather events threaten the lives and livelihoods of households across the developing world. Migration is a potentially important way to mitigate the cost of these events, but the degree to which it does in practice is not well known. This paper uses a repeated panel of household surveys from Indonesia to examine whether the effects of droughts on individual consumption are mitigated by the ability to migrate. By instrumenting between-survey migration with pre-existing migrant networks, we show that one standard deviation drop in annual precipitation in the origin location reduces consumption by 1.82% for non-migrant individuals, but that migrants are actually able to increase consumption. Given a one standard deviation drop in annual precipitation, the ability to migrate leads to an increase of about 13.9% in consumption over the medium run. These results suggest that removing barriers to migration is a promising strategy for mitigating climate damages.

1 Introduction

Damages from climate change are projected to disproportionately impact low income countries and individuals (Burke et al., 2015; Hsiang et al., 2019; Carleton et al., 2020). With few resources to adopt expensive mitigating technologies, migration often remains the main response to weather shocks including heat waves and droughts (Rigaud et al., 2018). Migration is recognized as a major mechanism for adaptation to climate change (Cruz and Rossi-Hansberg, 2021), and it is an important mechanism for the reallocation

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of economic activity form heavily affected areas to less or even positively affected areas (Colmer, 2021). However, the empirical evidence for the impact of migration in response to weather and climate on economic outcomes remains scarce. In this paper, we estimate the degree to which migration can limit consumption losses due to weather shocks.

One empirical challenge for studying the impact of migration is the limited availability of longitudinal surveys that track individuals after migration. We address this challenge by using the five waves of the Indonesia Family Life Survey (IFLS)[1], a detailed longitudinal survey that allows us to follow more than 32,000 individuals over 20 years in Indonesia, and documents their location, migration decisions, and several socio-economic characteristics over time. We combine this dataset with gridded rainfall data. In addition to housing the IFLS, Indonesia is a country where migration could play a substantial role in allowing households to adapt extreme weather events, which are likely to increase in frequency and severity due to climate change: it has high internal migration and almost half of the population is employed in the agricultural sector.

A second major challenge for studying the impact of migration on consumption is that the ability to migrate is often closely related to household characteristics that determine consumption directly. We overcome this endogeneity problem by building on the insights of Munshi (2003) and Munshi and Rosenzweig (2016) to construct an instrument based on migrant networks that we combine with individual weather shocks. We characterize the migration networks as the share of previously migrated individuals from the same ethnicity and origin location in the baseline period. The importance of networks for migration generally comes from being a source of economic support at potential destinations (Blumenstock et al., 2019). Additionally, Auwalin (2020) shows that ethnic identity is an important determinant of internal migration in Indonesia, suggesting that social networks are partly organized along ethnic lines.

This approach allows us to compare consumption responses of individuals with dif-

[1] Strauss et al. (2016).

ferent levels of mobility that are exposed to the same weather shock. This combination of pre-existing migrant networks with rainfall shocks is analogous to a shift share instrument (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). To account for the possibility that migrant networks can support household consumption through remittances, we employ a "direct effects" approach (Acharya et al., 2016). Our results indicate that the impact of migration on consumption is not explained by remittances from the migrant network.

Our main outcome in consumption, which has been previously used in the migration literature as a partial measure of welfare (Kleemans, 2015), and have also been shown to better represent well-being in low income countries (Meyer and Sullivan, 2003; De Magalhães and Santaeulàlia-Llopis, 2018). We find that mobile individuals are less affected by weather shocks. More specifically, our instrumental variable approach finds that one month of rainfall below average in the origin location leads to a reduction in consumption of about 2.3%. This effect is reversed by migration. Individuals that migrate in response to these negative rainfall shocks experience consumption increases of 5.3%, more than offsetting the negative impact of the rainfall shock. Another advantage of using consumption as an outcome is that IFLS records food and non-food consumption separately. We analyse both these outcomes separately, and find that migration offsets losses in food consumption more strongly than losses in non-food consumption.

We complement the main analysis with by examining changes in migration and consumption resulting from long-run differences in weather, following Burke and Emerick (2016). These estimates indicate that migration decisions are affected by long term changes in weather (rainfall), which suggests that migration is still an important adaptation strategy to climate change. Our results stress the importance of policies to improve mobility in face of climate change.

Our work is related to the broader climate impacts literature, which studies how climate change and extreme weather events will impact households and societies. Studies of the impact of weather shocks and climate change on economic outcomes generally find reductions in both productivity (Burke et al., 2015; Burke and Emerick, 2016) and consumption (Deschênes and Greenstone, 2007; Kleemans, 2015; Hsiang et al., 2017; Noack et al., 2019). Along similar lines, other work investigates how substantial spatial variation in weather and climate and nonlinear responses to their changes imply that neighboring regions can have very different economic outcomes in response to the weather and climate events (Deschênes and Greenstone, 2007; Hsiang et al., 2017). A growing literature also studies the impact of labor reallocation across sectors on climate damages (Colmer, 2021). Our study shows how migration, another type of reallocation, can mediate these types of effects.

Our paper also builds on work that identifies the benefits and limitations of migration as an economic strategy. Despite the potential importance of migration for improving economic efficiency and reducing inequalities, low quality infrastructure (Morten and Oliveira, 2018; Asher and Novosad, 2020), liquidity constraints (Bryan et al., 2014) and migration policies (Imbert et al., 2022; Missirian and Schlenker, 2017; Clemens et al., 2018) restrict the mobility of households across the developing world. It is generally accepted that these mobility frictions reduce economic efficiency and contribute to rural poverty (Beegle et al., 2011; Bryan and Morten, 2019; Morten and Oliveira, 2018).

Finally, our paper links most directly to studies that investigate the effects of weather and climate change on migration directly. Migration in response to weather shocks and natural disasters is well documented for a large range of settings (Gray and Mueller, 2012; Missirian and Schlenker, 2017; Barrios et al., 2006; Baez et al., 2017; Chen et al., 2017; Missirian and Schlenker, 2017; Henderson et al., 2017; Chen and Mueller, 2018; Hauer et al., 2020; Mueller et al., 2020a,b; Aragón et al., 2021; Albert et al., 2021; Branco and Féres, 2021) and for Indonesia specifically (Bohra-Mishra et al., 2014; Kleemans, 2015; Kleemans and Magruder, 2018; Bryan and Morten, 2019)[2]. In particular, these papers provide extensive

[2]See Cattaneo et al. (2020) for a recent review.

evidence that negative rainfall shocks induce migration. Our work builds on these findings by showing the impact of this migration on individual consumption in the face of shocks to annual rainfall.

The paper is organized as follows. Section 2 provides a background on internal migration in Indonesia. Section 3 describes the panel data, and the weather variables. Section 4 describes our empirical strategy. Section 5 shows our main results. Section 6 shows our long-differences results. Section 7 concludes and discusses policy implications.

2 Background: Migration in Indonesia

Our analysis is motivated by three facts and empirical findings in Indonesia: (1) High internal migration is an important characteristic of Indonesia's population; (2) Rainfall shocks are an important determinant of internal migration in the country; and (3) Internal migration patterns are partly determined along ethnic lines.

Internal migration flows in Indonesia are high and consist mostly of low income individuals moving out of rural areas (Auwalin, 2020). Internal migration in the country is also very high compared to international migration. According to estimates by the Badan Pusat Statistik (BPS), the Indonesian statistics bureau, the yearly average percentage of the population migrating internally was 4.3% from 1995 to 2014 (which covers most of our sample years), whereas for international migration this number was 0.17%.

There is substantive empirical evidence that rainfall is an important determinant of internal migration in Indonesia. In particular, Kleemans and Magruder (2018) find that negative rainfall shocks induce people to migrate internally. This pattern is associated with short-term negative rainfall shocks having a negative effect on income and wealth (Kleemans, 2015).

