Access to Financial Resources and Environmental Migration of the Poor*

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(work in progress)

Abstract

Despite an increasing number of studies, there is no scientific consensus on extent and conditions under which environmental factors influence migration. In particular, little is known about the role played by financial resources that may facilitate or hinder migration under environmental stress. It has been documented empirically that some households are found to migrate in response to environmental hazards, others remain in place, potentially being trapped due to lack of resources, the so called poverty constraints. However, little is known about how the access to financial resources influences the decision of a household to stay or migrate. On one hand, financial resources can help to alleviate poverty constrains, cover migration costs and thus increase migration (climate-driver mechanism), on the other hand the financial means can also improve the adaptation capacities of households at the place they reside, and thus reduce the migration responses to environmental changes (climate-inhibitor mechanism). In our paper, we utilize rich micro-data from Indonesia and exploit two sources of variation in climate and in cash transfers, to shed some light on households' migration decisions in response to climate shocks depending on their access to financial resources. Our results suggest that better access to financial resources facilitates climate-inhibitor mechanism for short-term rainfall shocks and natural disasters. At the same time, better accessibility of financial resources enhances climate-driver mechanism for accumulated rainfall shocks and temperature anomalies.

Keywords: Climate Change, Migration, Financial Resources, Adaptation

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1 Introduction

Anthropogenic influence on climate is resulting in the increase in average temperature and changes in precipitation patterns, rising sea levels and more frequent extreme weather events, such as droughts, heatwaves, and floods (IPCC, 2013; Jones and O'Neill, 2016). These trends will affect all countries; however, the impact of these changes will be felt more strongly by less developed ones (IPCC, 2014). Deterioration and hazardous environmental conditions are expected to lead to an increase in migration flows from affected areas. Since the 1980s, scholars and international organizations have predicted that environmental change will lead to a substantial increase in migration flows worldwide, with predictions ranging from 50 to 200 million additional climate migrants per year (Myers, 2002; Renaud et al., 2007; Stern, 2007; Biermann and Boas, 2010).

Despite an increasing number of studies, as of now, no scientific consensus exists as to what extent and under which conditions environmental factors influence migration. In particular, little is known about the role resources play in enabling or hindering mobility under environmental stress. While some households are found to migrate in response to environmental hazards, others remain in place, potentially being trapped due to lacking resources and liquidity constraints (Black et al., 2013; Zickgraf and Perrin, 2016). While this pattern has been observed in previous work, little is known empirically about how access to resources influences the decision of a household to stay or leave. Theoretically, additional resources can both increase or reduce environmental migration as they support *in-situ* adaptation. Likewise, the loss of resources due to an environmental shock can both trigger migration (climate driver mechanism) and reduce out-migration (climate inhibitor mechanism).

The proposed project investigates household migration behavior as a response to climatic shocks conditional on different possibilities to access financial resources. A particular focus will be placed on the situation of resource-constrained poor households. The project uses data from the Indonesian Family Life Survey (IFLS), which is an on-going longitudinal survey. The sample is representative of about 83 % of the Indonesian population and contains over 30,000 individuals living in 13 of the 26 provinces in the country. The survey contains detailed information about the migration history of individual household members. Additionally, due to the longitudinal panel nature of the data, it allows tracing back the migration of entire households, allowing us to estimate the impact of environmental conditions on mobility outcomes effectively. As a country particularly affected by environmental changes and rapid onset disasters, Indonesia offers interesting case to study the moderating effect of resources on environmental migration.

To identify the impact of slow and fast-onset environmental events on migration processes, we combine the IFLS data with additional secondary data sources. First, we use publicly available weather data from the Climate Research Unit (CRU) of the University of East Anglia to estimate the impact of changing environmental conditions on migration. In addition, we use the information on natural disasters from IFLS to look into fast onset events as well. To test for the moderating role of resources in influencing migration outcomes due to environmental stress, we make use of several cash transfer programs that was implemented in Indonesia starting from 2005. We look into three government programs that were aimed for poor households in Indonesia: two unconditional cash transfer programs and one conditional cash transfer program. We exploit temporal variation in the reception of unconditional cash transfer as well as temporal and spatial variation from the conditional cash transfer program. We make use of this variation and the longitudinal data of the IFLS to estimate the moderating impact of resource access on environmental migration.

Our results demonstrate heterogeneous responses to different kinds of climate shocks and the differential role of cash transfer in adaptation. We find that households, which received cash transfers, migrate less in response to current-year rainfall shocks. However, being exposed to rainfall shocks for several years, they change their behavior and utilize the money to move out of affected areas. Temperature shocks turned out to be significantly detrimental to migration decisions, which might be explained by the liquidity traps. The effect of the cash transfers (although non-significantly) supports this theory – we find that households who get financial support from the government migrate more after temperature anomalies than those who do not. Another finding suggests that households affected by natural disasters such as floods, landslides, and droughts tend to migrate less if they receive cash transfers, which is consistent with evidence that we find for short-term rainfall shocks. Our last finding suggests that members of the household that received cash transfers are less likely to change jobs into the risky agricultural sector; and more likely to leave occupation in the agricultural sector as a response to rainfall and temperature shocks.

This research may contribute to a better understanding of the adaptation to climate shock in particular in the form of migration, depending on having access to financial resources. From the policy perspective, the proposed study might shed some light on how the choice of adaptation mechanisms of poor households changes conditional on having additional financial resources.

The rest of this paper is organized as follows. Section 2 gives an overview of the related literature. Section 3 describes the setting and the data. Section 4 presents our proposed identification strategy. Section 5 presents our Results, Section 6 is dedicated to the Robustness Checks for our main results. Finally, Section 7 concludes.

2 Literature Review

There are two strands of the literature on which we are building. The first strand of the literature considers the influence of climate shocks on the migration. This field of research is developing rapidly; however, there are still questions that were not addressed by existing studies. The proposed project addresses one of them: how households decide whether to migrate as a response to climate shock depending on their access to resources. The second strand of the literature investigates how access to resources influences the household's decision to migrate. We give an overview of several studies in this field. Although the findings of the papers differ, there is evidence that the accessibility of financial resources can be a significant factor for the migration decision. This section firstly introduces literature on climate-migration nexus, then literature on the influence of access to financial resources on migration.

There is a growing body of literature that investigates the influence of climate shocks on migration. Part of this literature looks into the link between fast-onset events such as floods, landslides, earthquakes, hurricanes on migration flows. In most cases, studies find that migration after fast-onset events is over short distances and temporary (Cattaneo et al., 2019). Halliday (2006) exploits earthquakes in El Salvador as an exogenous shock for households and finds that migration to the United States increased at all wealth levels. However, the author finds that wealthier households tend to migrate more since they are less liquidity constrained. Saldana-Zorrilla and Sandberg (2009), using municipality-level data in Mexico, demonstrate that municipalities that experienced disasters (droughts, floods, hurricanes) more often exhibit higher migration rates in the period 1990-2000. Carvajal and Pereira (2010) uses panel data of households in Nicaragua to study how people adapt to natural hazards. The study shows that hurricane Mitch that hit Nicaragua in 1998 induced affected households to migrate more than those who were unaffected.

Another part of the literature covers the link between the slow-onset events such as the rise of the temperature, change of rain patterns, droughts on migration. Here the most relevant study for us is the paper by Thiede and Gray (2017). This study shows how migration in Indonesia is influenced by climate shocks in particular by rising temperature and monsoon delay. The authors find that increasing temperatures decrease the out-migration from affected areas, while monsoon delay does the opposite. Their results vary significantly for different groups of people depending on gender, age and other characteristics, which imply heterogeneous use of migration as adaptation strategy. Dillon, Mueller and Salau (2011) use panel data of Nigerian households to investigate how households respond to variability in the temperature and the days suitable for growing crops. The study shows that males decide to migrate as a response to ex-ante and ex-post risk. Mueller, Gray and Kosec (2014) study the effect of heat stress on the rural migration in Pakistan. The authors find that heat consistently increases the migration of men due to its adverse effects on farm and non-farm income.

