CSAE Working Paper WPS/2024-01

Weathering the Storm: Investigating the Role of Remittances as Immediate Disaster Relief in Developing Countries

Zubin Deyal

January 2024

Abstract

This paper investigates the impact of natural disasters on remittances in developing countries, which are particularly vulnerable to the immediate and long-term effects of such events. In addition to damaging economic capacity, natural disasters are large exogenous shocks which result in capital flight that exacerbates the immediate deficit that developing countries face in their aftermath. Though remittances have proven vital in addressing financing gaps for these countries, their immediate response to natural disasters has not been thoroughly studied. This paper expands the literature by offering a comprehensive analysis of the influence of natural disasters on monthly remittances across 30 developing countries for the 30-year period of 1993 to 2022. In utilising a dynamic fixed effects model on data sourced from respective Central Banks, I find an immediate rise in remittances post-disasters, notably in Asia, Central America, and South America, and specifically in response to hydrological and meteorological disasters. The rise in remittances is typically highest in the month after the disaster, with more intense disasters eliciting a larger increase in remittances. I also find evidence of remittance smoothing, as migrants seem to adjust allocations intertemporally. I further establish a countercyclical relationship between remittances and GDP growth, with inflation, nominal exchange rate depreciations, net migration, and disaster aid negatively impacting remittances. The finding that remittances increase after disasters is robust to different specifications, including System GMM, different periods, dependent variables, and monthly, yearly, and regional fixed effects.

Centre for the Study of African Economies
Department of Economics · University of Oxford · Manor Road Building · Oxford OX1 3UQ
T: +44 (0)1865 271084 · F: +44 (0)1865 281447 · E: csae.enquiries@economics.ox.ac.uk · W: www.csae.ox.ac.uk

Acknowledgements

This paper was initially prepared as a dissertation for my MSc in Economics for Development degree from Oxford University. I am indebted to my supervisor from the course, Chris Adam, who directed me to look at high-frequency remittance data and supported me continuously throughout the writing and analysis process. I also appreciate my colleague Chevano Baker, who provided advice on natural disaster recovery and thesis writing, himself publishing a distinction-awarded thesis on the same MSc programme years earlier.

Table of Contents

1. Introduction 4
2. Literature Review 6
3. Data Description and Variable Selection 8
    3.1 Monthly Remittances 8
    3.2 Natural Disaster Variables 10
4. Theoretical Rationale 13
5. Empirical Framework 14
    5.1 Diagnostic Tests 14
6. Empirical Results 16
    6.1 Baseline Regressions 16
    6.2 Different Disaster Types 20
    6.3 Different Regions 20
7. Robustness Checks 21
8. Conclusion 24
References 26
Appendix 30
    A1: Pearson Correlation Matrix 30
    A2: Hausman, Wooldridge, and Modified Wald Tests 30
    A3: Fisher Unit Root, VIF, and Pesaran Tests 30
Addendum 31
    D1: Robustness: Regional, Yearly, and Monthly Effects 31
    D2: Robustness: Dependent Variables & Time Periods 32

1. Introduction

Climate change has led to more severe and frequent natural disasters across the globe, causing devastation at an unprecedented magnitude, with particularly severe tolls on developing nations (Seneviratne, et al., 2012). These countries often suffer more due to poor infrastructure, misallocation of limited resources stemming from weak governance, and higher poverty rates in densely populated urban areas where the impacts on individuals are particularly severe (IMF, 2019; UN, 2020).[1] The effects of natural disasters are worsened by capital flight, whereby countries experience a significant outflow of private financial resources that increase financial deficits and limit rebuilding efforts (Benson & Clay, 2004; Rojas-Suárez, 1991). Though aid is often considered a means of increasing capital post-disaster, it faces inefficiencies as it is difficult to allocate individually (Noy, et al., 2012). Consequently, individuals and communities are frequently forced to rely on their own resources in times of crisis.