Mobility in Indonesia is associated with ethnicity. Indonesia has a large number of distinct ethnic groups (the 2010 census, for instance, identified over 1,400 distinct ethnic groups). As shown in Auwalin (2020), there are differences in migration behaviour among those ethnic groups. Hugo (2015) claims that ethnicity specific migration patterns can be driven by ethnic norms and cultural influences. Most importantly for this paper, the propensity to migrate persists over time within groups (Auwalin, 2020), which might be associated with past migrants facilitating migration of individuals with similar ethnic backgrounds.

3 Data

3.1 Household panel dataset

We use the Indonesia Family Life Survey (IFLS) to study migration choices as a response to rainfall shocks and ethnic networks. The IFLS is a longitudinal survey that is representative of about 83% of the Indonesian population, and it contains individuals living in 13 of Indonesia's 27 provinces (Strauss et al., 2016). The analysis is based on the five waves of the survey (1993, 1997, 2000, 2007 and 2014), which cover a period of 21 years. Around 88% of the households are contacted in all 5 waves (Strauss et al., 2016), which reflects intensive efforts to track respondents, making the IFLS uniquely suited for migration studies.

There is recall data on individual location and migration decisions for every individual and every year, which allows us to build a panel of the locations of 42,027 individuals over 20 years[3]. Here, we define a location as a sub-district or Kecamatan (administrative level 3). For our final sample, we keep only individuals who were interviewed in at least two consecutive waves, and whose birth place is in one of the 13 IFLS original provinces[4].

[3]Our main outcome is consumption, and because it is recorded only on the years of the survey wave, we do not use the yearly data on migration decisions in our main analysis.

[4]These are the provinces in which individuals were interviewed in the first sample wave in 1993. They are the following: North Sumatra, West Sumatra, South Sumatra, Lampung, Dki Jakarkta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Kalimatan, South Sulawesi (Strauss et al., 2016).

We also drop locations with 3 or less respondents in any year. Ethnicity information, ethnic social networks from the place of origin, and consumption data are available for 34,184 of these remaining individuals. Our main final sample is a panel dataset of individual locations, ethnicity and consumption for every survey wave starting in 1997[5], with a total of 95,040 individual-year observations. Table 1 provides summary statistics for our final sample.

Migration: Individuals' locations are recorded every survey year. We define migration at the individual level, as an indicator that equals one if the individual changed locations within Indonesia since the last survey wave. Although there is recall data on migration on a yearly basis [6], the measure we use captures all migration that is longer than 6 months Strauss et al. (2016), so it can be taken as a more permanent measure of migration that excludes seasonal and circular migration. The overall migration rate is 10.92%, as reported in Table 1.

Ethnicity and ethnic networks: We collect data on ethnicity from the fourth wave of IFLS. The survey recorded answers for 27 ethnicities, described in Table 8 in Appendix A. We build our ethnic social networks measure as the share of individuals belonging to the same ethnicity, who lived in the origin location at age 12, and who moved away (hereon, "ethnic networks"). In our regressions, we will focus on a fixed measure calculated on the first survey year[7], which has an average of 12.88%. Table 1 also reports the mean of our ethnic networks measure by migration status, which is "Migrant" if the individual moved at least once during our sample period, and "Non-migrant" otherwise.

[5]The first recorded location of residence is in 1993, the first survey year, and hence the individual migration indicator starts for between the first and second waves.

[6]We use yearly data on migration for supplementary analysis in Appendix B.1. The data is described in Appendix A.

[7]We are able to calculate this measure on the first survey year because we know where each individual was living when they were 12 years old, and we know their current location in every survey year.

Table 1: Descriptive Statistics

	All individuals		Non-migrant	Migrant
Migration	**Mean**	**SD**	**Mean**	
Migration	10.92%	0.312		
Share migrants-ethnicity*	12.88%	0.210	11.70%	16.70%
Consumption and income (in 2010 $K Rupiah)				
Food	338.48	298.51	311.98	429.17
Non-food	170.06	278.17	151.54	233.45
Income	440.87	495.70	412,25	566.36
Remittances	170.06	278.17	47.86	92.48
Demographics				
Age	39.16	13.59	40.34	34.00
Household Size	3.925	2.095	4.089	3.207
College Degree (%)	22.76	41.93	20.51	29.04
Urban (%)	61.43	48.68	58.47	74.44
Agricultural Worker (%)	24.90	43.24	28.48	10.88
Informal Worker (%)	38.86	48.74	42.27	24.21
Total Observations				
Number of Households	14,144		8,398	5,746
Number of Individuals	34,184		26,488	7,696

The table shows the mean value and standard deviation of the main variables in our models: The individual migration indicator; the ethnic networks measure; monthly values of per capita food and non-food consumption, income, and remittances, in 2010 $1,000 Rupiah (consumption is trimmed at the 1st and 99th percentile); several individual characteristics, namely, age, household size, indicator of having a college degree, indicator of urban location, indicator of employment in the agricultural sector, and indicator of informal employment. The table also reports the average of all variables by migration status. *Share migrants-ethnicity is the share of past migrants from the same origin location and ethnicity on the baseline period.

Consumption: Following Meyer and Sullivan (2003), Kleemans (2015) and De Magalhães and Santaeulàlia-Llopis (2018), we use overall, food and non-food consumption as partial measures of welfare. These outcomes are collected at the household level for every survey wave year. We calculate the individual per capita consumption within the household[8]. The average and standard deviations for the food and non-food consumption are reported in Table 1, as well as their averages by migration status. These are our main outcomes.

Table 1 also reports descriptive statistics for our secondary variables. We report total income, which is the per capital household income which includes earnings from formal and informal employment[9]. We also report remittances, which are total transfers from former household members living in other locations. Lastly, we show summary statistics for all demographic variables used in the analysis, namely, age, household size, indicator of having a college degree, indicator of urban location, indicator of employment in the agricultural sector, and indicator of informal employment.

3.2 Weather data and rainfall measures

Precipitation and temperature data are obtained from the Center for Climatic Research of the University of Delaware. We get monthly estimates in grids at a resolution of 0.5 by 0.5 degrees, which is approximately 50 by 50 kilometers at the equator. Instead of using annual data from each calendar year for precipitation, all measures are created from July until June, starting the year before, in order to reflect the growing seasons in Indonesia (Kleemans and Magruder, 2018).

In our main specification, we first calculate the mean rainfall deviations for each year between the survey rounds i.e.

$$\tilde{R}_{kt} = R_{kt} - \bar{R}_{kT}$$

where R_{kt} is the annual precipitation in Kecamatan k and year t and $\bar{R}_{kT}$ is the average annual precipitation between the years 1993 and 2014 in Kecamatan k. We then take the mean of this measures across all years between the survey rounds.

[8]We trim consumption data and drop observations below the 1st percentile and above the 99th percentile.

[9]Despite our main outcome being consumption, we show additional results using income as an outcome.

We then calculate the z-score for $\tilde{R}_{kS}$ using the historical national mean and standard deviation of rainfall. We use this transformation mainly for the ease of interpreting the results.

