Natural Disasters and Poverty Reduction: Do Remittances Matter?[1]

Linguère Mously Mbaye[2]

African Development Bank Group (Abidjan, Côte d'Ivoire) and IZA (Bonn, Germany)

Alassane Drabo[3]

FERDI (Clermont-Ferrand, France)

Abstract

Do private funds help mitigate poverty in the context of natural disasters? This paper aims to answer this question by looking at the joined effect of migrants' transfers and natural disasters on poverty level in developing countries. Using panel data from developing countries over the period 1984-2010 and a fixed effects model, our results show that private mechanisms, such as remittances, significantly alleviate poverty when natural disasters occur in these countries. Put differently, we find that the effect of remittances on poverty is all the more important when they are received in countries experiencing natural disasters. Our results are confirmed by various robustness tests to mitigate the endogeneity issues.

Keywords: Natural disasters; Remittances; Poverty

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[2] Corresponding author: Linguère Mously Mbaye. Contact: l.mbaye@afdb.org

[3] Contact Alassane Drabo: alassane.drabo@ferdi.fr

Introduction

There is a growing interest and acknowledgment of natural disasters as likely consequences of climate change (Stern report, 2007; IPCC, 2007). Natural disasters are often present in the news since many regions are more frequently experiencing climate driven disasters such as floods, storms or droughts. Different parts of the world are exposed and the consequences are disastrous, especially for poor regions. The first and immediate pictures of a disaster on a screen are destroyed infrastructure, homeless people and refugees seeking help, highlighting poverty as an inevitable consequence of such events, at least in the short-run.

These natural disasters can trigger important socioeconomic consequences. It has been found that the negative impact of these shocks on economic growth is particularly true for developing countries (Felbermayr and Gröschl, 2014; Noy, 2009; Dell et al., 2012; Loyza et al., 2012). Research also focusing on the specific link between natural disasters and poverty find a negative correlation between these two variables (e.g. Carter et al. 2007; Lal et al., 2009; Rodriguez-Oreggia et al., 201; Arouri et al., 2015). However, there is much less evidence on the role of private mechanisms, such as remittances, on poverty when natural disasters occur in developing countries. Among the few studies which investigated this relationship, it has been shown that in rural Vietnam, remittances help migrants' families to escape from poverty when natural disasters occur (Arouri et al., 2015). It has also been demonstrated in the case of the Philippines that remittances can play an insurance role when countries experience disasters such as rainfall shocks (Yang and Choi, 2007). Moreover, there is evidence showing that remittances improved the responses to natural disasters in countries that have a larger emigrant stock (Mohapatra et al., 2012).

Consequently, this paper contributes to this scarce literature by investigating in a short-term perspective the role of remittances in the mitigation of poverty when natural disasters occur. The value added of this study compared to the previous ones is fourfold. First, while the previous studies are interested in single countries- at the exception of Mohapatra et al., (2012) who use 4 countries- our paper uses panel data from 52 developing nations, in particular low- and lower-middle-income countries over the 1984-2010 period, generalizing the role of remittances in terms of geographical situation. Second, previous studies generally used household level data while this paper goes forwards by using country level observation as unit of analysis. Third, the cross-country and panel structure of the data that we use allow the elimination of the time-invariant unobserved heterogeneity and reduce the potential endogeneity due to the omitted variable bias. Finally, following Felbermayr and

Gröschl (2014), the paper considers measures of physical intensity of disasters. We use a disaster index aggregating different disaster intensity measures. We also use the disaggregated intensity measures such as the wind speed, the difference between the monthly maximum temperature and the monthly mean over the period, the occurrence of drought measured through a dummy equal one if at least for three successive months or five months within a year, rainfall level is below 50% of the period monthly mean, the occurrence of flood captured through the positive difference in precipitation over the long run mean, the maximum value recorded on the Richter scale and the maximum volcanic explosivity index. They help avoiding the potential measurement bias due to the misreporting of the number of affected people or economic damages due to disasters. Another advantage of using these variables is that they allow dealing with the potential endogeneity of the consequences of disasters which could be explained by the poverty level of countries per se. These measures have been compiled and used by Felbermayr and Gröschl (2014) to explore the relationship between natural disasters and economic growth. However, to the best of our knowledge, our study is the first that uses these exogenous measures of disasters to study the relationship between natural disasters, remittances and poverty.

Our estimates primarily focus on the poverty headcount ratio at $1.25 a day (ppp) as dependent variable. We also use an alternative measure of poverty which is the poverty gap at $2 a day (ppp). The interest variable is the interaction term between remittances and natural disasters. We are particularly interested in the latter to determine whether remittances play a role in mitigating poverty in the context of natural disasters. By doing so, we would like to test the assumption that because of their vulnerability, developing countries may not have the ability to deal with poverty issues in the context of disasters which will induce people to rely on migrants' transfers.