Cattaneo and Peri (2016) conduct a cross-country study to demonstrate that an increase in the temperature decreases the migration flow from the poor countries consistent with the hypothesis of the presence of liquidity constraints. Nawrotzki and Bakhtsiyarava (2017) use census and climate data for Senegal and Burkina Faso to understand whether the population adapts to climate shocks *in situ* or decide to migrate. They show that excessive precipitation increases international out-migration from Senegal while increasing temperature decreases migration out-flow from Burkina Faso. The authors conclude that adverse climate shocks can lead to trapping of the poor population and undermine their ability to migrate. Groschl and Steinwachs (2017) show in a cross-country study that droughts increase migration for middle-income countries consistent with the presence of liquidity constraints for migration in poor countries. Rich countries do not exhibit increased out-migration due to developed insurance schemes.

There is also a vast literature that considers a link between access to financial resources and migration. Stecklov et al. (2005) use data from the conditional cash transfer program Progresa/Oportunidades in Mexico to study its effect on the internal and external out-migration. The authors exploit the random program assignment to the treatment and control communities during a pilot phase. The results of the paper demonstrate that conditional cash transfers reduce out-migration to the United States but do not change internal migration patterns. Angelucci (2015) also uses data on the same conditional cash transfers program to study labor migration to the United States. In contrast with the paper by Stecklov et al. (2005) the author finds that better access to financial resources for poor households in Mexico increases labor migration to the United States. Specifically, conditional cash transfers allow less skilled migrants to move to the United States. The results of the two papers seem to be opposite; however, the studies focus on two different types of migration – overall and labor migration.

Bryan, Chowdhury, and Mobarak (2014) develop a model with risky migration and test it using data from a randomized trial. The authors randomly assign an $8.50 incentive to households in rural Bangladesh to temporarily out-migrate to the urban areas during the lean season. The study shows that financial incentives induce more people to migrate and increases their consumption. In this case, access to financial resources can work as a complement to migration because without it households were liquidity constrained or too risk-averse.

Poggi (2019) uses a quasi-random experiment in Thailand to study credit availability and internal migration. The author studies the effect of the Thailand Village and Urban Community Fund Program (VFP). In 2001, the Thai government introduced this micro-finance initiative, which distributed to each village one million Baht or US $24,000 in 2001 prices. A group of village members provided short-term credit to fellow villagers. The exploited variation comes from the equal amount of money that all of the villages got despite their size. Employing an instrumental variables approach, the author finds that borrowing reduces internal migration in the medium-term, but it does not affect migration when the policy is first introduced.

The reviewed studies demonstrate evidence supporting two different theories. The studies by Stecklov et al. (2005), Poggi (2019) support the theory that better access to financial resources improves living conditions on the place, making it less profitable to out-migrate. As a result, they observe decreasing migration flows. The studies by Angelucci (2015), Bryan, Chowdhury, and Mobarak (2014) support another view that better access to financial resources induces out-migration due to relaxing the liquidity constraints of the population. In our study, we will test similar theories in a slightly different framework that would also incorporate climate shocks. We attempt to understand whether better access to financial resources induce people to migrate after the climate shock (climate driver mechanism), or it results in the household decision to adapt to climate shock on the spot due to better adaptation capacity (climate inhibitor mechanism).

The studies by Halliday (2006), Nawrotzki and Bakhtsiyarava (2017), Cattaneo and Peri (2016), Groschl and Steinwachs (2017) elaborate on the climate inhibitor mechanism and liquidity constraints that poor countries or poor households face after the adverse climate shocks, thus making people unable to migrate. However, their findings are based on the comparison between rich and poor and do not reveal how poor households respond to climate shocks when they get better access to financial resources. Our proposed study may contribute to the literature by filling this gap. We will use the cash transfer programs in Indonesia as the case of better access to financial resources similar to Stecklov et al.

(2005), Angelucci (2015) papers.

3 Data

Climate change is already being felt in Indonesia today with more frequent droughts, heatwaves, and floods occurring in the country. These shocks will pose an increasing threat to the country's development (Climate Change Profile: Indonesia, 2018). The World Bank has ranked Indonesia 12th among 35 countries that face high mortality risks due to multiple hazards such as increasing temperature, changing rainfall patterns, and, more importantly, exposure to various natural disasters. Considering the high exposure of the country to environmental hazards, it offers a well-suited setting for our analysis.
Our choice of Indonesia is also based on the presence of the country's governmental cash transfer programs: Bantuan Langsung Tunai (BLT), Program Keluarga Harapan (PKH), and Bantuan Langsung Sementara Masyarakat (BLSM) conducted by the government of Indonesia. In our research, the reception of cash transfer serves as a case of better access to financial resources for poor households. The goal of two unconditional cash transfer programs was to supplement consumption of the poor population by providing them with some external finances. Although there is no spatial variation in getting these transfers there are temporal differences: we observe in the data that different households received the transfers in different years in small window. The goal of the PKH is the alleviation of poverty by providing families with children with financial resources if they fulfill basic obligations by utilizing health and education services. The useful (for our research design) features of this particular conditional cash transfer program is the gradual introduction of the program to other provinces. PKH first started with pilot-program and only after that gradually started to expand over the country, which creates for us time ans spatial variation in the access to this program. Seven provinces that participated in the pilot program are West Java, East Java, West Sumatra, North Sulawesi, Gorontalo, East Nusa Tenggara, and DKI Jakarta. Those provinces were chosen to represent various types of areas that are present in Indonesia (World Bank, 2012).

We concentrate on the population that is consistently staying poor in our studied period to have a best possible treatment and control groups. Thus, we focus on the households with similar characteristics that are eligible for the receiving of cash transfer programs. This paper is going to utilize variation in getting the cash transfers to understand how better access to financial resources influences the adaptation of the households to climate shocks; more specifically, we suggest investigating migration as an adaptation strategy.

To conduct the analysis, we are using data from several sources. The first source is the Indonesian Family Life Survey (IFLS), an on-going longitudinal survey in Indonesia. IFLS is representative of about 83% of the Indonesian population (Strauss, Witoelar, and Bondan, 2007) and has 5 waves: IFLS1 in 1993-1994, IFLS2 in 1997-1998, IFLS3 in 2000, IFLS4 in 2007-2008 and IFLS5 in 2014-2015. Since the PKH was introduced in 2007, the last three waves of the IFLS are appropriate sources of the information for the analysis. IFLS data is especially suitable for studying migration due to the high effort to track the respondents over time, which leads to low rates of attrition. This data set records all the moves longer than 6 months by people older than 12. In addition to detailed information about migration, IFLS also has data on socio-economic, demographic characteristics of the households and individuals.

The sources that provide data about weather characteristics are abundant. They include dataset produced by the Climatic Research Unit at the University of East Anglia, weather data obtained from the Center for Climatic Research at the University of Delaware, NASA MERRA-2 among others. All of the above datasets provide information about precipitation and temperature on the grids of 0.5 by 0.5 degrees, which corresponds to about 50 by 50 kilometers in Indonesia. We use weather data obtained from the Center for Climatic Research at the University of Delaware in particular the data about changes in temperature and precipitation that we used to investigate the effect of the slow-onset events on the migration.