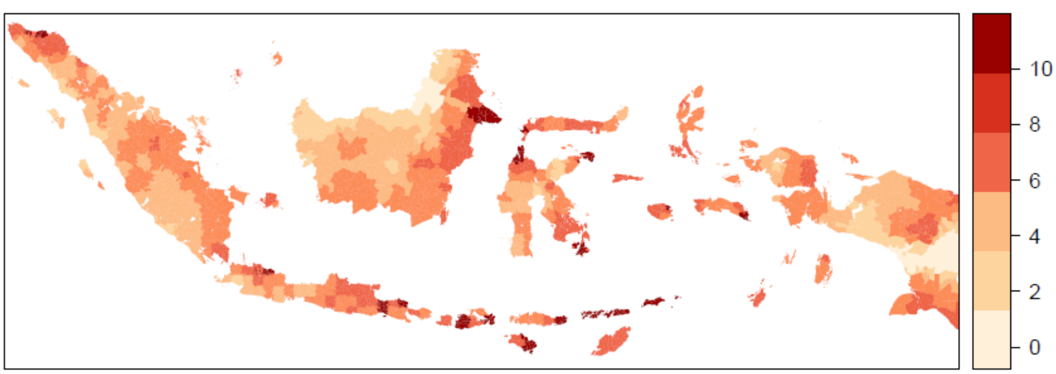
In order to more specifically capture the impacts of droughts, we also estimate our results using as an alternative measure the average number of months a year in which the monthly Kecamatan rainfall was below/above its monthly historical average.

$$MonthsBelow_{kS} = \frac{1}{x}\sum_{t \in S}\sum_{m=1}^{12} 1[R_{kmt} - \bar{R}_{kM} < 0]$$

For instance, $MonthsBelow_{kS}$ for the years between waves 2 and 3 for Kecamatan k will be: $MonthsBelow_{k2000} = \frac{1}{3}\sum_{t=1998}^{t=2000}\sum_{m=1}^{12} 1[R_{kmt} - \bar{R}_{kM} < 0]$. We will refer to this measure as "Months Below" for the remainder of the paper.

Figure 1 shows the geographical variation for one of one of our rainfall measures. It plots the Months Below by Kecamatan, averaged across all our sample years. The map shows significant variation in rainfall patterns across sub-districts. We present histograms for both of the rainfall measures in Figure 3 of Appendix A.

Figure 1: Rainfall



Note: the figure plots the average number of months within a year in which precipitation was below the monthly average ("months below") at the sub-district (Kecamatan) level.

4 Empirical Strategy

We are interested in understanding how migration can contribute to mitigating the negative impacts that negative rainfall shocks have on consumption. If we estimate an OLS regression having consumption as an outcome and migration as one of the explanatory variables, our estimates would likely be biased, since migration is endogenous. One potential source of bias is that individuals with higher income and consumption have more resources to migrate (Kleemans and Magruder, 2018). In order to deal with biases arising from endogeneity and reverse causality, we estimate a 2SLS model using an instrument for migration that is based on the networks of past migrants from the same origin and ethnicity. This instrument is analogous to a shift-share instrument, so we follow the approaches described in Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020).

4.1 Instrumental Variable

Our main empirical test consists of using an instrumental variable for migration, and investigating whether migration out of areas affected by negative rainfall shocks mitigates the consumption shortfalls. We estimate a 2SLS model:

$$Y_{ikt} = \beta_0 \hat{M}_{ikt} + \beta_1 (\widehat{M_{ikt} R_{kt}}) + \alpha_1 R_{kt} + \phi_i + \phi_t + X_{ikt} + \varepsilon_{ikt} \tag{1}$$

Where Y_{ikt} is log of the individual per capita consumption of household i in Kecamatan k and in survey year t[10], R_{kt} measures the rainfall shock, and $\hat{M}_{ikt}$ and $(\widehat{M_{ikt} R_{kt}})$ are predicted values of migration and its interaction with rainfall from the following first stage regressions:

$$M_{ikt} = a_0 M_{ikt} + a_1 (Networks_{ik}\ R_{kt}) + a_2 R_{kt} + \phi_i + \phi_t + X_{ikt} + \varepsilon_{ikt} \tag{2}$$

[10]We choose to do a log transformation of the dependent variables in order to interpret our coefficient in terms of percentage changes in consumption.

$$M_{ik} * R_{kt} = b_0 M_{ikt} + b_1(Networks_{ik}\ R_{kt}) + b_2 R_{kt} + \phi_i + \phi_t + X_{ikt} + \varepsilon_{ikt} \quad (3)$$

We add individual and year FEs, and X_{ikt} are controls for individual age and average temperature at the origin. The instruments are $Networks_{ik}$ and $Networks_{ik}R_{kt}$. $Networks_{ik}$ is share of residents of k belonging to the same ethnicity as i who moved away before the first year we measure location change (the "ethnic networks"). This share is calculated based on the people who lived in the origin location when they were 12 years old and who moved away before 1997.

As discussed in Section 2, the choice of the instrument is based on the importance of social networks for migration decisions, and how in Indonesia those networks are partially form along ethnic lines. Motivated by these findings, and in order to understand how relevant social networks are in our context, in Appendix B.1 we show additional results for how short-run (yearly) migration decisions are affected by rainfall and the presence of ethnic networks. We find that a negative rainfall shock induces out-migration (which is in accordance with previous findings), and that the presence of networks increases the probability of migration even further in the presence of negative rainfall shocks.

Having argued for the relevance of ethnic networks in determining migration patters, the first requirement we have to test for our instrument to be valid is a strong first stage. Table 2 reports our first stage results for each of the rainfall measures. Note that the direct effect of the ethnic network on the first stage outcomes is captured by the individual fixed effects, hence it is omitted in the first stage results.

Table 2: First Stage Results

VARIABLES	(1) Migration x Rain	(2) Migration x Rain
Networks x Rainfall (Zscore)	0.205***	
	(0.0108)	
Networks x Months Below		0.516***
		(0.0685)
Individual FE	✓	✓
Controls	✓	✓
Year FE	✓	✓
F-Stat	356.35	56.77
Observations	95,040	95,040
Number of individuals	32,788	32,788

Note: The table reports the results for the first stage regressions, using each measure of rainfall (zscore of average deviations, and Months Below). The dependent variable is the indicator of whether the individual changed locations since the last survey year times the rainfall measure. I include individual and year FEs, and control for age and temperature. The F-stat reported is the Kleibergen-Paap F statistic of the F test of excluded instruments. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In Table 2 all regressions control for individual and year FEs, and for age and temperature. Columns (1) and (2) report the first stage results using the zscore of rainfall deviations, and the Months Below measure, respectively. The coefficients are positive and significant. We report the F-statistic for the excluded instruments for both measures of rainfall. The F-stats reported are the Kleibergen-Paap F statistic of the F test of excluded instruments (Kleibergen and Paap, 2006). They are are sufficiently high, as indicated, especially in column (1), which shows we have a strong first stage.

The second requirement is that our instruments fulfill the exclusion restriction. Our instrument is composed of a shock variable (the rainfall variable) and an exposure variable that measures the mobility of the individuals (the migration network). It therefore follows the tradition of shift-share or Bartik instruments. Instrument validity therefore relies either on the exogeneity of the exposure variable (Goldsmith-Pinkham et al., 2020) or the randomness of the shock (Borusyak et al., 2022) conditional on household and year fixed effects. We discuss the instrument validity in the following section.