Although we use country fixed effects and exogenous measures of natural disasters, the study still faces challenges due to other source of bias. Subsequently, we also control for time fixed effects to capture the aggregate trends between natural disasters and poverty. Moreover, it is possible that remittances and natural disasters of the previous years also affect the poverty level. Subsequently, in addition of remittances and disasters at time t, we control for these variables at t-1. Another concern which remains is the endogeneity of remittances. It is likely that the poorest people are those who cannot afford migration costs, which means that poverty may determine the location choice and thus the ensuing amount of remittances received. More generally, the amount of remittances received can also be explained by the poverty level. We test the robustness of our results to this source of bias by using in our specifications the logarithm of the lagged amount of remittances instead of the contemporaneous one. Indeed if the amount of remittances received in t-1 can influence the level of poverty in t, it is very unlikely to observe the opposite relationship. Finally, we used a GMM system estimator to test the robustness of our results. Interestingly, the results show that in the context of natural disaster, the amount of remittances received contributes to decrease the level of poverty. More precisely, we found that for countries experiencing an increase in the disaster index by 1% and receiving the average logarithm of remittances, the poverty headcount ratio at $1.25 a day decreases by 1.145 percentage points. These results suggest that the reducing effect of remittances on poverty is even more important in countries which experience natural disaster. A more detailed analysis shows that the results are mainly driven by storms and hurricanes as well as extreme temperature events.

The remainder of the paper is organized as follows. Section 2 presents the literature related to the relationship between natural disasters, remittances and poverty. Section 3 presents the empirical framework by discussing the methodology, endogeneity issues and presenting the data. Section 4 discusses the results and Section 5 concludes.

2. Related literature

This paper draws upon the literature on the impact of natural disasters on economic growth and poverty as well as the role of remittances in the aftermath of natural disasters.

2.1 Natural disasters, economic growth and poverty

Some studies demonstrated that natural disasters are positively correlated with higher rate of human capital accumulation, higher productivity and thus economic growth (Skidmore and Toya, 2002). However, this positive relationship between natural disasters and economic growth has been challenged in the literature. It has been documented that disasters can have a short-term negative impact on GDP (Noy and Nualsri, 2007; Raddatz, 2009, and Loayza et al., 2009). Indeed, Natural disasters can destroy productive and social infrastructures, reduce economic activities and increased fiscal deficit at the moment when affected countries need more income to respond to the damages caused by disasters (to build infrastructure, increase social expenditure and implement redistribution policies). The economic productivity, economic growth and status of economic development are thus negatively affected (Felbermayr and Gröschl, 2014). The adverse effects of disasters on economic growth are particularly observed in the developing countries which are the most vulnerable (Noy, 2009;

Dell et al., 2012; Loayza et al., 2012). For instance, from a cross-country analysis, Barrios et al. (2010) use data from 1960 to 1990 of 60 countries including 22 African countries and find that since the sixties a decrease in rainfall is responsible of the reduction between 15 and 40% of the gap in the African GDP per capita compared to other developing countries.

These studies suggest that the negative effect of natural disasters on economic growth can push people into poverty and trigger important socioeconomic consequences. For instance, the destruction of assets of people belonging to the middle class can induce households towards chronic poverty, whereby they lack the required income to revert to their previous situation. These households do not have the capacity to rebuild their homes, substitute lost assets and fulfill the conditions to secure their basic needs. Moreover, since it is difficult for them to quickly replace their lost assets, this could put them into a poverty trap (Carter et al. 2007). Other findings show that disasters exacerbate poverty because the most vulnerable generally live in unfavorable and exposed conditions such as marginal lands and poorly constructed houses. This is often synonymous of their unsafe living environment and sensitivity to disasters which increase their poor economic status. Consequently, poor people are unable to take advantage of disaster-proof technology, relocation to less dangerous regions or benefit from insurance mechanisms (Lal et al. 2009). For instance, studies in Ethiopia and Honduras showed that the poorest households are those which struggle most with shocks and adopt costly coping strategies in terms of both short- and long-term well-being (Carter et al., 2007). From a panel of Indonesian household data, Silbert and Useche (2012) found that natural disaster risk increases projected poverty rates and economic development factors such as income, urbanization and institutional strength. Another example from a household survey data from Phillipines in 1998 assess the distributional impact of the recent economic crisis and found that the largest share of the overall impact on poverty is attributable to the El-Niño shock as opposed to shocks mediated through the labor market (Datt and Hoogeveen, 2003). Rodriguez-Oreggia et al. (2013) investigate the effects of natural disasters on human development and poverty levels at the municipal level in Mexico. Using panel data, they show that the occurrence of natural disasters exacerbates food and extreme poverty by about 3.7 percent, capacities poverty by 3 percent and assets poverty by 1.5 percent. More recently, Arouri et al. (2015) assess the effect of natural disasters on the welfare and poverty of rural households in Vietnam, as well as their resilience to disasters using commune-fixed effect regressions. They found that storms, floods and droughts have negative effects on household income and expenditure.