For the natural disasters we used the data from IFLS, since this survey also has information about natural disasters happening in different parts of Indonesia. This data turned out to be more precise for our purposes rather than our initial choice, EM-DAT. Data from the International Disaster Database EM-DAT record natural disasters and can be used to study the effect of the fast-onset events. EM-DAT contains data on the occurrence and effects of mass disasters in the world from 1900 until today.

After combining the data about precipitation and temperature with different books from IFLS we had the household-year panel dataset, that contains information about poor households in Indonesia with several socio-economic characteristics as well as the history of weather and natural disasters that they experienced each year. Here are summary statistics of our panel data set.

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Migration	0.08	0.26	0.00	1.00	17,546
1 Person Migration	0.05	0.23	0.00	1.00	17,546
Family Migration	0.03	0.17	0.00	1.00	17,546
Cash Transfer	0.16	0.36	0.00	1.00	17,546
Temperature Shock	0.15	0.36	0.00	1.00	17,546
Rainfall Shock	0.08	0.27	0.00	1.00	17,542
Flood	0.03	0.18	0.00	1.00	17,546
Landslide	0.01	0.10	0.00	1.00	17,546
Tsunami	0.00	0.01	0.00	1.00	17,546
Drought	0.02	0.13	0.00	1.00	17,546
Assests	2.00	0.93	1.00	4.00	17,544
Urban	0.33	0.47	0.00	1.00	17,546
Household's Size	4.88	2.47	1.00	16.00	17,536
Female household head	0.13	0.34	0.00	1.00	17,354
Share of children	0.35	0.23	0.00	1.00	17,534
Share of females	0.53	0.20	0.13	1.00	17,411
Share of mobile	0.37	0.16	0.08	1.00	15,814
Muslim	0.85	0.35	0.00	1.00	17,534

4 Identification Strategy

We use the status of receiving the cash transfer in particular year as a variation in the access to resources. Since we have two sources of variation in cash transfers and in climate, we propose to use following approach:

$$M_{ist} = \alpha_1 + \alpha_2 * X_{ist} + \mu_t + \mu_i + \mu_s$$

$$+\beta_1 * ClimateShock_{ist}$$

$$+\beta_2 * CashTransfer_{ist}$$

$$+\beta_3 * (CashTransfer_{ist} * ClimateShock_{ist}) + \epsilon_{ist}$$

where i indexes households, s indexes sub-districts, and t indexes time.

X_{ist} is a vector of the control variables of the household, μ_t and μ_s,μ_i are time, sub-district, and household fixed effects. The outcome variable M_{ist} is the migratory decision of the household - dummy variable that equals one if a household sends migrant and zero if not. The variable $CashTransfer_{ist}$ is a dummy variable, which equals to 1 if the household has cash transfer in this year, 0 if not. The variable $Climate_{ist}$ can be discrete (1 if household hit by climate shock, 0 if not) or continuous (deviation from the historical mean in precipitation/temperature).

We are interested in the coefficient before the interaction term. The obtained coefficient will measure variation in migration for the cash transfer group relative to the non-cash transfer group for households that were strongly hit by climate shock, relative to those that were hit less, between the before and after period.

Changing rainfall patterns demonstrate more variability in Indonesia than variation in the temperature which is visible on the Figure 1 and Figure 2, with larger variation in the rainfall than temperature. As a result, floods and landslides are one of the most frequent disastrous events that happen in Indonesia, both of them facilitated by the heavy rains. Because of that we concentrate on the rainfall variation more but we also explore temperature variation as well as natural disasters such as floods, landslides and droughts. Thus, we try to explore two types of climate shocks slow-onset events (temperature and precipitation anomalies) and fast onset events (natural disasters).

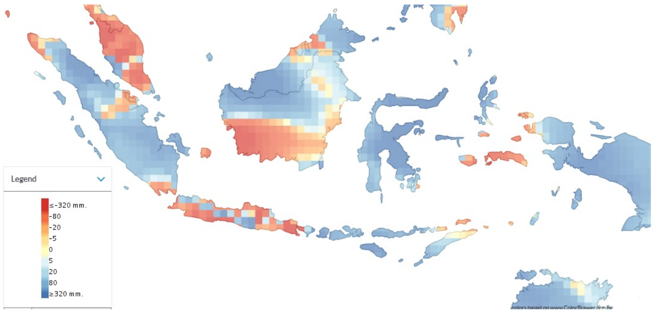

Figure 1: Trends in Rainfall, 1901-2012

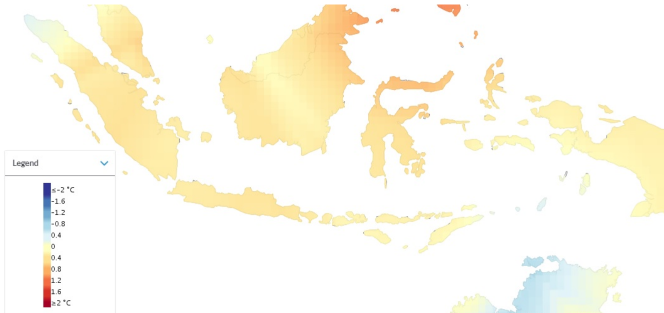

Figure 2: Trends in Temperature, 1901-2012

Notes: Figure 1 present areas in Indonesia with less rain than historical mean(red) and with more rain than historical mean (blue). Figure 2 does the same for the temperature trends - higher temperatures (red) and lower (blue).
Source: Climatic Research Unit at the University of East Anglia

For a sub-district s in year t, we define its own rainfall anomaly as:

$$RA_{st} = \frac{Rainfall_{st} - \overline{Rainfall_s}}{SD_s} \tag{1}$$

where s indexes sub-districts, and t indexes time. We say that the household is hit by the shock if it leaves in the sub-district where in year t $|RA_{st}| > 2$. Thus, if we observe in the data that subdistrict s experienced rainfall anomaly in year t that was highly drastic, we designate rainfall shock to that district. Figure 3 demonstrates distribution of rainfall anomalies by their magnitude.

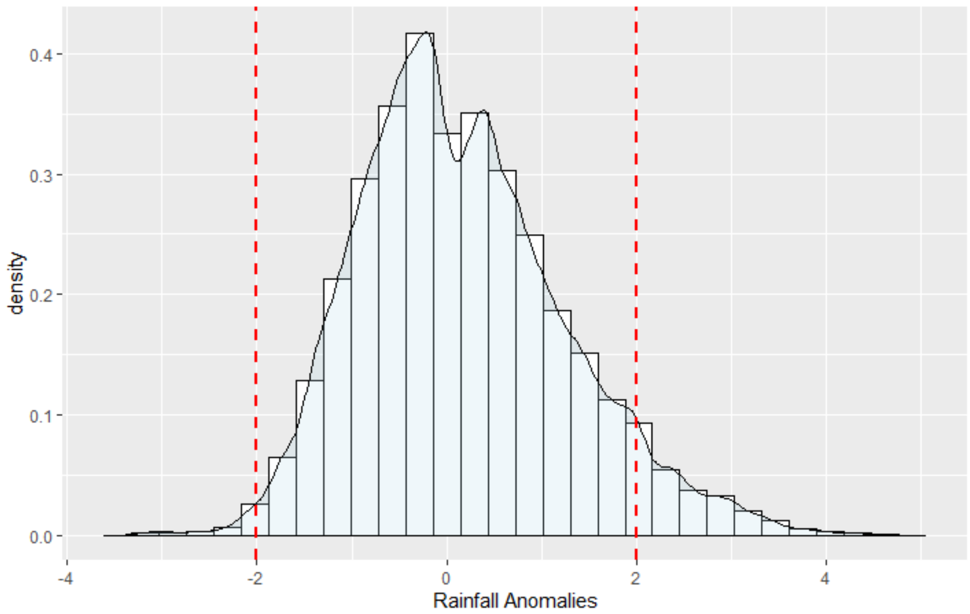

Figure 3: Rainfall Anomalies Distribution

Notes: Figure 3 presents a histogram of rainfall anomalies in the studied period. Red lines are thresholds for creating rainfall shocks variable; if the value of rainfall anomaly lies beyond red line, we consider this a rainfall shock.
Source: Authors' calculation based on the data from Climatic Research Unit at the University of East Anglia

Figure 4 demonstrates the rainfall anomalies in Indonesia in different years. As we can see there is no clear pattern in the rainfall anomalies area-wise, which supports the identification strategy that we building on - the unexpected deviations from normal historical amount of rain for certain areas.