4.2 Instrument Validity

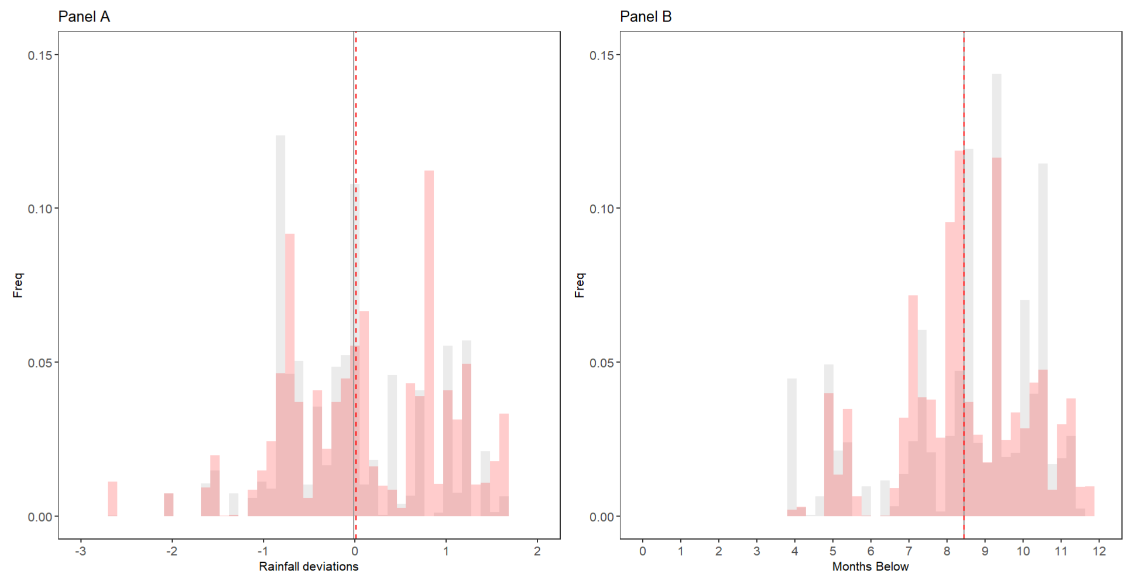
Here, we follow the approach in Borusyak et al. (2022) which allows endogenous exposures (i.e., the ethnic network shares) but requires as-good-as random (rainfall) shocks. This validity argument is based on the idea that the instrument cannot pick up the differential consumption trend if the shock is randomly assigned to individuals with and without migrant networks or similarly if the rainfall shocks do not follow a clear trend.

The reason for focusing on the Borusyak et al. (2022) approach is that migrant networks can be endogenous because: (1) some ethnicities in Indonesia migrate more (Auwalin, 2020), and are better off in terms of consumption, and (2) the distance from the origin location to larger and more developed cities that attract more migrants may be associated with both past migration and can directly affect consumption.

The central assumption that we need for our instrument is therefore that the rainfall shocks are as good as randomly assigned, conditionally on household and year fixed effects, which means they are not related to differential growths in the outcome of individuals with different migration networks.

To test for the validity of our instrument based on the assumptions in Borusyak et al. (2022), we show the distribution of the raw rainfall data for both of our measures in Figure 2, $\tilde{R}Zscore_{kS}$ and $MonthsBelow_{kS}$, in Panels A and B, respectively. We plot the distributions separately for individuals with high (above the median, in grey) and low (below the median, in red) exposure to the ethnic networks share. The figure shows that the distribution and the mean of rainfall shocks are similar for individuals with high and low ethnic networks in the baseline period. This result suggests that the rainfall shock is as good as randomly distributed such that the instrument is uncorrelated with any consumption trend that is correlated with the exposure variable.

Figure 2: Rainfall Distribution by Baseline Migration



Note: The figures plot the distribution of the zscore of rainfall deviations, and the number of months in which the rainfall was below the average (on the left hand and right hand graphs, respectively), that the individuals are exposed to on the baseline period, divided into individuals for whom the share of ethnic networks is below (red) above (grey) the median.

We present additional validity test following Goldsmith-Pinkham et al. (2020), and testing for exogenous exposure of the ethnic networks share. The procedure and results are described in Tables 10 and 11, in Appendix **??**.

5 Results

Tables 3 and 4 report the results of OLS estimates and IV regressions of our baseline model in 1, using $\tilde{R}Zscore$ and $MonthsBelow$ as rainfall measures, respectively.

Table 3: OLS and IV: individual log per capita consumption

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total	Food	Non-food	Total	Food	Non-food
Rain (Zscore) x Change of Residence	0.0297**	0.0248*	0.0560***	-0.157**	-0.217***	-0.220**
	(0.0135)	(0.0136)	(0.0179)	(0.0645)	(0.0655)	(0.0931)
Rain (Zscore)	-0.00373	0.00142	-0.0125	0.0182**	0.0287***	0.0182
	(0.0117)	(0.0112)	(0.0178)	(0.00791)	(0.00804)	(0.0115)
Change of Residence	0.400***	0.396***	0.398***			
	(0.0183)	(0.0171)	(0.0243)			
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	95,040	95,040	95,040	95,040	95,040	95,040
Number of individuals	32,788	32,788	32,788	32,788	32,788	32,788

Note: The table displays the results of OLS and IV regressions of consumption on an interaction between an indicator of individual migration and the the zscore of the accumulated rainfall deviations in the origin location. I include individual and year FEs, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The OLS results in columns (1) to (3) of Table 3 suggest that the change of residence (i.e., migration) increases consumption, but that a positive rainfall shock in the place of origin combined with migration out of that location increases consumption even further. Similarly, for columns (1) to (3) in Table 4 migration out of areas that faced an increase in the number of above the average dry months coupled actually harms consumption even further. However, migration could be endogenously determined by household characteristics, which would lead to biased coefficients. More specifically, individuals with higher consumption are also more likely to migrate, which not only generates a positive bias in the migration coefficient, but also potentially affects the rainfall coefficient and its interactions, as described in Acharya et al. (2016). Using an instrument for migration and estimating the 2SLS model described above allows us to address these concerns.

Columns (4) to (6) of Table 3 show our IV results. Our coefficient of interest (which is the interaction coefficient between $\tilde{R}Zscore_{kS}$ and the indicator for change of residence) in column (4) indicates that a one standard deviation decrease in rainfall leads to a reduction in consumption of about 1.82% for non-migrant individuals, but taht the ability to migrate leads to a increase of about 13.9% in consumption, more than offsetting the negative impact of the rainfall shock. When we look at food and non-food consumption in columns (5) and (6), respectively, the magnitudes are similar, although statistically stronger for food consumption. The interaction coefficient in column (5) suggests that given a one standard deviation reduction in rainfall at the origin, the total food consumption increases by 21.7% if the individual migrated out of that location, which offsets by more than 7 times the direct negative impact of negative rainfall shocks on consumption.

Similarly, the results in column (4) in Table 4 suggest that one month of rainfall below average in the origin location reduces consumption by 2.31%, but if the individual migrates out consumption increases by roughly 5.3%, more than offsetting the negative impact of the rainfall shock. The individual results for food and non-food consumption in columns (4) and (5) suggests that the effect is dominated by food consumption; the interaction coefficient in column (5) shows that given one more month of rainfall below average at the origin, the total food consumption increases by 12.37% if the individual migrated out of that location, which offsets by about 4 times the direct negative impact of dry months on consumption.

The IV results in tables 3 and 4 lead to a similar conclusion, which is that migration helps individuals mitigate the negative impacts that negative rainfall shocks have on consumption, more than offsetting losses in consumption. For the remainder of the main analysis, we will show only the results for the zscore measure of rainfall. We present all of our results using the Months Below measure in the Appendix.

Table 4: OLS and IV: individual log per capita consumption

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total	Food	Non-food	Total	Food	Non-food
Months Below x Change of Residence	-0.0289***	-0.0247***	-0.0418***	0.0759***	0.124***	0.0765*
	(0.00971)	(0.00941)	(0.0125)	(0.0290)	(0.0311)	(0.0416)
Months Below	-0.00246	-0.000959	-0.0102	-0.0231***	-0.0304***	-0.0335***
	(0.00806)	(0.00797)	(0.0122)	(0.00682)	(0.00730)	(0.00993)
Change of Residence	0.603***	0.570***	0.691***			
	(0.0734)	(0.0707)	(0.0947)			
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	95,040	95,040	95,040	95,040	95,040	95,040
Number of individuals	32,788	32,788	32,788	32,788	32,788	32,788