Remittances, defined as funds sent by migrants to their home countries, are a major source of funding for developing countries. They stood at US$626 billion in 2022 and have been the highest source of external finance for developing countries since 2015 (Ratha, et al., 2022).[2] They bolster national economies, helping to maintain the balance of payments, service external debt, and expand fiscal space (Maimbo & Ratha, 2004). Remittances have also been found to stimulate growth in many countries by providing capital for businesses, infrastructure, and other sectors (Cazachevici, et al., 2020; Ekanayake & Moslares, 2020).[3] They are a large transfer to less prosperous nations that tend to remain resilient during economic instability, contributing to financial security and serving as a reliable form of income (Frankel, 2010).

In theory, remittances are countercyclical due to the informal contract between the migrant and the household, where migration is a superior strategy due to the migrant's movement to places with different economic cycles (Lucas & Stark, 1985). In the absence of functional insurance markets, migrants are compelled to respond to shocks at home due to altruism or self-interest. This informal contract makes remittances more resilient to natural disasters than other financial flows. Further, remittances can complement aid as they are more targeted, directly reaching households in need, and can be sent quickly, free from the delays that often impede the aid process, such as approval, distribution, and logistical challenges (Kpodar, et al., 2021; Maghsoudi & Moshtari, 2020; Stojanov & Strielkowski, 2013).

[1] Sometimes known as the adaptation deficit, it refers to the fact that poor countries are more heavily affected by extreme weather events and future climate change than rich countries (Fankhauser & McDermott, 2013).
[2] Excluding China, remittances are the premier source of external finance, exceeding FDI and ODA.
[3] The effects are however different between countries, with Cazachevici, et al., 2020 especially noting that some countries in Africa do not benefit from remittances through higher economic growth.

Despite their theoretically countercyclical nature, the current literature surrounding the response of remittances to natural disasters is divided. The cross-country studies show mixed results, with some supporting remittances increasing post-disaster, and others suggesting remittances do not increase at all, or if they do, it happens slowly. All the existing cross-country studies also focus on the annual remittance response, which presents a few problems. Firstly, it agglomerates disasters annually, which makes it difficult to unpack the response to different disasters throughout the year, including different types and intensities. Moreover, endogeneity becomes a more serious problem, as yearly changes in data can also reflect the effects of remittances. Secondly, annual data restricts the sample, concentrating remittances and disasters into a few individual observations. Under these small sample sizes, Nickell Bias becomes a concern with fixed effects models that have small timeseries, and identification becomes more difficult as some countries have natural disasters affecting all years for which data is available. Thirdly, the approach ignores the speed at which response occurs, a vital consideration if remittances must help the immediate, short-term recovery process.

This study adds to the literature by pooling data from the Central Banks of 30 developing countries to analyse the response of monthly remittances to natural disasters for the 30-year period of 1993 to 2022. The results through a dynamic fixed effects model show that remittances increase following disasters, both in the month of the disaster and the month after. More intense disasters elicit a higher increase, with migrants intertemporally smoothing remittances in the second month following a disaster. Increases in remittances are found in Asia, Central America, and South America, with Hydrological and Meteorological disasters in particular evoking increases. The countercyclical nature of remittances is demonstrated by their significant negative relationship with GDP growth. Inflation, nominal exchange rate depreciations, net migration, and disaster-related aid also have negative and significant impacts on remittances. The results are robust to numerous specifications, including System GMM, monthly, yearly, and regional fixed effects, and different time periods and dependent variables.

The remainder of the paper is as follows. Section 2 reviews the literature with a focus on cross-country studies. Section 3 describes the data, including remittances, natural disasters, and other control variables. Section 4 outlines a simplified theoretical framework. Section 5 presents the econometric model and different diagnostic tests through which the methodology was derived. Section 6 outlines the results while Section 7 tests their robustness. Section 8 then concludes with a short summary and a few policy implications.