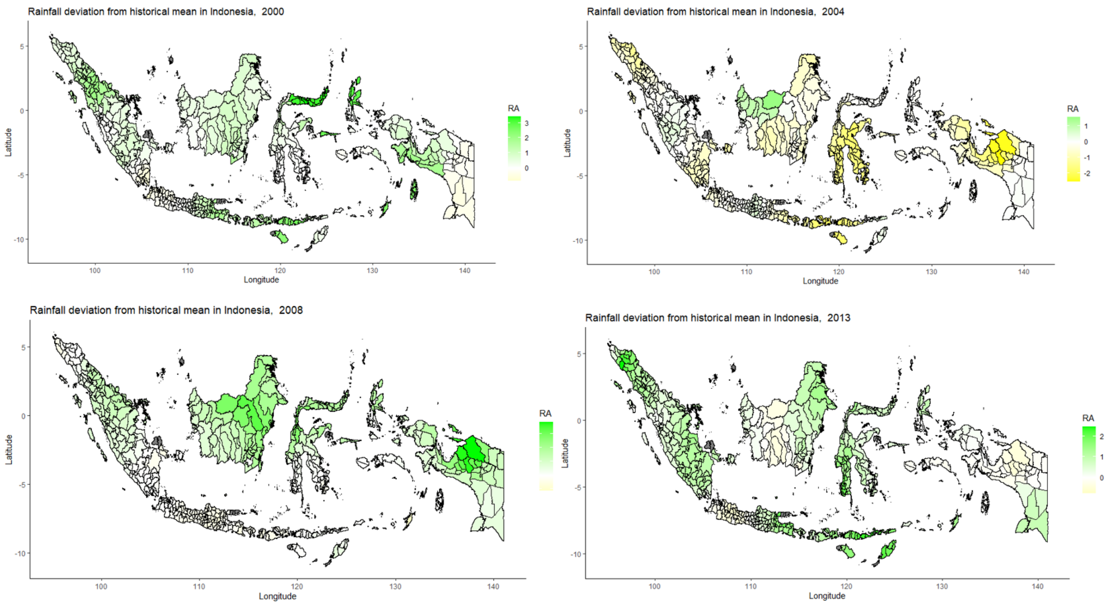

Figure 4: Rainfall Anomalies in Indonesia

Notes: Figure 4 presents maps of rainfall anomalies in different years. Green color means higher than historical mean amount of rain, yellow - lower
Source: Authors' calculation based on the data from Climatic Research Unit at the University of East Anglia

For a sub-district s in year t, we define its own temperature anomaly as:

$$TA_{st} = \frac{Temperature_{st} - \overline{Temperature_s}}{SD_s}$$

where s indexes sub-districts, and t indexes time.

As we can see in Figure 5, the distribution of temperature anomalies in Indonesia is not centered around 0. Unlike rainfall, temperature in the studied period was much more higher than historical means. Following the literature, we define that the household is hit by the shock if it leaves in the sub-district where in year t $TA_{st} > 2$ and $TA_{st} < 0.4$. Second cut-off was chosen to contain the same percentage of negative shocks as positive ones. In the same manner as for the rainfall shocks we designate temperature shock to the district if it experienced drastic deviation from historical mean temperature.

As Figure 6 demonstrates, temperature in Indonesian districts also demonstrates variability throughout the years, although somewhat less than precipitation. To make sure that migration is not dictated by anticipation of the shocks rather than shocks themselves,

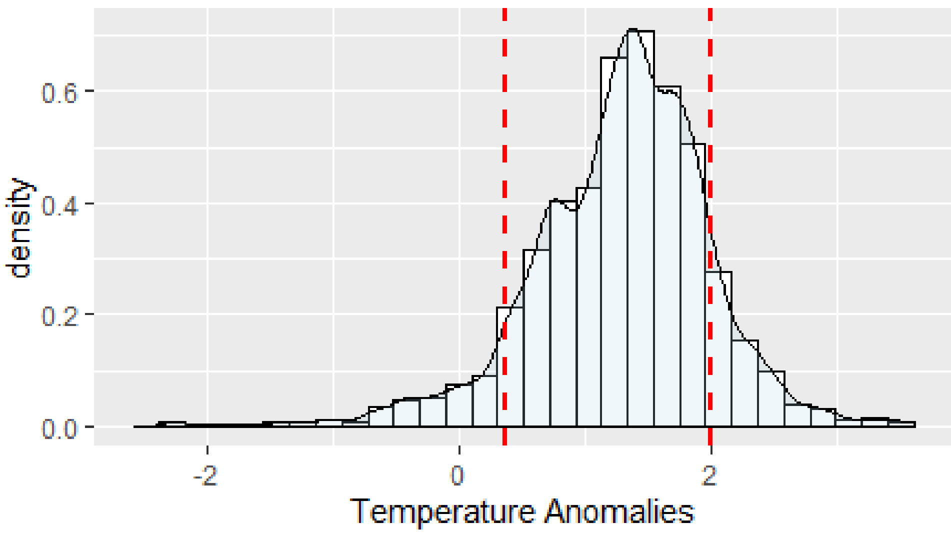

Figure 5: Temperature Anomalies Distribution

Notes: Figure 5 presents a histogram of temperature anomalies in the studied period. Red lines are thresholds for creating temperature shocks variable; if the value of temperature anomaly lies beyond red line, we consider this a temperature shock.
Source: Authors' calculation based on the data from Climatic Research Unit at the University of East Anglia