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The table displays the results of OLS and IV regressions of consumption on an interaction between an indicator of individual migration and the number of months in which rainfall was below the historical monthly average in the origin location. I include individual and year FEs, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Our estimation relies on the variation in migration that comes from migrant networks. However, these networks not only affect outcomes directly through supporting migration, but also possibly in an indirect way through sending remittances back to the origin location. To separate both effects, we use the method of Acharya et al. (2016) to disentangle the direct effects of weather induced migration on consumption from the indirect effect of remittances. More specifically, we estimate the average controlled direct effect (ACDE) of precipitation interacted with migration. We do that by first estimating the "demediation function". More specifically, we first estimate 2SLS regressions for consumption, controlling for the transfers from individuals living outside the Kecamatan (i.e., remittances):

$$Y_{ikt} = \beta_0 \hat{M_{ikt}} + \beta_1 (M_{ikt} \hat{*} R_{kt}) + \beta_2 Transfers_{ikt} + \alpha_1 R_{kt} + \phi_i + \phi_t + X_{ikt} + \varepsilon_{ikt} \tag{4}$$

Where $\hat{M_{ikt}}$ and $M_{ikt} \hat{*} R_{kt}$ are predicted values of migration and its interaction with rainfall from first stage regressions similar to 2 and 3, but adding $Transfers_{ikt}$ as control. We then use the predicted value of $\hat{\beta_2}$, and calculate the "demediated" outcome, i.e.: $Y'_{ikt} = Y_{ikt} - \hat{\beta_2} * Transfers_{ikt}$. Y'_{ikt} is the consumption resulting from keeping remittances fixed. We then run equation 1 with Y'_{ikt} as the outcome. The results for food and non-food consumption are reported in columns (1) and (2) of table 5. The estimation gives us the ACDE of our variables of interest on consumption, while maintaining remittances fixed. Note that the coefficients of the interaction terms only change marginally as compared to our baseline results in table 3, and the main conclusions remain the same.

The distance from the origin location to larger and more developed cities that attract more migrants may be associated with both past migration and can directly affect the welfare of those living there, through improved infrastructure, access to services and labor markets, and trade. That might cause a spurious correlation between migration as captured by our ethnic networks measure, and consumption, hence invalidating our instrument. We address this concern by including district FEs in our model. The location FEs will capture time invariant components that associates origin location with potential destinations, like distance and other geographic factors (such as being surrounded by mountainous or rugged terrain, or by water, which affects mobility). The results are reported in columns (3) and (4) of table 5. Again, the sign, magnitude and significance of our estimated interaction coefficient remain similar.

The inclusion of district FEs does not deal with confounding factors that change over time. A related concern is that households close to cities have larger migrant networks and respond differently to weather shocks due to their location. For example, households may move to cities during weather shocks. Although this response is related to migration or individual mobility, it can also be seen as a consequence of the economic opportunities of a location.

Table 5: IV with demediated outcome, adding FEs

VARIABLES	(1) Food	(2) Non-food	(3) Food	(4) Non-food	(5) Food	(6) Non-food
Rain (Zscore) x Change of Residence	-0.212***	-0.218**	-0.208***	-0.218**	-0.208***	-0.128
	(0.0656)	(0.0932)	(0.0658)	(0.0930)	(0.0712)	(0.0997)
Rain (Zscore)	0.0284***	0.0181	0.0289***	0.0193*	-0.000281	-0.0499***
	(0.00805)	(0.0115)	(0.00803)	(0.0115)	(0.0128)	(0.0181)
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓		
District FE			✓	✓		
Prov x Year FE					✓	✓
Observations	95,035	95,040	95,034	95,040	95,035	95,040
Number of individuals	32,787	32,788	32,787	32,788	32,787	32,788

Note: The table displays the results IV regressions of consumption on an interaction between an indicator of individual migration and the zscore of the accumulated rainfall deviations in the origin location. The outcome is adjusted using a demediation function that controls for remittances. I add individual, year, district, and province by year FEs as indicated, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We address this concern by including an interaction between province and year FEs in columns (5) and (6) of table 5[11]. It is worth noting that the inclusion of location by year FEs allows us to more generally account for pull factors that might change the expected net utility of migrating. For instance, the province by year indicators capture some of the regional weather variation at potential destinations that are important determinants of weather induced migration decisions.

Note that the effect of food consumption is still significant and has the same sign and similar magnitude. For non-food consumption the magnitude is lower although the sign remains the same, with a higher standard error. Note also that the coefficient of rainfall takes the opposite sign and is not statistically difference from zero. This is likely because most of the rainfall variation is absorbed by the province by year FEs: rainfall shocks are highly spatially correlated (Hossain and Ahsan, 2018).

[11]We run and report the same specifications as in table 5 using Months Below as the rainfall measure, and report the results on table 12 in Appendix B.3. The conclusions are similar.

Finally, although we argue based on previous literature that consumption better captures individual well-being, we test our main specification using income as an alternative outcome. The results are reported in Table ?? in Appendix B.3. The conclusions for income are similar, which is that negative rainfall shocks reduce income for non-migrants, but that migration more than offsets these damages.

Overall, our IV results suggest that, given a negative rainfall shock at the origin, there is an increase in consumption for individuals who migrated compared to the ones who didn't. The results are more robust for food consumption. This provides strong empirical evidence that migration can mitigate the impacts of negative rainfall shocks on consumption[12].

So far, our analysis has focused on weather shocks. However, we argue that similar results apply to climate change as well. In the next section we build on the approach of Burke and Emerick (2016) to estimate the impact of long term differences in weather (i.e., climate) on migration and consumption.

6 Long differences

Our results so far have shown the effects of short and medium run rainfall shocks on consumption, and how migration can help mitigate those shocks. A more interesting endeavour, however, would be to try to link the evidence we found to climate change. As we know, climate change is related to long-term changes in weather that can cause increases in temperatures, disruptions in rainfall patterns, and extreme weather events (Hsiang and Kopp, 2018). In the long run, individuals can adjust to these changes in ways that are unavailable to them in the short run, so that impacts that are calculated in the short run as a response to weather might be higher than the damages from changes in climate in the long run.

[12]In Appendix B.3 We also run placebo tests with both measures of rainfall, by estimating the reduced form regressions dividing the sample into migrants and non-migrants in Tables 15 and 16.

Here we attempt to shed some light on this issue, and to try to relate our estimates to long-run changes in rainfall patterns that can be a result of climate change. We do that by estimating a long-differences (LD) model similar to Burke and Emerick (2016). With the method, the relationship between climate and migration is estimated from long-term changes in average conditions instead of short-run year-to-year variation. More specifically, we estimate:

$$\Delta Mig_{ikt} = \beta 1_{LD} \Delta Rain_{kt} + \beta 2_{LD} \Delta \text{Temp}_{kt} + \Delta \varepsilon_{ikt} \tag{5}$$

Where $\Delta Mig_{ikt} = Mi\bar{g}_{akt} - Mi\bar{g}_{bkt}$, and $Mi\bar{g}_{akt}$, $j = a, b$ is the average over multi year periods in the beginning and end of the sample years.

Generating unbiased estimates of $\beta 1_{LD}$ requires that changes in rainfall between the two periods are not correlated with time-varying unobservables that also affect migration, conditional on changes in temperature (which is correlated with rainfall and affects migration). Even though we recognize the possibility of there being other potential time-varying confounders, here we simply want to shed some light on the link between migration as a response to weather shocks and migration as a response to climate change. The goal is to compare $\beta 1_{LD}$ with the yearly FE's estimates:

$$Mig_{ikt} = \beta 1_{FE} Rain_{kt} + \beta 2_{FE} \text{Temp}_{kt} + \phi_i + \phi_t + \varepsilon_{ikt} \tag{6}$$

If individuals use alternative forms of adaptation to climate change other than migration, we should expect $\beta 1_{LD}$ to be lower in magnitude than $\beta 1_{FE}$. Following Burke and Emerick (2016), $1 - \beta 1_{LD} / \beta 2_{FE}$ gives the percentage of the negative short-run impact that is offset in the longer run.