2.2 Heterogeneity in the effect of natural disasters on poverty

Another issue in the relationship between natural disasters and poverty is the heterogeneity of the former's impact. Karim and Noy (2014) evaluated the poverty consequences of natural disasters through a meta-regression analysis of the existing literature. They found strong heterogeneity in the impacts of disasters on poverty even though several general patterns emerge. More precisely, they found that incomes are negatively affected after natural disasters, while consumption is also reduced, albeit to a lesser extent than income. Accordingly, poor households smooth their food consumption by reducing their consumption of non-food items (spending on housing, health and education). However, the authors did not find any consistent long-term effects. This is also similar to results found by Gignoux and Menendez (2016). The latter assesses the effects of earthquakes in rural Indonesia since 1985. They found that in the short-term, meaning two years after the shock, the earthquake caused some economic losses. However, individuals started recovering between two and five years after the earthquake. Between six and twelve years after the shock, individuals' total expenditure per capita was 10% higher than before the shock. The positive impact of the earthquake on the total expenditure, in the long term, was explained by the external aid which allows reconstituting physical assets and investing in public infrastructures. They did not find any large population movement or reallocation of labor across sectors. These studies show that the impact of disasters on poverty is not necessarily the same between the short and long term. Moreover, the heterogeneity in the impact of disasters on poverty also depends on the transfers received by the communities after the shocks and which help mitigating the negative consequence of the earthquake.

2.3 Role of remittances

Countries affected by the same kind of disaster do not suffer to the same degree, and some households within the same country are more resilient than others because of the availability of insurance mechanisms such as remittances. For instance, Silbert and Useche (2012) show that natural disaster risk disproportionately affects consumption-constrained households. Households with greater self-insurance strategies and higher levels of human capital are better protected against repeated shocks than less-endowed and -educated ones. Arouri et al. (2015) find that higher mean expenditure and more equal expenditure distribution in the commune in Vietnam through access to micro-credit, internal remittances and social allowances increase resilience to natural disasters. Consequently, migrants' remittances help their families left-behind escaping from poverty in general and the consequences of natural disasters in particular. Studies show that remittances increase in the aftermath of disasters and help reducing the negative effect of shocks by playing an insurance role for households (Mohapatra et al., 2012; Yang and Choi, 2007; Yang, 2008). Moreover, it is generally accepted in the literature that sending money back to the home country reduces poverty through the accumulation of human and physical capital, reduced income inequalities and increased consumption (Adams and Page, 2005; Gupta and al., 2009; Adams and Cuecuecha, 2013). Remittances can thus be considered as channels mediating the effect of natural disasters on poverty and well-being. For instance, Prakash (2007) investigates the consequences of remittances inflows from Gulf regions on the Kerala economy and shows that remittances not only strongly increase the levels of income, consumption and acquisition of assets, but also reduce poverty. However, this effect may adversely affect the poor since the prices of land, construction materials, consumer foods, charges for health, education and transport subsequently increase. Using data for 59 industrial and developing countries over 1970–2000, Acosta et al. (2008) analyzed the effect of workers' remittances on economic growth, inequality and poverty reduction in Latin American and Caribbean (LAC) countries and find that remittances increase growth and reduce inequality and poverty.

The question that the study at hand addresses is related to the role of the amount remittances in poverty reduction when natural disaster occurs. Consequently, we develop an empirical framework where we discuss the methodology used as well as the endogeneity issues and data.

3. Empirical framework

3.1 Data

We use 2 different measures of poverty from the World Development Indicators (World Bank Databases): the poverty headcount ratio at $ 1.25 a day (PPP), the percentage of population living in households with consumption or income per person below the poverty line of $1.25 a day, adjusted for purchasing power parity (PPP); and the poverty gap at $2 a day (PPP) which is the mean shortfall from the poverty line expressed as a percentage of the poverty line of $2 a day, adjusted for purchasing power parity (PPP). This measure reflects the depth of poverty as well as its incidence.

Our natural disaster variables are from the GeoMet data (Game) constructed by Felbermayr and Gröschl (2014). We use the plain disaster index which aggregates the different disaster intensity measures. We also used the disaggregated intensity measures to assess the relationship between natural disasters, remittances and poverty by disaster type. The first component of the disaster index is the wind speed measuring the maximum total wind speed in knots for storms and hurricanes. The second component is the disaster index which measures extreme temperature events through the percentage difference between the monthly maximum temperature and the monthly mean over the period (1979-2010). The third component of the disaster index is drought, a dummy taking the value 1 if at least for three successive months or five months within a year, rainfall level is below 50% of the period monthly mean. The fourth component is flood measured as the positive difference in precipitation over the long run mean. The fifth component of the disaster index is the Richter scale which measures the maximum value recorded on the Richter scale. Finally the last component of the Disaster Index is the volcanic eruption measured as the maximum volcanic explosivity Index.[4] For comparison purpose we use in our estimates the standardized values of the various disaster types. The remittance variable measures the logarithm of the transfers received in the countries during the period analyzed.