2. Literature Review

The literature on the response of remittances to natural disasters in receiving countries comprises cross-country and single-event studies, some of which confirm remittances increase following natural disasters, while others suggest that remittances respond sluggishly or not at all. The cross-country studies, which are the focus of this review, analyse remittances annually. These annual studies have identification problems as they agglomerate disasters into one yearly variable, making it difficult to gauge the effect of natural disaster types and to determine the speed at which remittances adjust. Disasters are also identified differently across studies, with some considering disaster types while others account for intensity through damages or the number of people affected. Moreover, these studies use a mix of methods including dynamic fixed effects which is only accurate with sufficiently long timeseries, and system or difference GMM and panel VAR models to specifically address endogeneity.[4]

Several cross-country studies argue that remittances increase in response to natural disasters.[5] David (2010) in his study of 78 countries from 1970 to 2005 found under a dynamic fixed effects model that remittances increase in response to climatic disasters. In a panel VAR model, the study also found climatic disaster shocks were responsible for 16% of the variance in remittances at a 10-year horizon. The study however did not quantify disaster intensities and used limited explanatory variables, namely the interest rate differentials and exchange rates. Mohapatra et al. (2012) report similar results in their dynamic fixed effects study of 129 developing countries over a 30-year period. The study used limited controls, namely the emigrant stock, GDP per capita, and a time trend, finding that remittances increased in response to more severe natural disasters. Similarly, Bettin & Zazzaro (2018), through the System GMM estimator, found remittances increased in 98 low and middle-income countries which suffered at least one annual disaster between 1990 and 2010, with effects persisting two years after the impact. Though the study had several controls including aid, migrant stock, and GDP per capita, it did not include a time trend, and the sample for some countries was small, with some countries registering a disaster every year. The impact could therefore have been down to general increases in remittances over the period and identification problems.

Other papers suggest that remittances may have a more nuanced response to disasters. In a fixed effects model assessing 36 countries from 1970 to 2002, Yang (2008) found that

[4] All the cross-country studies examined used country-clustered standard errors.

[5] Some studies have explored how remittances impact output in disaster recovery. Mbaye & Drabo (2017) in their fixed effects model found that a 1% increase in the disaster index and average remittances led to a 1.145% decline in poverty. Combes & Ebeke (2011) discovered remittances dampened the destabilising effects of disasters on output within the range of 8%-17% of GDP but amplified it beyond this threshold.

hurricanes only led to an increase in remittances amongst poorer nations, while richer nations depended more on aid. Though the study used a time trend, it only controlled for the migrant stock. Arezki & Brückner (2011) also noticed through their dynamic fixed effects model that remittances increased in response to rainfall shocks in countries with thin financial markets, but the response was significantly negative in countries with more developed ones. The study, which covered 42 Sub-Saharan African countries from 1960 to 2007, used domestic credit to GDP to proxy financial development but did not use any other control variables. In a similar vein, Amuedo-Dorantes et al. (2010) in their panel VAR analysis found that annual remittances increased only in 27 Small Island Developing States (SIDS) following disasters but did not increase across the remaining 92 developing countries. Though the study found aid crowded out remittances, it did not account for other controls or disaster intensity.[6]

Other studies conclude that remittances do not respond to disasters. Through a novel gravity model analysing data from 1980 to 2004, Lueth & Ruiz-Arranz (2006) found that remittances do not increase across the 11 recipient countries they studied in response to natural disasters but rather that they were correlated to the home country's business cycle. However, the results are undermined by the study not using any measure of disaster intensity to narrow down on disasters over the period. Naudé & Bezuidenhout (2012) in analysing 23 Sub-Saharan African countries from 1980 to 2007, found that remittances did not increase in response to total natural disasters under either a fixed effects model or the difference GMM estimator, with incomes, migration, and the exchange rate being more important determinants.