Table 6: Long Differences

	Migration		Food consump		Non-food consump	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Short run	Long run	Short run	Long run	Short run	Long run
Precipitation	-0.270**	-0.167**	0.0326***	0.101***	0.0448***	0.0850***
	(0.105)	(0.0829)	(0.0105)	(0.0170)	(0.0171)	(0.0182)
Individual and year FE	✓		✓		✓	
Observations	890,609	30,690	36,691	5,867	36,691	5,867

Note: The table displays the results of fixed effects and long-differences regressions for migration and consumption on rainfall. Columns (1) and (2) show results for migration, and columns (3) and (4), and (5) and (6) for food and non-food consumption, respectively. All short-run regressions account for individual and year FEs. Standard errors are clustered by county and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Column (1) and (2) report the results of equations 6 and 5, respectively. The endpoints average for column (2) are calculated over a period of 3 years. The coefficient in column (2) is smaller in magnitude, suggesting that people are using other forms of adaptation in the long run that are not captured by our short run estimates. These coefficients tell us that $1 - \beta 1_{LD}/\beta 2_{FE} = 38\%$ of short-run migration is offset in the long run[13]. This simple calculation suggests that about 62% of short-run migration as a response to weather shocks still occurs in the long-run as a response to climate change.

The goal here is to show how relevant migration still is in the long run as an adaptation strategy. If we go back to the resulting coefficient in column (4) of Table 3, it tells us that migrants are able to increase their individual consumption by 13.9% given a one standard deviation decrease in rainfall, compared to non-migrants. If we consider that 62% of weather-induced migration still occurs in the long run, the resulting back-of-the-envelope calculation suggests that there is an increase of approximately 0.139*62% = 8.6% in consumption in the long run associated with migration out of areas facing a one standard deviation drop in rainfall.

[13]We also changed the endpoints average to a period of 2 and 4 years, and the general conclusion is people still migrate in response to negative long-run changes in precipitation, but less than in the short-run.

Are accumulate rainfall shocks over the long run still detrimental to consumption? In order to answer this question we will estimate equations 5 and 6 with food and non-food consumption as outcomes. Columns (3) and (4), and (5) and (6) show the results for food and non-food consumption, respectively. The coefficients of the short-run FE estimation in columns (3) and (5) are smaller in magnitude than the LD coefficients in columns (4) and (6), suggesting that positive accumulated rainfall shocks lead to an increase in consumption that is stronger than the short-run rainfall. This is in accordance with the findings in Kleemans (2015), that show that accumulated rainfall shocks increase income and wealth. It also suggests that, despite the existence of more forms of adaptation in the long run (Burke and Emerick, 2016), the exposure to accumulated negative rainfall shocks is even more detrimental to consumption than short to medium run exposure.

7 Conclusion

Our findings suggest that individuals respond to negative rainfall shocks by migrating out of affected areas, and that this response is stronger in the presence of ethnic networks. The presence of social networks of individuals with the same ethnic background at potential destinations increases the expected net benefits of migration, and help individuals cope with rainfall shocks by increasing mobility

Using an instrumental variable for migration which is based on the share of ethnic networks, our main results suggest that individuals use migration to mitigate the impacts of short-run weather changes on consumption, which is a partial measure of welfare. More specifically, our estimates show that a one standard deviation decrease in rainfall leads to a reduction in consumption of about 1.82%, but if the individual migrates out consumption increases by roughly 13.9%, more than offsetting the negative impact of the rainfall shock. To test for the validity of our instrument, we add controls and several fixed effects, and apply the controlled direct effect method to tease out the effects of remittances sent by past migrants. We also apply recent validity test methods for shift-share instruments assuming that the network shares are conditionally exogenous, while taking into account confounding factors. Our 2SLS estimates are robust to these additional tests, especially for food consumption. Further, we apply validity tests that allow for endogenous shares but assume exogenous (rainfall shocks), and show that our rainfall shocks are as good as randomly assigned.

We also run placebo tests to further test for the validity of our instrument, namely, that the effects as estimated by the reduced-form model is only statistically significant for people who migrated at least once during our sample period, and that didn't receive remittances.

Furthermore, we run a long-differences model to link the estimates for short-run responses to weather changes to long-run changes in rainfall patterns due to climate change. We find that more than half of the short-term migration response to rainfall is present in the long-run, which suggests that migration is still an important form of adaptation to climate change. A back of the envelope calculation suggests that migration can lead to an increase in consumption of about 8.6% in the long run, given a one standard deviation drop in yearly precipitation.

Our study highlights the importance of increasing mobility as an effective adaptation strategy to weather and climate damages. That is true especially for developing countries like Indonesia, where a significant part of the population relies on agriculture and hence are more affected by extreme weather events that are becoming more common as a result of climate change. The importance of mobility in these countries is lies on the fact that other forms of adaptation to climate change are less accessible, and mitigation strategies are scarce.

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A Data Appendix

Table 7 shows some descriptive statistics for the yearly data that is used in the short-term migration analysis in Appendix B.1. This data spams over all 21 sample years. This is possible because there is yearly recall data on location and migration decisions. We report the means and standard deviations for the migration indicator, for the ethnic networks measure, and for individual age. The table also reports the mean by migration status. The migration variable here is an indicator of whether the individual moved in that year, and it includes circular and temporary (less than 6 months) migration. We keep only individuals that are born in one of the 13 IFLS provinces, and drop locations with 3 of less respondents in any year. In this sample, there is a total of 64,539 individuals and 18,738 households.

Table 7: Descriptive Statistics (yearly)

				Mean (by status)	
		Mean	**SD**	**Non-migrant**	**Migrant**
Migration		1.58%	0.125		
Share migrants eth		13.90%	0.186	13.37%	16.37%
Age		36.44	18.56	38.08	28.70
Total Households	18,738				
Total individuals	64,539				

The table shows the mean value and standard deviation of the main variables for the short-term analysis: The individual migration indicator and the ethnic networks measure, as as well individual age. The table also reports the average of all variables by migration status.

Table 8 shows the 27 ethnic groups that are recorded in the fourth wave of IFLS (the only wave in which ethnicity is part of the survey questionnaire), and the number of individuals who reported as belonging to each group. Javanese is the dominant ethnicity, representing nearly 45% of individuals in the sample, followed by Sundanese and Sasak, each representing 12% and 5% of the individuals interviewed, respectively.

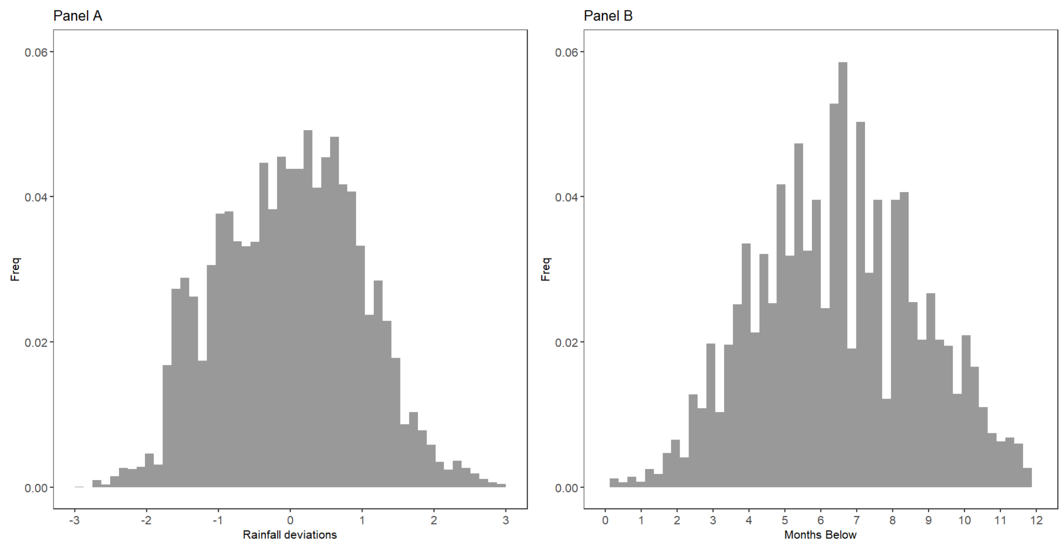
Table 8: Ethnic Groups

Ethnicity	Number of individuals
Javanese	15280
Sundanese	4087
Balinese	1099
Batak	1398
Buglis	1554
Chinese	321
Maduranese	1091
Sasak	1673
Minang	1392
Banjar	1356
Bima-Dompu	251
Makassar	362
Nias	158
Palembang	139
Sumbawa	197
Toraja	319
Betawi	1324
Dayak	21
Melayu	158
Komering	45
Ambon	5
Manado	3
Aceh	12
SumbagSel lain	1405
Banten	102
Cirebon	430
Gorontalo	3

Note: The table reports the number of individuals in the sample who belong to each of the 27 ethnicities recorded in IFLS.