In our estimates, we control for country characteristics such as the total population and the population density. Population variables capture the size of the country which both can affect the level of poverty as well as the incidence of both disaster and remittances on the poverty level. We also control for the urbanization rate. Indeed, although the share of poor living in urban areas is increasing, there is the view that urbanization decreases poverty with most of the poor people still living in rural areas (e.g Ravallion et al., 2007; Chen and Ravallion, 2010). However, it has also been demonstrated that urbanization rate could decrease poverty around rural areas due to the positive spillover effects arising from internal remittances or non-farm employment in rural areas (Calì and Menon, 2013). Moreover, urbanization rate is also a proxy for internal migration. In all cases, it is important to capture these rural-urban demographic dynamics that could affect poverty. Following Felbermayr and Gröschl (2014), we take into account the quality of the institutions through a polity index normalized between 0 standing for the most autocratic countries and 1 standing for the most democratic ones. Finally, we also control for the growth rate of real GDP per capita which captures the economic factors of the country such as unemployment or infrastructure. This

[4] Please see Felbermayr and Gröschl (2014) for a detailed explanation of the methodology used to create the Disaster Index.

variable is defined as the difference between the logarithm of GDP per capita in t and $t-1$, adjusted in purchasing power parity. [5]

3.2 Methodology

In this paper we investigate the relationship between natural disasters, remittances and poverty by using a panel data from 52 developing countries, in particular low and lower middle income countries over the period 1984 to 2010. The countries were selected following World Bank classification of the level of development of countries. [6] We focus on the following country-fixed effects regression, where the unit of observation is the country i at year t:

$$Poverty_{i,t} = \alpha_1 disaster_{i,t} * remit_{i,t} + \alpha_2 disaster_{i,t} + \alpha_3 remit_{i,t} + \alpha_{ki} X_{k,i,t-1} + \mu_i + \kappa_t + \varepsilon_{i,t} \quad (1)$$

$Poverty_{i,t}$ reflects the different outcomes measuring poverty. Since we mainly focus on the incidence of remittances and natural disaster on poverty, our main interest variable is the interaction term between natural disasters ($disaster_{i,t}$) and logarithm of remittances ($remit_{i,t}$). $X_{k,i,t-1}$ is the vector of variables controlling for the characteristics of the country with one year lag. μ_i stands for the country-fixed effects which control for the time-invariant country characteristics that may be related to poverty. We also include time fixed effects through the variable κ_t to capture additional variation. $\varepsilon_{i,t}$ is the unexplained residual.

3.3 Endogeneity issues

Although we use country fixed effects which control for unobservable time invariant country characteristics, we still have to address some endogeneity issues related to the main interest variables. The first issue is related to the choice of exogenous natural disasters variables. Unlike the number of people killed or affected as well as the economic costs of the damages caused by disasters[7] which could be misreported or misevaluated, and which could also be influenced by the level of poverty of countries, we use exogenous measures of natural

[5]See Appendix A for the Descriptive statistics and Appendix B for variable definitions and sources.

[6] The countries are low and lower middle income countries for which we have data for the various variables considered over the period.

[7] These variables are available in EM-DAT database provided by the Centre for Research on the Epidemiology of Disaster (CRED).

disasters from the Geomet-data (GAME) compiled over the period 1979-2010 by Felbermayr and Gröschl (2014). Using primary data from geophysics and climatology, these authors constructed the physical intensity measures of disasters events depending on the month, year and country in which they occur. For the purpose of our paper we use the country-year level data set.

However, using an exogeneous measure of disaster may not be enough to deal with other sources of bias. Consequently, we also control for time fixed effects. It is likely that poverty at time t is affected not only by disasters and remittances at t but also at t-1. Subsequently, we use an alternative specification controlling for natural disasters and remittances which happened at t-1, in addition to the t level variables.

The other concern is related to the endogeneity of remittances. The amount of remittances received can also be explained by the level of poverty. Ideally we would use an instrumental variable which has to be correlated to poverty only through its effect on remittances. Unfortunately we have not found such strong instrument which respects this exclusion restriction and with data covering the period studied. Subsequently, we use various alternative specifications to test the robustness of our results. First, we use the interaction term between natural disaster and the logarithm of the amount of remittances received in t -1 which is assumed to be more exogenous than the contemporaneous amount. If the amount of remittances received in t-1 can influence the level of poverty in t, it is very unlikely to observe the opposite relationship. Another concern which remains here is that estimating such dynamic model with the use of fixed effects may lead to a Nickell bias (Nickell, 1981). However, since this bias is minimized in long panel (Judson and Owen, 1999), this is not a major issue due to the fact that we have 26 years of observations.[8] Finally, we further account for dynamics in the model and check the robustness of our results by instrumenting the endogenous explanatory variables with their lagged values through a GMM model.