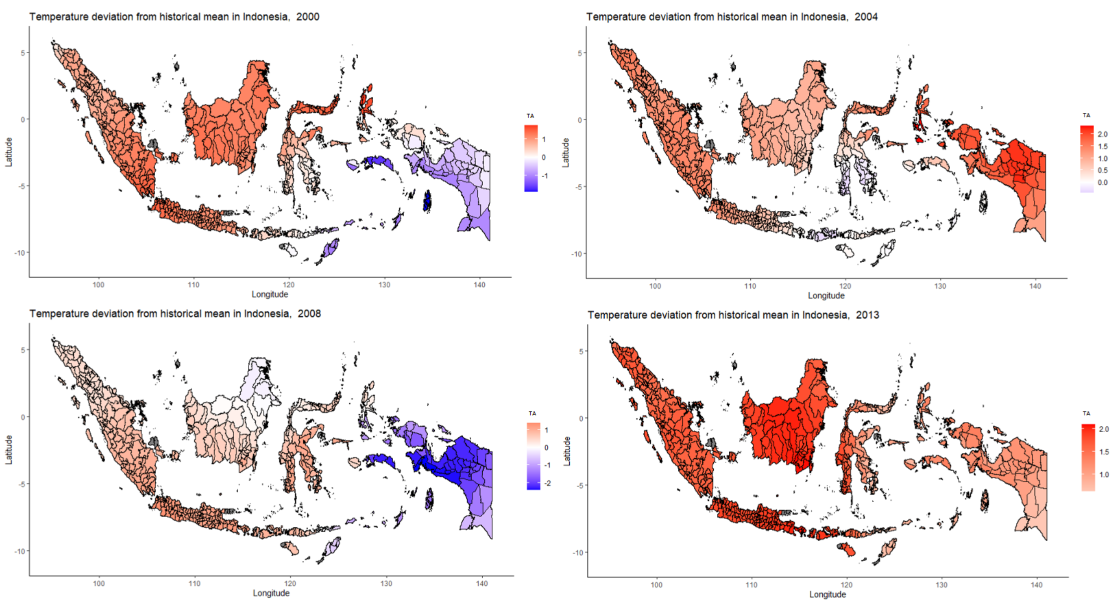

Figure 6: Temperature Anomalies in Indonesia

Notes: Figure 6 presents maps of temperature anomalies in different years. Red color means that temperature was higher than historical mean , blue - lower
Source: Authors' calculation based on the data from Climatic Research Unit at the University of East Anglia

we check that empirically in the Appendix.

5 Results

5.1 Rainfall Shocks

For what follows we will concentrate on the precipitation shocks in the data. Based on the literature (Thiede and Gray (2017), Mueller, Gray and Kosec (2014), Nawrotzki and Bakhtsiyarava (2017)), we construct of the shock climate variable was the following: if average yearly precipitation in kecamatan (sub-district) deviated from historical mean (calculated on the time span from 1901-2015) more than 2 standard deviations, the kecamatan is considered to have a shock.
Table 2 demonstrates relationship between rainfall shocks, cash transfer status and migration decisions. To make sure that our identification is not threatened by anticipation of the shock and causal relationship between cash transfer and shock, we empirically test it. Table 13, which checks that getting the cash transfer in year t is not dictated by getting hit by rainfall shock in year t (orthogonality checks) and Table 12 with leads of shock are in the Appendix.

In line with Thiede and Gray (2017), precipitation variation in form of rainfall shocks is not significantly important for migration decisions. Table 2 demonstrates that interaction term of cash transfer and rainfall shock is decreasing migration in treated areas: under the shock households which had access to the government cash transfer in that year decide to migrate less frequently compared to those who didn't receive the cash transfer. The result is stable in size and significance both in specification with and without controls. We can conclude that the effect of interest - the interaction between rainfall shock and receiving cash transfer has significant negative effect on migration of poor households only, which suggests that interaction term facilitates climate inhibitor mechanism in a short term. The logic is similar to insurance mechanism: since migrating is costly strategy both in terms of finance and in terms of mental costs, affected households use the finance provided by the government as a means to adapt to short term shock on the place rather than choosing costly migratory behaviour. To strengthen this result in the

Table 2: Rainfall Shocks, CT, and Migration

	Migration and Rainfall Shocks		Migration, CT, and Rainfall Shocks	
	(1)	(2)	(3)	(4)
Rainfall Shock	-0.0151	-0.0146	-0.0093	-0.0090
	(0.0127)	(0.0126)	(0.0142)	(0.0141)
Cash Transfer			0.0084	0.0075
			(0.0077)	(0.0078)
Rainfall Shock × Cash Transfer			-0.0402**	-0.0391**
			(0.0190)	(0.0191)
Observations	18440	18291	18440	18291
Controls	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the baseline results of the regression analysis. The dependent variable is all migration decisions. Columns (1) and (2) report the coefficient estimate after estimating rainfall shock influence on migratory decisions without and with controls. Columns (3) and (4) report the key estimates from fitting our main model with and without controls, respectively. Controls include: household size, the share of mobile hh members, assets, muslim, urban

section with Robustness check, we do several different specifications. First, we change the definition of the shock from yearly dummy to how many months in given year the rainfall exceed monthly historical mean (Table 9). We find similar pattern, with cash transfer decreases the probability of migration as a response to rainfall shock. Then, we try the same baseline specification but we change the studied period to larger one - from 1997 till 2014 (Table 10). We use a smaller period in the main specification because cash transfer programs started from the year 2005. To have data more or less symmetrically distributed around those dates, we use three waves of IFLS beginning from 2000. In this check as well, the result survived the inclusion of additional time periods and we still observe negative effect of interaction term on migration decision.

We found some evidence on behavioral change from cash transfer as a response to a current shock. However, we were also interested in the influence of being exposed to rainfall shock several times. Thus, next we explore accumulated rainfall shocks and their connection with migration and moderating effect of cash transfers.

We already found evidence that cash transfer can play a moderating role in facilitating the climate inhibitor mechanism for the short-term shock in period t. However, being exposed to the rainfall anomalies multiple times might change the behaviour of the households. We construct a measure of accumulated shock for several periods that happens if household received sum of the rainfall anomalies exceeding certain threshold. We defined Accumulated shock=1 if $\sum_{t-n}^{t} |RA_{st}| > Cutoff$. The baseline results of the model with n=3 and *Cutoff*=5. can be seen in Table 3.To make sure that our results are not dictated by chosen thresholds we do robustness checks with different number of years for which shock is calculated and different cutoffs, they can be found in Table 11 in the Robustness Check section. Orthogonality check is in the Appendix, Table 14.

Table 3: Accumulated Rainfall Shocks, CT, and Migration

	Migration, Accumulated Shock for 4 periods		
	(1)	(2)	(3)
	All	1 person	Family
Accumulated Shock for 4 Periods	-0.0234**	-0.0197**	0.0066
	(0.0093)	(0.0085)	(0.0071)
Cash Transfer	0.0066	0.0035	-0.0163*
	(0.0077)	(0.0069)	(0.0095)
Accumulated Shock for 4 Periods × Cash Transfer	-0.0124	-0.0096	0.0997**
	(0.0132)	(0.0114)	(0.0389)
Observations	21114	21114	21114
Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from fitting our main model. Outcome variables are all moves, moves done by one person, and moves done by part or whole households stored in Columns (1), (2), and (3), respectively. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Here several things are of interest. First, the accumulated shocks have heterogeneous effect on migratory decisions of poor population depending on the types of moves. It seems to decrease the probability of sending 1 migrant from the household but the sign for migration of the whole household is different. The interaction term seem to have negative effect on all moves and moves made by 1 person but has positive significant effect on moves done by families, which implies that for this group cash transfer facilitates climate driver mechanism. That might be explained by the households changing their beliefs about how hazardous the place of residence is: one period shock might not be enough for households to change their beliefs but being exposed to shock several times leads to reassessment of risk of being hit by rainfall shock in the future, which leads to household choosing the migration option as adaptation strategy.

5.2 Temperature Shocks

In this section we move to another slow-onset event that is threatening Indonesia, which is increasing temperature. We try to unpack whether cash transfer distort the behaviour of poor households as a response to drastic temperature shocks. Our baseline estimations that replicate the same models we estimated for rainfall shocks are in Table 4.