Figure 3 show histograms of both of the rainfall measures used in our analysis. Panel A plots the distribution of the zscore of the average yearly precipitation deviations from the mean, and Panel B plots the average number of months within a year that had a monthly precipitation above the mean.

Figure 3: Rainfall Histograms



Note: Panel A plots the distribution of the zscore of the average yearly precipitation deviations from the mean, and Panel B plots the average number of months within a year that had a monthly precipitation above the mean.

B Additional Results and Robustness Checks

B.1 Migration and rainfall in the short-run

In this section we will look at short term (yearly) impacts of rainfall on migration, and test how ethnic networks impact migration through rainfall shocks.

Firstly, we will start by estimating a simple OLS model to test the effect of rainfall and ethnic networks on migration:

$$M_{ikt} = \alpha_1 ShareEthMig_{ikt-1} * R_{kt} + \alpha_1 R_{kt} + \alpha_2 ShareEthMig_{ikt-1} + X_{ikt} + \phi_i + \phi_t + \varepsilon_{ikt} \quad (7)$$

Where M_{ikt} is an indicator that equals one if the individual i migrated out of Kecamatan k in year t times 100. Here we are testing the short-term (i.e., yearly) effects, so that

t is every year from 1994[14] to 2014. $ShareEthMig_{ikt-1}$ is the share of people from the same ethnicity as i that lived in Kecamatan k when they were 12 years old, and moved away until the year before. R_{kt} is the standardized measure of total yearly precipitation in each sub-district. We add individual and year FEs, and province by year fixed effects in a robustness test. X_{ikt} are controls for individual age and average temperature. Table 9 shows the results. The first three columns don't include the interaction with the ethnic networks measure, so that we are simply testing the impact of rainfall on migration. Columns (1) to (3) show a significant and negative coefficient for the z-score adjusted yearly precipitation at the origin location, suggesting that individuals are more likely to migrate given a negative rainfall shock, which is consistent with previous findings (Bohra-Mishra et al., 2014; Kleemans, 2015; Kleemans and Magruder, 2018).

Column (4) of Table 9 adds lagged measure of ethnic networks and its interaction with rainfall, as in equation 7. The coefficient of the networks measure indicate that individuals are more likely to migrate the higher the share of previous migrants from the same origin location and ethnic group. The coefficient of the interaction term suggests that, given a negative rainfall shock, the presence of networks increase the probability of migration.

[14]Because the first wave the location data is recorded is 1993, 1994 is the first year where migration decisions, including origin and destination locations, are recorded.

Table 9: Rainfall, Networks and Migration

Mean dep. var. = 1.32%	(1)	(2)	(3)	(4)
Rainfall	-0.275***	-0.108**	-0.270**	-0.144
	(0.0586)	(0.0520)	(0.105)	(0.140)
Share Ethnicity t-1				0.677***
				(0.157)
Share Ethnicity t-1 x Rainfall				-0.279**
				(0.139)
Individual FE	✓	✓	✓	✓
Controls		✓	✓	✓
Year FE	✓	✓		
Prov x Year FE			✓	✓
Observations	916,093	890,609	890,609	532,152
R-squared	0.133	0.133	0.135	0.155

Note: The dependent variable is an indicator that equals one if the individual migrated that year times 100. Column (1) - (3) report the coefficients of the standardized measure of total yearly precipitation in the origin sub-district, adding controls (subdistrict's annual average temperature and individual's age) and FEs. Column (4) adds the lagged measure of ethnic networks and its interaction with rainfall. All regressions include individual and year or province by year FEs. Standard errors are clustered by county and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B.2 Additional Instrument Validity

Here we follow Goldsmith-Pinkham et al. (2020) and focus on validity tests assuming exogenous exposure of the ethnic networks share. For that, we explore the relationship between the ethnic networks share at time zero (our instrument) with individual and location characteristics in the same period (i.e., 1993) that may be correlated with changes in consumption and that if omitted from the model. We can think of several factors that might predict how consumption grows over time, namely, individual and family income and education (Krueger and Lindahl, 2001), and factors related to labor market and employment characteristics. For instance, workers employed in the formal sector and in non-agriculture activities may experience a relatively higher growth in income and consumption (Elgin and Birinci, 2016). The relationship between urbanization and income growth is also an important and well studied one (Spence et al., 2008).

If $ShareEthMig_{ik}$ is correlated with those factors, that might indicate that there are omitted variable biases in our 2SLS estimation. In Table 10 we present cross-sectional correlations between our instrument and some individual and location characteristics on the baseline period, namely: the individual's household income and household size, a dummy that equals one if someone in her household has a college degree, an indicator for job informality, for job in agriculture, and for the place of residence being urban. We see a strong correlation for urban status, informal employment and employment in agriculture, and to a lesser degree for household size.

Table 10: Correlations with the instrument

HH income	-1.96e-05
	(2.33e-05)
HH college = 1	0.145
	(1.138)
Urban status	1.749***
	(0.474)
HH size	0.170*
	(0.0896)
Agricultural worker	-2.650***
	(0.500)
Informal worker	-1.029**
	(0.477)
Observations	2,172
R-squared	0.046

Note: The table displays the results of OLS regressions of the ethnic networks measure against the individual's household income and household size, a dummy that equals one if someone in her household has a college degree, an indicator for job informality, for job in agriculture, and for the place of residence being urban. Standard errors are in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We re-run our main specifications including the variables that are correlated with our instrument as controls, and present the results in Table 11[15]. Further, we recognize that those correlations with observable variables might also indicate the importance of un-

[15] The results for the *MonthsBelow* measure are reported in Table 13 of Appendix B.3.

observed confounders. Hence, in columns (1) to (3) of Table 11 we present our most saturated model, which also includes province by year FEs and district FE, in addition to individual and year FEs. The magnitudes of our coefficients of interest remain similar, and the sign doesn't change. Although the standard errors are higher for non-food consumption, the statistical significance remains for food consumption.

Lastly, we recognize that these controls might affect individuals differently depending on the rainfall shocks that they are exposed to throughout the sample years. Hence, in addition to adding the controls, we add an interaction between each of these controls and the rainfall measure in columns (4)-(6) of Table 11. The magnitudes of our coefficient of interest remain very similar. The validity tests and robustness checks presented suggest that our results are robust to different specifications.