4. Results

The main results of the relationship between natural disaster, remittances and the poverty headcount ratio at $ 1.25 a day (ppp) are presented in Table 1. Column 1 presents the simple correlation between the interaction term Log remittances*Disaster Index, the specific variable of disaster, Log remittances and poverty. The interaction term is significant and

[8] This explanation also holds for the use of the lagged control variables which are assumed to be more exogenous than the contemporaneous ones.

negative, the disaster index is significant and positive while the specific variable log remittances is significant and negative. In terms of interpretation, the significant and negative sign of the interaction term suggests that remittances decrease poverty in the context of natural disasters. The previous results remain while we introduce in Column 3 the control variables, such as the type of regime (democratic or autocratic), the total population, the population density, the urbanization rate and the growth rate of the GDP per capita, with one year lag. However, these estimates do not take into account the unobservable time invariant characteristics which can bias the results. Consequently, to rule out this source of bias, we use a country fixed effects model (Column 4 to 5 of Table 2). The results in Column 4 are similar to what we found with the random effects. Moreover, they are robust to the inclusion of the time trend, except for the log remittances which still has the expected negative sign but becomes insignificant (Column 5 of Table 2).[9] However, the fact that this variable is not statistically significant anymore should not be interpreted as if remittances do not have an effect on poverty. The effect of remittances should be put into perspective with the effect of the interaction term. The fact that remittances loses its significance while the interaction term remains negative and significant means that the reducing effect of migrants' transfers on poverty is even more important in countries which experience natural disaster. When we focus on the country and time fixed-effect specification as our benchmark, the result indicates that for a country where the disaster index increases by 1% within a year, the poverty headcount ratio at $1.25 a day changes by 24.667-1.301*Log Remittances, on average. Consequently, for countries experiencing an increase in the disaster index by 1% and receiving the average logarithm of remittances, the poverty headcount ratio at $1.25 a day is expected to decrease by 1.145 percentage points (24.667-1.301*19.84=-1.145). This result is very interesting because it means that when a shock occurs, remittances allow countries to decrease their poverty level. This should be put into perspective with results found in the literature and showing that transfers (such as aid) after disaster can be beneficial to the communities, in the long term (Gignoux and Menendez, 2016). It is likely that public transfers benefit to communities many years after a shock, because they require time and organization before reaching the communities and starting producing effect. In our case, we show that private transfers such as remittances occurring in the aftermath of natural disasters are beneficial even in the short term.

[9] The probability of the Hausman test is lower than 10% confirming that the fixed effects model is better than the random effects model.

In Table 2 we look at the combined effect of the disaggregated measures of the disaster and remittances on poverty. Results show that the coefficient associated to the interaction term of each of the disaster type is negative. However, only results from Column 1 to 3 including the interaction term log remittances*wind speed, log remittances *Δ temperature and log remittances*drought are significant. Coefficients associated with the interaction term between log remittances and flood, Richter scale and volcanic explosivity, respectively are not statistically significant (Column 3 to 6). These findings suggest that the effect of remittances in terms of poverty reduction is higher when countries experience storms and hurricanes (measured through wind speed), extreme temperature events and drought.

To test the robustness of our results, we start by adding to the previous estimate the logarithm of remittances as well the natural disasters which happened the previous year, as control variables. Overall the results presented in Table 3 (Column 1 to 7) are similar to the ones found in Table 2 except for Column 1 and 2 where the logarithm of remittances at t becomes significant.

We further test the robustness if our results to the endogeneity of remittances. We start by replacing the log of remittances at t by the log remittances at t-1 which is assumed to be more exogenous than the contemporaneous measure. Unlike the estimates of Table 3 where we control both for log remittances at t and t-1 as well as disasters at t-1, we only consider here remittances at t-1 and disasters at t. Overall, results from previous table are confirmed, except for the interaction term between drought and log remittances which becomes insignificant. A more conservative approach would thus consider that the effect of remittances on poverty when disasters occur is only mainly driven by storms and hurricanes as well as extremes temperature events.

To further test the robustness of our estimations, we use a GMM system estimator (Blundel and Bond, 1998). The GMM system allows to further account for dynamics in the model instrumenting the endogenous variables with their lagged values. However, because of the use of lags, countries in our sample which have missing variables before the period studied will be dropped which will dramatically reduce the number of observations. Consequently, to avoid losing too many countries, we run the GMM estimates based upon a 5 years average over 1986 to 2010 will lead to 5 periods of 5 years each. We run the GMM estimates by introducing the poverty variable with one period lag, in addition to the explanatory variables at time t. For remittances, the interaction term between remittances and natural disasters, GDP growth, lagged poverty as well as the population variables, we use at least 2 period lags for their instruments. For the other explanatory variables such as natural disasters and institutions quality which we consider as predetermined, we use one period lag for their instruments. Moreover, since all lags of variables have been used as instruments and because of the small sample size, we also limit the bias of over-instrumentation[10].