Table 4: Temperature Shocks, CT, and Migration

	Migration and Temperature Shocks		Migration, CT, and Temperature Shocks	
	(1)	(2)	(3)	(4)
Temperature Shock	-0.0113	-0.0129	-0.0168*	-0.0184*
	(0.0091)	(0.0092)	(0.0101)	(0.0103)
Cash Transfer			0.0068	0.0060
			(0.0083)	(0.0083)
Temperature Shock=1 × Cash Transfer=1			0.0280	0.0284
			(0.0197)	(0.0193)
Observations	17541	17406	17541	17406
Controls	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the baseline results of the regression analysis. The dependent variable is all migration decisions. Columns (1) and (2) report the coefficient estimate after estimating temperature shock influence on migratory decisions without and with controls. Columns (3) and (4) report the key estimates from fitting our main model with and without controls, respectively. Controls include: household size, the share of mobile hh members, assets, muslim, urban

We find that temperature variation is significantly important for migration decisions -

households that experienced high temperatures tend to migrate less than those who did not. This finding is again in line with what Thiede and Gray (2017) found in their paper - temperature deviations significantly decreases probability of migration. However, we did not find any significant effect of cash transfers on migratory behaviour of the households. We might note though, that solo cash transfer effect is positive, the same it was for the rainfall shocks and interaction term of interest has positive sign, which in turn is the opposite of what we found for the rainfall shocks. The effect is close to being significant at the 10% level so we may presume that temperature shocks are perceived differently than rainfall shocks and that is the reason for different use of cash transfer in this case. Table 5 demonstrates the effect of accumulated temperature shocks and cash transfers. Although non-significantly, the main pattern remains as in the case of accumulated rainfall shocks - migration of whole or part of the household are facilitated by cash transfer as adaptation strategy to shock.

Table 5: Accumulated Temperature Shocks, CT, and Migration

	Migration					
	n=2		n=3		n=4	
	All	Family	All	Family	All	Family
Accumulated Shock	-0.0018	0.0048	-0.0034	0.0032	-0.0111	-0.0029
	(0.0107)	(0.0062)	(0.0105)	(0.0075)	(0.0127)	(0.0071)
Cash Transfer	-0.0005	0.0018	0.0020	0.0028	0.0029	0.0009
	(0.0084)	(0.0070)	(0.0089)	(0.0071)	(0.0100)	(0.0079)
Accumulated Shock × Cash Transfer	0.0314*	0.0005	0.0238	-0.0036	0.0139	0.0032
	(0.0162)	(0.0101)	(0.0177)	(0.0093)	(0.0174)	(0.0099)
Observations	17406	17406	17406	17406	17406	17406
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating our main model. Outcome variables are all moves and moves done by part or whole households. Columns (1) and (2) present the results for accumulated shocks calculated for two periods. Columns (3) and (4) show the results for accumulated shocks calculated for three periods. Finally, Columns (5) and (6) present the results for accumulated shocks calculated for four periods. Controls include: household size, the share of mobile hh members, assets, muslim, urban

5.3 Natural Disasters

In this section, we will take a look at how natural disasters influences the decision about migration in our data. The natural disasters are assumed to be unexpected event and are often used in different areas of research as source of exogenous variation (Halliday (2006) Carvajal and Pereira (2010)). We try to incorporate the interaction term into the same model to understand if recipients of cash transfer programs react to natural disasters differently than non-recipients. The results are presented in Table 6.

Table 6: Natural Disatsers, CT, and Migration

	Migration					
	Flood		Landslide		Drought	
	All	Family	All	Family	All	Family
Event	-0.0066	-0.0086	-0.0029	-0.0059	0.0077	0.0065
	(0.0132)	(0.0058)	(0.0176)	(0.0132)	(0.0158)	(0.0109)
Cash Transfer	0.0047	0.0024	0.0049	0.0034	0.0042	0.0030
	(0.0070)	(0.0068)	(0.0071)	(0.0068)	(0.0070)	(0.0067)
Event × Cash Transfer	-0.0035	-0.0176	-0.0112	-0.0626***	0.0172	-0.0636*
	(0.0205)	(0.0205)	(0.0236)	(0.0207)	(0.0312)	(0.0347)
Observations	21114	21114	21114	21114	21114	21114
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating our main model with three types of shock. Outcome variables are all moves and moves done by part or whole households. Columns (1) and (2) present the results for floods. Columns (3) and (4) show the results for landslides. Finally, Columns (5) and (6) present the results for droughts. Controls include: household size, the share of mobile hh members, assets, muslim, urban

We see from Table 6 that interaction term has mostly negative effect on migration decisions, meaning that poor households use additional money to adapt to the shock in the place they reside rather than move away. This is supported by the evidence from the literature that records short-term movements out of affected area after the natural disaster but coming back in the longer term. The findings of Table 6 also mimic the results from rainfall shocks (short-term).

5.4 Change of Occupation

Next we will take a look at another adaptation strategy that household can use to cope with the climate shocks - occupational change. We will also attempt to uncover how the presence of the conditional cash transfer program influences the decision about occupation and how the households act when they are exposed to climate shock and receive the transfer. We assume that agriculture is the sector that suffers from rainfall and temperature shocks the most and we look into two outcome variables: change out of agricultural sector and change to agricultural sector, expecting the opposites signs from our interaction term. We consider stayers only (households that didn't have migration recorded) because migration and change of occupation mostly happen simultaneously. Tables 7 and 8 examine the relationship between change into and out of agriculture, cash transfers, rainfall and temperature shocks.

Table 7: Rainfall Shocks, CT, and Occupational Choices in Agriculture

	Out of Agriculture	Into Agriculture
	(1)	(2)
Rainfall Shock	-0.0054	0.0092
	(0.0098)	(0.0128)
Cash Transfer	0.0073	0.0180**
	(0.0082)	(0.0084)
Rainfall Shock × Cash Transfer	0.0346	-0.0426***
	(0.0282)	(0.0150)
Observations	8594	8594
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Sub-district Fixed Effects	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating model, where outcomes are change occupation by hh member out (Column 1) and into agriculture (Column 2). Controls include: household size, the share of mobile hh members, assets, muslim, urban

Table 8: Temperature Shocks, CT, and Occupational Choices in Agriculture

	Out of Agriculture	Into Agriculture
	(1)	(2)
Temperature Shock	-0.0161**	-0.0071
	(0.0065)	(0.0074)
Cash Transfer	0.0081	0.0175**
	(0.0079)	(0.0082)
Temperature Shock × Cash Transfer	0.0153	-0.0082
	(0.0145)	(0.0162)
Observations	8437	8437
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Sub-district Fixed Effects	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating model, where outcomes are change occupation by hh member out (Column 1) and into agriculture (Column 2). Controls include: household size, the share of mobile hh members, assets, muslim, urban

Tables 7 and 8 indicate the evidence that getting cash transfer decreases the probability of households members to change their job into risky agricultural sector after shock and also although not that evidently that it allows for higher change out of agriculture for those households, which receive cash transfer. Both interaction terms are of the same sign for rainfall (Table 7) and temperature shocks (Table 8).

6 Robustness Check

We did several robustness checks to make sure that the patterns we observe in our baseline results are robust to several modifications. First, to strengthen our result, we also consider second discrete measure of rainfall shock. For a sub-district s, we define its monthly rainfall anomaly as:

$$RA_{sm} = \frac{Rainfall_{sm} - \overline{Rainfall_s}}{SD_s}$$

where s indexes sub-districts, and m indexes months.We define Rainfall Shock for a given year=Number of months in a given year with $|RA_{sm}| > 2$. Table 9 summarizes the results from our baseline and from new measure of the shock.