Though the micro literature is more in support of remittances increasing in response to natural disasters, and often look at higher frequency data than the cross-country studies, they tend to focus on single disaster incident.[7] Further, they may suffer from selection bias with researchers analysing specific instances in which they suspect remittances would have increased following a disaster, either due to the severity of the disaster or the country's reliance on remittances. These studies therefore cannot answer whether remittances increase generally

[6] The authors proposed that SIDS may experience disasters more intensely, possess more altruistic migrants, or suffer fewer disruptions to their financial system.

[7] Giannelli & Canessa (2022) found households affected by a flood in Bangladesh in 2014 had an increased likelihood of receiving remittances and migrating to offset 28% of losses. Clarke & Wallsten (2004) similarly found that remittances increased 25 cents for every dollar in damage caused by Hurricane Gilbert in Jamaica. Some macroeconomic studies for single countries find remittances also increase following disasters, including Mitrut & Wolff (2014) who find increases after the 2004 Tsunami in Indonesia, and Yang & Choi (2007) who found remittances increased following rainfall shocks in the Philippines. Suleri & Savage (2006) and De et al. (2014) find that individuals use remittances to recover from natural disasters, while Mohapatra et al. (2009) provide evidence of instances where remittances rose after sudden natural disasters.

in response to natural disasters, nor whether there are differences across disasters or regions, they can only speak to specific and possibly biased examples.

To date, the only known cross-country study that utilises data at a higher frequency than annual is Bragg et al. (2018). The study found that in the quarter following 18 major disasters across 12 countries from 2000 to 2014, remittances rose, but there was seldom an increase in the disaster year which exceeded the average. However, the study did not employ empirical analysis or consider explanatory variables. Instead, the findings were based on differences in average rates in disaster versus non-disaster periods, without any econometric procedures. The need for further research is therefore clear, especially through high-frequency data that can increase the sample, better isolate natural disasters, and provide clarity on whether remittances increase following a disaster, and if they do, the speed at which the transfer occurs. As guided by the literature, the baseline uses a dynamic fixed effects model given the long timeseries, with SGMM used later on for robustness. The controls are also in-line with the literature, outlined fully in the following section.

3. Data Description and Variable Selection

3.1 Monthly Remittances

The panel was created by compiling monthly remittance data for 30 developing countries from their respective Central Banks for the period of January 1993 to December 2023 (Table 1). Though the timeseries were continuous for all countries once recording started, the panel is unbalanced as the start date differed across countries.[8] Remittances were adjusted by dividing them by the population, converting them to US$, and deflating them to constant 2010 prices. Per capita was preferred for scaling because it best preserved underlying monthly changes and allowed easy comparisons of the benefit to affected individuals post-disasters.[9]

A total of 7,037 monthly remittance data points were collected, with an average value of US$21.68.[10] Central America (US$29.79), Europe (US$28.73), and Asia (US$22.13) had the highest average amounts, while South America (US$6.04) and Africa (US$1.70) trailed. Tonga had the highest average per capita remittances (US$102.54), followed by Jamaica (US$55.79), Armenia (US$50.89), Samoa (US$50.56), El Salvador (US$44.58), and the Dominican Republic (US$41.17). From 1993 to 2000, remittances remained stable, then rose steadily from US$11.94 in 2001 to US$21.81 in 2008. After the financial crisis, between 2009

[8] Remittance data was not available for Brazil and North Macedonia so personal transfers were used instead.
[9] To ensure accuracy, data was cross-referenced with World Bank annual estimates.
[10] For the remainder of the document, remittances are in constant 2010 US$. Zambia had particularly low remittances for the period under consideration because of this, as the country went through a rebasing in 2013 that ultimately skewed the value of remittances, making them considerably lower (Bank of Zambia, 2012).

and 2014, remittances hovered around US$20 but subsequently climbed from 2014 to a peak of US$32.68 in 2022 (Figure 1). Remittances also differ by month as they are notably higher in December (US$24.92) and drop at the beginning of the year, with January (US$18.41) and February (US$18.63) seeing particularly low levels (Figure 2).