The Hansen test of overidentification restrictions and the Arellano–Bond test for second-order autocorrelation (column 1 to 7 of table 5) do not allow rejection of the hypothesis concerning the validity of the lagged variables in level and in difference as instruments, nor the hypothesis of no second-order autocorrelation. Results presented in Table 5 confirm the negative effect of the interaction term between remittances and the disaster index as well as the effects of wind speed and difference in temperature.[11]

Finally, we test the robustness of our estimations with an alternative measure of poverty, which is the poverty gap at $2 a day (Table 6). The results for the fixed effects model are similar in terms of significance and sign, but the size of the coefficient is smaller. For countries experiencing an increase in the disaster index by 1% within a year and receiving the average logarithm of remittances, the poverty gap at $2 a day is expected to decrease by 0.638 percentage points (19.063-0.993*19.84=-0.638).

5. Conclusion

The occurrence of natural disasters generally destroys the population's living conditions and plunges them into poverty. Many strategies and methods are implemented to mitigate the consequences of natural disasters on poverty at the individual, household, country and more global level. One way to escape from these likely disastrous new living conditions is thus to rely on private mechanisms such as migrants' transfers. This paper has investigated this issue and analyzed the relationship between natural disasters, remittances and poverty. Interestingly, the findings obtained through a fixed effects model approach shows that private transfers such as remittances significantly contribute to decrease poverty in the context of natural disasters. Findings also show that this effect is mainly driven by storms and hurricanes as well as extreme temperatures events. These results are robust to the use of alternative specifications and the GMM system estimator. This implies that in the aftermath of natural disasters, private funds and remittances, in particular, are beneficial to countries.

[10] We limit the bias of over-instrumentation by using the GMM option collapse of stata

[11] We have less observations and countries in the GMM system due to the missing data, in particular when we use two year lag. This also explains that we could not run the estimates for the variable drought.

Subsequently, migrants' transfers are an important channel in terms of helping origin countries to deal with poverty when they experience natural disasters and are at their most vulnerable.

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Table 1: Natural disasters, remittances and poverty: Main results

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Random effects		Country fixed effects		
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)
Log remittances*Disaster Index	-1.102***	-0.965***	-1.226***	-1.295***	-1.301***
	(0.42)	(0.31)	(0.44)	(0.35)	(0.40)
Disaster Index	21.452**	18.218***	23.894***	24.606***	24.667***
	(8.41)	(6.10)	(8.71)	(6.97)	(8.14)
Log remittances	-4.256***	-3.270***	-4.121***	-2.813***	-1.308
	(0.75)	(0.84)	(0.78)	(0.82)	(0.97)
Polity Index (lag)		1.183		1.994	-1.865
		(6.07)		(7.27)	(7.09)
Log population (lag)		2.105		-7.966	-1.601
		(2.31)		(15.98)	(16.55)
Population density (lag)		-0.017		-0.050	-0.047
		(0.02)		(0.03)	(0.03)
Urban population (lag)		-0.737***		-0.414	-0.142
		(0.16)		(0.41)	(0.45)
GDP growth per capita (lag)		5.986		4.004	0.541
		(8.23)		(8.46)	(9.52)
Time fixed effects	No	No	No	No	Yes
Observations	313	312	313	312	312
R-squared	0.17	0.5	0.33	0.41	0.52
Number of countries	51	51	51	51	51
Hausman test				chi2 (7)=22.23	
				Prob>chi2=0.0045	

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. Overall R-squared presented in Column 1 and 2 and within R-squared presented from Column 3 to 5. All estimates include a constant.

Table 2: Effects of Natural disasters and remittances on poverty according to the type of disasters

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Country fixed effects					
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log remittances*Wind speed	-1.254*					
	(0.73)					
Wind speed	24.524*					
	(14.61)					
Log remittances*Δ temperature		-0.308***				
		(0.07)				
Δ temperature		5.515***				
		(1.38)				
Log remittances*drought			-0.579**			
			(0.27)			
Drought			11.823**			
			(5.66)			
Log remittances*flood				-0.330		
				(0.29)		
Flood				5.596		
				(5.63)		
Log remittances*Richter scale					-0.591	
					(0.44)	
Richter scale					9.041	
					(8.69)	
Log remittances*Volcanic explosivity						-0.384
						(0.45)
Volcanic explosivity						7.690
						(9.32)
Log remittances	-1.685	-0.596	-1.128	-0.963	-0.626	-0.888
	(1.23)	(1.01)	(1.12)	(1.10)	(1.02)	(1.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	312	312
R-squared	0.50	0.50	0.49	0.49	0.50	0.49
Number of countries	51	51	51	51	51	51

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 3: Robustness checks: Effects of natural disasters and remittances on poverty controlling for remittances and disasters variables in t and t-1

Dependent variable: Poverty headcount ratio at $ 1.25 a day (ppp)