Table 9: Rainfall Shocks, CT, and Migration

	Migration			
	Rainfall Shock (Yearly Measure)		Rainfall Shock (Monthly Measure)	
	(1)	(2)	(3)	(4)
Rainfall Shock	-0.0093	-0.0090	-0.0023	-0.0022
	(0.0142)	(0.0141)	(0.0031)	(0.0031)
Cash Transfer	0.0084	0.0075	0.0126	0.0119
	(0.0077)	(0.0078)	(0.0085)	(0.0086)
Rainfall Shock × Cash Transfer	-0.0402**	-0.0391**	-0.0111	-0.0114*
	(0.0190)	(0.0191)	(0.0069)	(0.0069)
Observations	18440	18291	18440	18291
Controls	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating our main model with two different measures of rainfall shocks. Columns (1) and (2) are baseline results with the shock defined in the main result section. Columns (3) and (4) use a different measure of rainfall shock based on the number of months in the given year with severe rainfall anomalies. Controls include: household size, the share of mobile hh members, assets, muslim, urban

As we can see from Table 9, even if we change the way how we define rainfall shock, we still obtain the same pattern in the results. We still find that households that received cash transfer migrated less as a response to current rainfall shock compared to households without cash transfer.

Second robustness check was inclusion of the earlier waves of IFLS. We concentrated on the information from the last 3 waves of IFLS since cash transfer programs were introduced only after 2000. However, to check that result still stands we present results with all waves in Table 10.

Table 10: Rainfall Shocks, CT, and Migration

	Migration	
	(1) Rainfall Shock, 2000-2014	(2) Rainfall Shock, 1997-2014
Rainfall Shock	-0.0153	-0.0152
	(0.0126)	(0.0111)
Cash Transfer	0.0122	0.0141^{*}
	(0.0078)	(0.0078)
Rainfall Shock × Cash Transfer	-0.0353^{*}	-0.0339^{*}
	(0.0205)	(0.0205)
Observations	17850	20545
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Sub-district Fixed Effects	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating our main model for two different periods. Column (1) is baseline results from 2000 to 2014. Column (2) uses different timespans from 1997 to 2014; we use one more wave of the IFLS survey for this specification. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Again our result survived the robustness check and we find the same pattern and even the same magnitude of the effect of cash transfer on migration decision after rainfall shock. Therefore, we conclude that our result for short-term rainfall shock is stable and does not change with modifications. Next we try battery of robustness check for accumulated shocks. We vary the number of years for which shock is calculated as well as threshold, the results are presented in the Table 11 below:

As Table 11 demonstrates the pattern we observe for our baseline results is also present in our robustness checks for different modifications of the model.

Table 11: Rainfall Shocks, CT, and Migration

	Migration									
	n=2		n=3		n=4, cutoff=5		n=4, cutoff=4.5		n=4, cutoff=5.5	
	All	Family	All	Family	All	Family	All	Family	All	Family
Accumulated Shock	-0.0010	-0.0004	-0.0019	0.0087	-0.0234**	0.0066	-0.0075	0.0052	-0.0178**	0.0015
	(0.0101)	(0.0066)	(0.0079)	(0.0063)	(0.0093)	(0.0071)	(0.0060)	(0.0051)	(0.0089)	(0.0084)
Cash Transfer	0.0065	-0.0163*	0.0078	-0.0162*	0.0066	-0.0163*	0.0086	-0.0088	0.0068	-0.0164*
	(0.0076)	(0.0091)	(0.0078)	(0.0094)	(0.0077)	(0.0095)	(0.0079)	(0.0100)	(0.0076)	(0.0094)
Accumulated Shock × Cash Transfer	-0.0128	0.1189***	-0.0192	0.1045**	-0.0124	0.0997**	-0.0164	0.0404	-0.0137	0.1059***
	(0.0129)	(0.0445)	(0.0130)	(0.0406)	(0.0132)	(0.0389)	(0.0112)	(0.0283)	(0.0126)	(0.0405)
Observations	21114	21114	21114	21114	21114	21114	21114	21114	21114	21114
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-district Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate from estimating our main model. Outcome variables are all moves and moves done by part or whole households. Columns (1) and (2) present the results for accumulated shocks calculated for two periods. Columns (3) and (4) show the results for accumulated shocks calculated for three periods. Columns (5)-(10) present the results for accumulated shocks calculated for four periods with different cutoffs for creating shock variables. Controls include: household size, the share of mobile hh members, assets, muslim, urban

7 Conclusion

In light of the forcasted adverse changes in temperature, precipitation, and increased frequency of natural hazards, research that investigates how environmental stress influences the livelihood of people become highly relevant. Although the literature that considers the link between climate shocks and migration has grown significantly over the last decades, there are still gaps that need to be fulfilled to understand better different factors that might be important for people's decision to migrate. One of those factors is seemed to be access to financial resources. This access is especially crucial for poor households since they have fewer opportunities to build resilience against climate shocks.

Our study investigates how cash transfer programs in Indonesia influences the decision of poor households to migrate in response to climate shocks. We suggest using the Indonesian Family Life Survey as well as data about climate and conditional cash transfer to answer the research question. The proposed research can help to understand whether better access to financial resources induce poor households to migrate (send a migrant) or induces them to adapt to climate shocks on the place they reside. The results may be beneficial from the policy perspective as it can unravel, which strategy poor households choose to adapt to the climate shocks if they are provided with financial aid programs. The limitation of this study is that we can only observe moves longer than 6 months, which leaves migration for the smaller periods unobserved for us.

Our findings suggest that cash transfer program influences the behaviour of poor households in response to climate shock but it does so in different ways. First, it allows poor households not to choose migration as immediate response to rainfall anomalies and natural disasters playing role of the insurance from costly adaptation strategy facilitating climate inhibitor mechanism. At the same time receiving cash transfer gives additional resources for the whole households to relocate in response to long-term rainfall shock exacerbating the climate driver mechanism for such hazardous shocks. We also find evidence of more prominent influence of temperature changes on migration, our result show that temperature shocks significantly decrease probability of migration for poor households, which can suggest the presence of liquidity traps created by this kind of shock. This is may be supported by our finding that households who receive cash transfers overcome the trap and migrate more in response to temperature shocks compared to those who do not receive it. Natural disasters demonstrated similar pattern as rainfall shock - households with cash transfers migrate less in response to floods, landslide and droughts. Here the explanation might lay in the nature of these shocks, they are usually rare and unexpected so one event is not enough to change the people's belief about how hazardous the place of their residence is. As a result, people who were affected by natural disaster and possibly lost some assets can use the money provided by government to deal with consequences on the place they reside. Finally, we wanted to explore what households who are deciding to stay do to adapt to climate shocks. In particular, we were interested in the occupational choices in agricultural sector. We find that he members of the household that received cash transfer are less likely to change job into risky agricultural sector and more likely to leave occupation in the agricultural sector as a response to rainfall and temperature shocks.

We see many further developments in this project. We are currently working on the effect of the conditional cash transfer only since the experimental nature and gradual expansion of PKH creates a unique opportunity that we want to exploit for our identification strategy. We are also trying different types of climate shocks measure since it is visible from our result that different shocks may have different effects on migration. Another endeavor is to create a panel of individuals to complement our current research on the households level. Other interesting questions that potentially can be answered: are the households that decide to send the migrate or migrate altogether better off in terms of consumption? What happens in the labor market, and how do climate shocks influence the occupational choices of people? Another extension of this study is the heterogeneous effects of access to financial resources and climate shocks on migration. Heterogeneous effects with respect to the age and gender of the household head are seemingly important dimensions to investigate because they can allow for better tailoring of the policies concerning climate adaptation. We hypothesize that households with higher shares of males and mobile people and households with male heads are more likely to migrate or send migrants to respond to climate shocks if they have better access to financial resources.