				Disasters (25th)				
Country	Region	Remittances Per Capita	Monthly Observations	Total	G	H	M	Source
Armenia	EU	50.89	228	5	0	0	1	Central Bank of Armenia
Bangladesh	AS	8.10	54	10	0	5	5	Bangladesh Bank
Bolivia	SA	8.02	192	31	1	21	1	Central Bank of Bolivia
Brazil	SA	1.04	336	95	0	82	1	Central Bank of Brazil
Bulgaria	EU	12.36	155	6	0	6	0	Bulgarian National Bank
Cape Verde	AS	22.68	219	4	1	1	0	Bank of Cape Verde
Colombia	SA	7.96	276	65	9	55	3	Bank of the Republic
Comoros	AS	5.99	284	6	3	2	2	Central Bank of the Comoros
Dominican Republic	CA	41.17	156	21	0	8	11	Central Bank of the Dominican Republic
El Salvador	EU	44.58	360	28	6	5	8	Central Reserve Bank of El Salvador
Fiji	AS	28.28	359	25	0	5	18	Reserve Bank of Fiji
Georgia	EU	22.51	282	12	2	8	0	National Bank of Georgia
Guatemala	CA	27.05	336	49	7	23	12	Bank of Guatemala
Haiti	CA	16.55	35	4	1	2	1	Bank of the Republic of Haiti
Jamaica	CA	55.79	347	14	0	2	9	Bank of Jamaica
Kenya	AF	2.40	228	42	1	28	0	Central Bank of Kenya
Kyrgyzstan	EU	22.29	216	9	4	3	1	National Bank of the Kyrgyz Republic
Mexico	CA	15.27	335	92	16	32	55	Bank of Mexico
Nicaragua	CA	13.25	275	35	2	16	11	Central Bank of Nicaragua
North Macedonia	EU	9.29	261	13	1	7	4	National Bank of the Republic of Macedonia
Pakistan	AS	5.65	210	38	7	24	4	State Bank of Pakistan
Paraguay	SA	4.55	233	28	0	13	0	Central Bank of Paraguay
Philippines	AS	13.32	359	201	35	94	129	Bangko Sentral ng Pilipinas
Samoa	AS	50.57	359	3	1	0	1	Central Bank of Samoa
Sri Lanka	AS	21.11	167	45	0	34	4	Central Bank of Sri Lanka
Suriname	SA	13.93	141	2	0	2	0	Central Bank of Suriname
Tonga	AS	102.54	83	2	0	0	2	National Reserve Bank of Tonga
Turkey	AS	2.73	359	35	19	21	2	Central Bank of the Republic of Turkey
Ukraine	AS	20.31	60	3	0	1	0	National Bank of Ukraine
Zambia	AF	0.48	132	5	0	3	0	Bank of Zambia
Total			7037	928	116	503	285	
Average		21.69	235					
Where G, H, M stands for Geophysical, Hydrological, Meterological respectively.								