	Country Fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-1.398***						
	(0.41)						
Disaster Index	26.589***						
	(8.34)						
Disaster Index (lag)	0.118						
	(0.82)						
Log remittances*Wind speed		-1.431*					
		(0.74)					
Wind speed		28.088*					
		(14.95)					
Wind speed (lag)		0.100					
		(0.83)					
Log remittances*Δ temperature			-0.317***				
			(0.08)				
Δ temperature			5.651***				
			(1.60)				
Δ temperature (lag)			0.047				
			(0.31)				
Log remittances *drought				-0.594**			
				(0.26)			
Drought				12.154**			
				(5.47)			
Drought (lag)				0.019			
				(0.63)			
Log remittances *flood					-0.301		
					(0.31)		
Flood					5.101		
					(6.13)		
Flood (lag)					-0.157		
					(0.66)		
Log remittances *Richter scale						-0.684	
						(0.41)	
Richter scale						10.990	
						(8.10)	
Richter scale (lag)						-2.294*	
						(1.29)	
Log remittances*Volcanic explosivity							-0.376
							(0.46)
Volcanic explosivity							7.497
							(9.38)
Volcanic explosivity (lag)							-0.059
							(0.72)
Log remittances	-2.393**	-2.714**	-1.462	-2.016	-1.340	-1.232	-1.425
	(1.13)	(1.33)	(1.15)	(1.44)	(1.34)	(1.11)	(1.14)
Log remittances (lag)	1.316	1.146	1.073	1.061	0.469	0.927	0.693
	(0.93)	(1.04)	(1.11)	(1.44)	(1.33)	(1.08)	(1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	308	308	308	308	308	308	308
R-squared	0.53	0.51	0.51	0.5	0.49	0.52	0.49
Number of countries	50	50	50	50	50	50	50

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 4: Robustness checks for the endogeneity of remittances: Effect of natural disasters and remittances on poverty using the lagged of the logarithm of remittances

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Country fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances (lag)*Disaster Index	-1.145***						
	(0.39)						
Disaster Index	21.350***						
	(7.80)						
Log remittances (lag)*Wind speed		-1.130*					
		(0.61)					
Wind speed		22.021*					
		(12.29)					
Log remittances (lag)*Δ temperature			-0.265***				
			(0.06)				
Δ temperature			4.475***				
			(1.17)				
Log remittances (lag)*drought				-0.432			
				(0.30)			
Drought				8.707			
				(6.38)			
Log remittances (lag)*flood					-0.123		
					(0.29)		
Flood					1.786		
					(5.51)		
Log remittances (lag)*Richter scale						-0.696*	
						(0.40)	
Richter scale						10.958	
						(7.71)	
Log remittances (lag)*Volcanic explosivity							-0.347
							(0.42)
Volcanic explosivity							6.881
							(8.49)
Log remittances (lag)	-0.744	-1.137	-0.249	-0.719	-0.691	-0.220	-0.628
	(0.96)	(1.12)	(1.04)	(1.16)	(1.13)	(1.04)	(1.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	308	308	308	308	308	308	308
R-squared	0.51	0.50	0.50	0.49	0.49	0.50	0.49
Number of countries	50	50	50	50	50	50	50

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 5: Robustness checks: GMM system estimates of the relationship between natural disasters, remittances and poverty

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	GMM						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-1.202**						
	(0.59)						
Disaster Index	25.721**						
	(12.21)						
Log remittances*Wind speed		-1.554*					
		(0.94)					
Wind speed		34.967*					
		(19.62)					
Log remittances*Δ temperature			-0.208**				
			(0.09)				
Δ temperature			3.449*				
			(1.91)				
Log remittances *drought				-0.428			
				(0.51)			
Drought				4.955			
				(10.22)			
Log remittances*flood					0.924		
					(0.80)		
Flood					-17.604		
					(14.52)		
Log remittances*Richter scale						1.124	
						(1.35)	
Richter scale						-24.008	
						(26.72)	
Log remittances*Volcanic explosivity							1.055
							(0.76)
Volcanic explosivity							-18.241
							(15.32)
Log remittances	-3.010	-2.726	-1.486	-1.472	0.219	-2.149	-1.486
	(1.85)	(1.77)	(1.35)	(1.33)	(1.50)	(1.70)	(1.53)
Poverty headcount ratio at $1.25 a day (lag)	0.834***	0.838***	0.811***	0.840***	0.811***	0.752***	0.724***
	(0.13)	(0.11)	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114	114	114	114	114	114	114
Number of countries	42	42	42	42	42	42	42
Hansen test for overidentification : chi2(19)	22.91	23.32	17.71	20.25	15.45	18.20	16.89
Prob > chi2	0.241	0.223	0.542	0.380	0.694	0.509	0.597
Arellano-Bond test for AR(2): z	-1.17	-1.21	-1.65	-1.52	-1.61	-1.51	-1.24
Pr > z	0.242	0.227	0.100	0.128	0.107	0.132	0.214

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively.