Table 11: Robustness checks

VARIABLES	(1) Total	(2) Food	(3) Non-food	(4) Total	(5) Food	(6) Non-food
Rain (Zscore) x Change of Residence	-0.162**	-0.189**	-0.148	-0.152	-0.191*	-0.121
	(0.0788)	(0.0787)	(0.124)	(0.0999)	(0.105)	(0.143)
Rain (Zscore)	-0.0262	-0.00116	-0.0915***	-0.0374	-0.0238	-0.0543
	(0.0175)	(0.0175)	(0.0279)	(0.0264)	(0.0271)	(0.0379)
Individual, District and Prov x Year FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Controls x Rain (Zscore)				✓	✓	✓
Observations	39,608	39,608	39,608	39,608	39,608	39,608
Number of individuals	19,705	19,705	19,705	19,705	19,705	19,705

Note: The table displays the results for IV regressions of food and non-food consumption on an interaction between an indicator of individual migration and the rainfall deviations. I add individual, district, and province by year FEs. In the first three columns I control for age, temperature, urban status, informal employment and employment in agriculture, and household size. In the last three columns I controls for the interaction between these covariates and our rainfall measure. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B.3 Additional Robustness Checks

Next, we re-run our specifications using the Months Below measure. Table 12 reports the second stage results using the using the "demediated" consumption measures as outcomes, following Acharya et al. (2016). Similarly to Table 5, I add district FEs in columns (3) and (4), and province by year FEs in columns (5) and (6). The results lead to similar conclusions as in Table 5. More specifically, it indicates that one month of rainfall below average in the origin location reduces food consumption by 3-5.5%, but if the individual migrates out consumption increases by roughly 7.8-9.1%, more than offsetting the negative impact of the rainfall shock.

Table 12: IV with demediated outcome, adding FEs

VARIABLES	(1) Food	(2) Non-food	(3) Food	(4) Non-food	(5) Food	(6) Non-food
Months Below x Change of Residence	0.122***	0.0761*	0.121***	0.0739*	0.132***	0.0315
	(0.0313)	(0.0418)	(0.0312)	(0.0416)	(0.0394)	(0.0500)
Months Below	-0.0304***	-0.0335***	-0.0319***	-0.0368***	-0.0542***	-0.0424**
	(0.00731)	(0.00993)	(0.00707)	(0.00960)	(0.0135)	(0.0174)
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓		
District FE			✓	✓		
Prov x Year FE					✓	✓
Observations	95,035	95,040	95,034	95,040	95,035	95,040
Number of individuals	32,787	32,788	32,787	32,788	32,787	32,788

Note: The table displays the results for IV regressions of consumption on an interaction between an indicator of individual migration and the number of months in which rainfall was below the historical monthly average in the origin location. The outcome is adjusted using a demediation function that controls for remittances. I add individual, year, district, and province by year FEs as indicated, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13 reports the second stage results using the Months Below measure, and including urban status, informal employment and employment in agriculture, and household size as controls. Similarly to Table 11, the results in the first three columns include these covariates, and in the last three columns it add its interactions with *MonthsBelow*. The magnitudes of our coefficients of interest remain similar, and the signs do not change. The coefficient of interaction is even higher in magnitude for food consumption, as compared to Table 12.

Table 13: Robustness checks

VARIABLES	(1) Total	(2) Food	(3) Non-food	(4) Total	(5) Food	(6) Non-food
Months Below x Change of Residence	0.0832*	0.128**	0.0583	0.117**	0.163***	0.0800
	(0.0465)	(0.0519)	(0.0728)	(0.0483)	(0.0556)	(0.0664)
Months Below	-0.0606***	-0.0751***	-0.0616**	-0.0800***	-0.0948***	-0.0841***
	(0.0189)	(0.0211)	(0.0296)	(0.0228)	(0.0260)	(0.0315)
Individual, District and Prov x Year FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Controls x Rain (Zscore)				✓	✓	✓
Observations	39,608	39,608	39,608	39,608	39,608	39,608
Number of individuals	19,705	19,705	19,705	19,705	19,705	19,705

Note: The table displays the results for IV regressions of consumption on an interaction between an indicator of individual migration and the number of months in which rainfall was below the historical monthly average in the origin location. I add individual, district, and province by year FEs. In the first three columns I control for age, temperature, urban status, informal employment and employment in agriculture, and household size. In the last three columns I controls for the interaction between these covariates and our rainfall measure. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14 reports the IV results using income as an outcome. Columns (1) and (2) use the zscore of rainfall deviations, and the months below measures for rainfall, respectively. The coefficients tell us that a one standard deviation decrease in rainfall (one more month below the rainfall average) leads to a decrease in income of about 5.9% (2.8%) for non-migrants, but if the individual migrates out income increases by 39% (9.8%), again more than offsetting the negative impact of the rainfall shock.

Table 14: IV with income as an outcome

VARIABLES	(1) Log Income	(2) Log Income
Rain (Zscore) x Change of Residence	-0.393***	
	(0.110)	
Rain (Zscore)	0.0587***	
	(0.0125)	
Months Below x Change of Residence		0.0976**
		(0.0485)
Months Below		-0.0282**
		(0.0115)
Individual FE	✓	✓
Year FE	✓	✓
Observations	76,514	76,514
Number of individuals	30,559	30,559

Note: The table displays the results IV regressions of income on an interaction between an indicator of individual migration and (1) the accumulated rainfall deviations in the origin location; and (2) the number of months in which rainfall was below the historical monthly average in the origin location. The outcome is adjusted using a demediation function that controls for remittances. I include individual and year FEs, and control for age and temperature. Standard errors are clustered by county and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Lastly, we estimate the results of the reduced form regressions separately for: (a) individuals who moved at least once during our sample period and did not receive any remittances, and (b) individuals who never moved and received a positive amount of remittances. The results are reported in Tables 15 and 16. These results indicate that negative rainfall shocks lead to a reduction in consumption, but less so the higher the share of ethnic social networks outside the origin, and only for (a). This provides further evidence that the effects captured by our 2SLS are indeed a result of migration, and not of some of the confounding factors mentioned.

Table 15: Reduced form: movers and recipients of transfers

	Movers			Non-movers		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total	Food	Non-food	Total	Food	Non-food
Rain (Zscore) x Networks	-0.119**	-0.132**	-0.121**	0.0824	0.0832	0.0204
	(0.0504)	(0.0562)	(0.0482)	(0.226)	(0.233)	(0.288)
Rain (Zscore)	0.0204	0.0281	0.0242	-0.0374	-0.0395	-0.0163
	(0.0199)	(0.0203)	(0.0270)	(0.0587)	(0.0608)	(0.0817)
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	19,026	19,026	19,026	11,470	11,470	11,470
Number of individuals	7,616	7,616	7,616	10,802	10,802	10,802
R-squared	0.199	0.117	0.273	0.206	0.111	0.339

Note: The table displays the results of reduced-form regressions of consumption on an interaction between the zscore of the accumulated rainfall deviations in the origin location, and a fixed share of migrants from the same ethnicity who moved away from that location. Columns (1)-(3) report the results for individuals who moved at least once and didn't receive remittances, and columns (4)-(6) for individuals who never moved and received remittances. I include individual and year FEs, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16: Reduced form: movers and recipients of transfers

	Movers			Non-movers		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total	Food	Non-food	Total	Food	Non-food
Months Below x Networks	0.0959***	0.133***	0.0468	0.198	0.142	0.415
	(0.0342)	(0.0372)	(0.0352)	(0.185)	(0.182)	(0.252)
Months Below	-0.0175	-0.0210*	-0.0261*	0.0185	0.0334	-0.0705
	(0.0111)	(0.0110)	(0.0155)	(0.0429)	(0.0416)	(0.0658)
Individual FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	19,026	19,026	19,026	11,470	11,470	11,470
Number of individuals	7,616	7,616	7,616	10,802	10,802	10,802
R-squared	0.199	0.118	0.273	0.209	0.113	0.343

Note: The table displays the results of reduced-form regressions of consumption on an interaction between the number of months in which rainfall was below the historical monthly average in the origin location, and a fixed share of migrants from the same ethnicity who moved away from that location. Columns (1)-(3) report the results for individuals who moved at least once and didn't receive remittances, and columns (4)-(6) for individuals who never moved and received remittances. I include individual and year FEs, and control for age and temperature. Standard errors are clustered by individual and in parenthesis, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.