Table 1 - Remittances & Disasters by Country

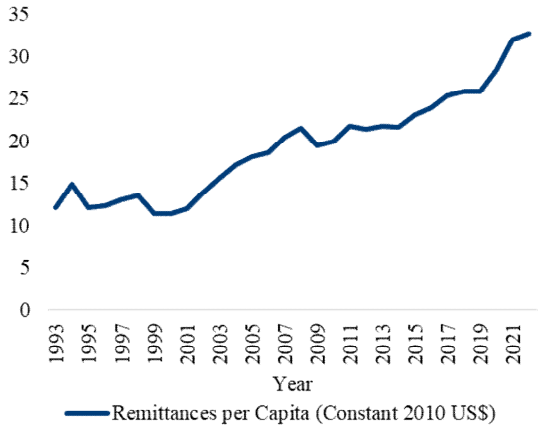

Figure 1 - Remittances by Year

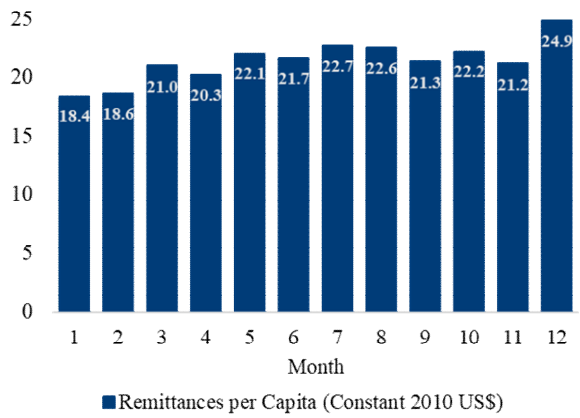

Figure 2 - Remittances by Month

3.2 Natural Disaster Variables

The Emergency Events Database (EM-DAT) documents natural disasters and is managed by the Center for Research on the Epidemiology of Disasters (CRED). EM-DAT covers over 25,000 disasters since 1900, including information on the type, the number of affected people, and damages in US$.[11] A total of 1816 natural disasters were observed for the countries in their respective months, yielding a 0.2581 probability of a country witnessing a natural disaster in a given month. However, EM-DAT thoroughly documents disasters, such that even small ones like minor floods have their own entries. The database also identifies some disasters with the same origin – such as a cyclone which led to a landslide – into distinct entries.

Therefore, disaster dummies were used to identify major disasters, with intensities greater than the 25th, 50th, 75th, and 90th percentiles. Multiple percentiles were used to examine whether more intense disasters resulted in larger increases in remittances. The disaster dummies were assigned a value of 1 if the damages (relative to the log of GDP) or the number of people affected (relative to the log of the population) surpassed the specific percentile. Otherwise, the variables were assigned values of 0. The transformation using logs considers the proportional effect of disasters on nations based on their size and economic standing. This approach contrasts with conventional intensities that diminish the impact of disasters in smaller countries by looking at damages or the people affected alone. Some also skew the significance towards smaller nations when these variables are apportioned against the GDP and population.

		Disaster Types (25th)			*Disaster Intensities (Percentiles)*			
Region	Remittances per Capita (US$)	Geophysical	Hydrological	Meterological	25th	50th	75th	90th
Africa	1.70	1	31	0	47	31	19	10
Asia	22.13	66	187	167	372	301	188	83
Central America	29.79	26	83	99	215	135	65	24
Europe	28.73	13	29	14	73	33	16	4
South America	6.04	10	173	5	221	144	57	20
Total		116	503	285	928	644	345	141

Table 2 - Remittances and Disasters by Geographies

Of the total disasters, 928 disasters exceeded the 25th percentile, 644 exceeded the 50th percentile, 345 surpassed the 75th percentile, and 141 went beyond the 90th percentile (Table 2). The Philippines had the most disasters at the 25th percentile level (201), followed by Brazil (95), Mexico (92), Colombia (65) and Guatemala (49) (Table 1).[12] In terms of continents, Asia

[11] A natural disaster is entered into the database if it meets at least one of these criteria: (1) ten or more fatalities; (2) a hundred or more affected individuals; (3) a state of emergency; or (4) a call for international assistance.
[12] Disaster frequencies in this paragraph and the relevant tables are described at the 25th percentile level as it is the most inclusive definition of natural disasters in this study that considers the relative intensities.

had the most across all percentiles, while Central America and South America have similar amounts at every intensity. To further examine heterogeneity in the response of remittances to different disasters, after factoring in intensity, disasters were subdivided into three main categories: geophysical comprising earthquakes, mass movements, and volcanic eruptions; hydrological comprising floods, wave action, and landslides; and meteorological comprising storms, extreme temperatures, and cyclones. At the 25th intensity, hydrological disasters were most frequent (503) while meteorological (285) and geophysical (116) followed (Table 2).