Table 6: Robustness checks: Effect of natural disasters and remittances on poverty using an alternative measure of poverty

Dependent variable: Poverty gap at $2 a day (ppp)

	Country fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-0.993***						
	(0.29)						
Disaster Index	19.063***						
	(5.93)						
Log remittances*Wind speed		-1.117**					
		(0.50)					
Wind speed		22.157**					
		(10.17)					
Log remittances*Δ temperature			-0.207***				
			(0.05)				
Δ temperature			3.713***				
			(0.97)				
Log remittances*drought				-0.355*			
				(0.19)			
Drought				7.296*			
				(4.04)			
Log remittances*flood					-0.183		
					(0.21)		
Flood					2.852		
					(4.10)		
Log remittances*Richter scale						-0.205	
						(0.36)	
Richter scale						1.878	
						(7.13)	
Log remittances*Volcanic explosivity							-0.290
							(0.31)
Volcanic explosivity							5.822
							(6.22)
Log remittances	-1.017*	-1.404*	-0.495	-0.814	-0.742	-0.634	-0.655
	(0.63)	(0.81)	(0.64)	(0.71)	(0.70)	(0.68)	(0.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	317	317	317	317	317	317	317
R-squared	0.521	0.51	0.50	0.49	0.49	0.50	0.49
Number of countries	52	52	52	52	52	52	52

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Appendix A: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Poverty headcount ratio at $1.25 a day (ppp)	24.71	22.58	0	85.92	313
Poverty gap at $2 a day (ppp)	18.9	15.9	0	67.13	317
Disaster Index (Standardized values)	-0.21	0.87	-2.55	3.27	313
Wind speed (Standardized values)	-0.31	0.73	-2.72	3.55	312
Δ temperature (Standardized values)	0.32	2.48	-0.23	18.04	312
Drought (Standardized values)	0.01	1.02	-0.26	3.92	312
Flood (Standardized values)	0.02	0.99	-0.93	7.45	312
Richter scale (Standardized values)	0.12	0.98	-1.68	2.08	312
Volcanic explosivity (Standardized values)	0.1	1.2	-0.31	8.19	312
Log remittances	19.84	2.16	9.35	24.62	313
Polity Index	0.62	0.3	0.05	0.95	312
Log population	9.76	1.44	7.5	14.1	312
Population density	118.89	153.52	1.79	1142.29	312
Urban population	43.24	16.82	4.99	82.47	312
GDP growth per capita (lag) (ppp)	0.06	0.06	-0.22	0.39	312

Appendix B: Variables definition and source

Variables	Definition	Source
Poverty headcount ratio at $ 1,25 a day (PPP) (% of population)	Percentage of population living in households with consumption or income per person below the poverty line of $1.25 a day, adjusted for purchasing power parity (PPP)	PovcalNet database-World Bank
Poverty gap at $2 a day (PPP) (%)	Poverty gap is the mean shortfall from the poverty line (counting the non poor as having zero shortfall), expressed as a percentage of the poverty line of $2 a day, adjusted for purchasing power parity (PPP). This measure reflects the depth of poverty as well as its incidence.	Online World Bank WDI
Disaster Index	Sum of disaster types	Geomet data (Game), Felbermayr and Gröschl (2014)
Wind speed	Maximum wind speed in knots for storms and hurricanes, combined measure	Geomet data (Game), Felbermayr and Gröschl (2014)
Δ temperature	Difference of monthly temperature over the long run mean	Geomet data (Game), Felbermayr and Gröschl (2014)
Drought	Dummy equal 1 if for 3 month in a row or 5 months within year, rainfall level is below 50% of the long run mean, 0 otherwise	Geomet data (Game), Felbermayr and Gröschl (2014)
Flood	Positive difference in precipitation over the long run mean	Geomet data (Game), Felbermayr and Gröschl (2014)
Richter scale	Maximum Richter scale for earthquakes	Geomet data (Game), Felbermayr and Gröschl (2014)
Volcanic explosivity	Maximum Volcanic Explosivity Index for volcanoes	Geomet data (Game), Felbermayr and Gröschl (2014)
Remittances	Personal remittances, received (Current US$)	Online World Bank WDI
Polity Index	Polity Index between 0 and 1	Polity IV
Population	Total population (in thousands)	Penn World Table
Population density	Number of inhabitants per km²	Online World Bank WDI
Urban population	Urbanization rate	Online World Bank WDI
GDP growth per capita (ppp)	difference between the logarithm of GDP per capita in t and $t-1$, adjusted in purchasing power parity	Penn World Table

Appendix C: List of countries

Albania	Honduras	Paraguay
Angola	India	Philippines
Armenia	Indonesia	Rwanda
Azerbaijan	Jordan	Senegal
Bangladesh	Kenya	Sri Lanka
Bolivia	Kyrgyz Republic	Syrian Arab Republic
Burkina Faso	Lao PDR	Tajikistan
Burundi	Liberia	Tanzania
Cameroon	Madagascar	Thailand
China	Mali	Togo
Congo, Rep.	Mauritania	Tunisia
Cote d'Ivoire	Morocco	Uganda
Ecuador	Mozambique	Ukraine
Egypt, Arab Rep.	Nepal	Vietnam
El Salvador	Nicaragua	Yemen, Rep.
Ethiopia	Niger	Zambia
Guatemala	Pakistan	
Haiti	Papua New Guinea	