References

Angelucci, M. (2015). MIGRATION AND FINANCIAL CONSTRAINTS: EVIDENCE FROM MEXICO. *Review of Economics and Statistics*, 97(1), 224-228. doi:10.1162/RESTa00487

Biermann, F., Boas, I. (2010). Preparing for a Warmer World: Towards a Global Governance System to Protect Climate Refugees. *Global Environmental Politics*, 10(1), 60-+. doi:10.1162/glep.2010.10.1.60

Black, R., Arnell, N. W., Adger, W. N., Thomas, D., Geddes, A. (2013). Migration, immobility and displacement outcomes following extreme events. *Environmental Science Policy*, 27, S32-S43. doi:10.1016/j.envsci.2012.09.001

Bryan, G., Chowdhury, S., Mobarak, A. M. (2014). UNDERINVESTMENT IN A PROFITABLE TECHNOLOGY: THE CASE OF SEASONAL MIGRATION IN BANGLADESH. *Econometrica*, 82(5), 1671-1748. doi:10.3982/ecta10489

Cahyadi, N., Hanna, R., Olken, B.A., Prima, R.A., Satriawan, E., Syamsulhakim, E. (2018). Cumulative Impacts of Conditional Cash Transfer Programs: Experimental Evidence from Indonesia. *NBER Working Paper No. 24670*, doi:10.3386/w24670

Carvajal, L., Pereira, I. (2010). Evidence on the Link between Migration, Climate Shocks, and Adaptive Capacity. In: Fuentes-Nieva R., Seck P.A. (eds) *Risk, Shocks, and Human Development*. Palgrave Macmillan, London. doi:10.1057/978023027412911

Cattaneo, C., Beine, M., Frohlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., Schraven, B. (2019). Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy*, 13(2), 189-206. doi:10.1093/reep/rez008

Cattaneo, C., Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122, 127-146. doi:10.1016/j.jdeveco.2016.05.004

Climate Change Profile: Indonesia (2018). Ministry of Foreign Affairs of the Netherlands. Retrived from https://www.government.nl/binaries/government/documents/publications/2019/02/05/climate-change-profiles/Indonesia.pdf

Dillon, A., Mueller, V., Salau, S. (2011). Migratory Responses to Agricultural Risk in Northern Nigeria. *American Journal of Agricultural Economics* 93(4), 1048-1061. doi:10.1093/ajae/aar033

Groschl, J., and Steinwachs, T. (2017). Do natural hazards cause international migration? *CESifo Economic Studies* 63, 445–80.

IPCC (2013), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, in Stocker T. F., D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgeley (eds.), Cambridge University Press.

IPCC (2014), *Climate change 2014: impacts, adaptation, and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press.

Jones, B., O'Neill, B. (2016). Spatially explicit global population scenarios consistent with the shared socioeconomic pathways, *Environmental Research Letters*, 11(8), 10. doi:10.1088/1748-9326/11/8/0840

Halliday, T. (2006). Migration, risk, and liquidity constraints in El Salvador. *Economic Development and Cultural Change*, 54(4), 893-925. doi:10.1086/503584

Mueller, V., Gray, C., Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. *Nature Climate Change*, 4(3), 182-185. doi:10.1038/nclimate2103

Myers, N. (2002). Environmental refugees: a growing phenomenon of the 21st century. *Philosophical Transactions of the Royal Society B-Biological Sciences*, 357(1420), 609-613. doi:10.1098/rstb.2001.0953

Nawrotzki, R. J., Bakhtsiyarava, M. (2017). International Climate Migration: Evidence for the Climate Inhibitor Mechanism and the Agricultural Pathway.*Population Space and Place*, 23(4). doi:10.1002/psp.2033

Poggi, C. (2019). Credit Availability and Internal Migration: Evidence from Thailand. *Journal of Development Studies*, 55(5), 861-875. doi:10.1080/00220388.2018.1498969

Renaud, F., Bogardi, J.J., Dun, O. Warner, K. (2007). Control, adapt or flee: how to face environmental migration?. *UNU-EHS InterSecTions*. UNU- EHS

Saldana-Zorrilla, S. O., Sandberg, K. (2009). Spatial econometric model of natural disaster impacts on human migration in vulnerable regions of Mexico. *Disasters*, 33(4), 591-607. doi:10.1111/j.1467-7717.2008.01089.x

Stecklov, Guy Winters, Paul Stampini, Marco Davis, Benjamin. (2005). Do Conditional Cash Transfers Influence Migration? A Study Using Experimental Data From the Mexican Progresa Programme. *Demography.* 42. 769-90. doi:10.1353/dem.2005.0037

Stern, N. (2007). The economics of climate change: The Stern review, Cambridge University Press. doi:10.1017/CBO9780511817434

Strauss J, Witoelar F, Bondan S. (2016). The fifth wave of the Indonesia family life survey: overview and field report. RAND.

Thiede, Brian Gray, Clark. (2017). Heterogeneous Climate Effects on Human Migration in Indonesia. Population and Environment. 39. 10.1007/s11111-016-0265-8.

World Bank. (2012). PKH Conditional Cash Transfer Social Assistance Program and Public Expenditure Review 6. Jakarta, Indonesia: World Bank.

Zickgraf, C., and N. Perrin. (2016). Immobile and Trapped Populations. In *Atlas Der Umweltmigration*, edited by F. Gemenne, D. Ionesco, and D. Mokhnacheva, 44–46. München: oekom.

8 Appendix

Table 12 shows that leads of the rainfall shock could not predict migration decisions. Thus, people are not reacting to the predicted shocks.

Table 12: Leads

	Migration	
	(1)	(2)
Rainfall Shock t+1	-0.0092	
	(0.0126)	
Rainfall Shock t+2		-0.0127
		(0.0134)
Observations	17099	15937
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Sub-district Fixed Effects	Yes	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate of leads of rainfall shocks and their influence on migration decisions. Neither of leads can predict the migration. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Table 13 checks that receiving the cash transfer in period t is not caused by the rainfall shock in t.

Table 13: Orthogonality Check, Rainfall Shocks

	Cash Transfer
	(1)
Rainfall Shock	-0.0126
	(0.0181)
Observations	18291
Controls	Yes
Time Fixed Effects	Yes
Household Fixed Effects	Yes
Sub-district Fixed Effects	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate of rainfall shocks on receiving of cash transfer. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Table 14 shows that receiving the cash transfer in period t is not caused by the accumulated rainfall shock in t.

Table 14: Orthogonality Check, Rainfall Shocks

	Cash Transfer
	(1)
Accumulated Shock	-0.0142
	(0.0097)
Observations	21114
Controls	Yes
Time Fixed Effects	Yes
Household Fixed Effects	Yes
Sub-district Fixed Effects	Yes

Standard errors in parentheses

Sub-district Clustered SE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate of accumulated rainfall shocks on receiving of cash transfer. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Table 15 shows that leads of the temperature shock could not predict migration decisions. Thus, people are not reacting to the predicted shocks.

Table 15: Leads

	Migration	
	(1)	(2)
Temperature Shock t+1	-0.0159	
	(0.0097)	
Temperature Shock t+2		-0.0072
		(0.0103)
Observations	16275	14912
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Sub-district Fixed Effects	Yes	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate of leads of temperature shocks and their influence on migration decisions. Neither of leads can predict the migration. Controls include: household size, the share of mobile hh members, assets, muslim, urban

Table 16 checks that receiving the cash transfer in period t is not caused by the temperature shock in t.

Table 16: Orthogonality Check, Temperature Shocks

	Cash Transfer
Temperature Shock	0.0147
	(0.0125)
Observations	17406
Controls	Yes
Time Fixed Effects	Yes
Household Fixed Effects	Yes
Sub-district Fixed Effects	Yes

Standard errors in parentheses
Sub-district Clustered SE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the coefficient estimate of temperature shocks on receiving of cash transfer. Controls include: household size, the share of mobile hh members, assets, muslim, urban