3.3 Control Variables

The choice of controls is limited by the monthly timeframe of the analysis.[13] Nevertheless, a few key variables from the literature are included as controls (Table 3). [14]

Controls for political stability from the WGI (Worldwide Governance Indicators) and financial openness from the Chinn-Ito Index were included. Political stability leads to a more predictable and secure environment, including the smooth operation of formal remittance channels, that ultimately enable migrants to send money home. In contrast, political instability can disrupt these transfers, forcing migrants to rely on informal channels, which may be less secure and more expensive (Agbegha, 2006). Greater financial openness should also stimulate remittances as fewer capital controls should make it easier to send money, especially through the formal channels through which the remittance data is tracked (Beine, et al., 2012).

A variable capturing the effects of migration is also included in the form of the net migration rate - the difference between inward and outward migration (people entering versus leaving the country) defined per 1000 of the population. Though the abroad migrant stock may have been a better control variable, estimates for migrant stocks are only published at five-year intervals for many of the countries under consideration.[15] Despite not isolating outward migration, the coefficient is expected to be negative as lower net migration (or negative net migration) should suggest that a country has more migrants abroad to send remittances. The monthly interpolation of the variable is lagged by a year to account for the fact that migrants may take time abroad to settle and start working (Ghosh, 2006).

[13] A few potential controls could not be used due to limitations in monthly estimates, including unemployment.
[14] Monthly values were obtained for variables such as disaster aid, the exchange rate change, and CPI inflation. For real GDP growth, financial openness, political stability, and net migration, monthly values were interpolated by reverse compounding to derive monthly estimates.
[15] Outward migration alone as its own variable is also not reported.

A disaster-related aid dummy which takes the value of 1 where a country gets disaster aid in a particular month is also included as a control variable, based on the AidData Dataset.[16] The relationship between aid and remittances is complicated, especially following a disaster, as remittances can impact aid, and both can increase simultaneously following severe disasters. Nonetheless, aid is generally thought to reduce remittances after a disaster as it provides an alternative source of funds for disaster relief for affected families (Amuedo-Dorantes & Pozo, 2006; Bettin, et al., 2014; Kpodar & Goff, 2012). The coefficient is therefore expected to be negative as having a disaster aid programme in a particular month should crowd out remittances by reducing the need for external support from migrants.[17]

Variable	Mean	Std. Dev.	Minimum	Maximum	Expectation	Source
Remittances per Capita	21.4163	22.1815	0.0768	168.9745	+	Various Central Banks (2023)
Disaster Aid Programme	0.0787	0.2693	0	1	-	AidData Core 3.1 (2016)
Exchange Rate Change	0.378%	0.0292	-88.58%	54.37%	-/+	IMF IFS (2023)
Financial Openness	0.5240	0.3160	0	1	+	Chinn-Ito Index (2020)
GDP Growth	0.254%	0.0032	-1.54%	1.18%	-	IMF IFS (2023)
Inflation	0.584%	0.0128	-7.06%	23.38%	-	IMF IFS (2023)
Net Migration Rate (per 1000)	-4.8349	5.5709	-31.2	10.1	-	UN WPP (2022)
Political Stability	-0.3957	0.7814	-2.81	1.3439	+	WGI (2023)

Note: International Monetary Fund, IMF; International Financial Statistics, IFS; United Nations, UN; World Population Prospects, WPP; World Governance Indicators, WGI.

Table 3 - Variables Summary Statistics & Sources

The percentage change in the nominal exchange rate, and inflation, are included with one-month lags to reduce endogeneity concerns.[18] It is unclear from the literature the effect that the nominal exchange rate has on remittances. Theoretically, a depreciation of the nominal exchange rate should mean that remittance senders get more value for money and respond by increasing the total remittances (Rahman, et al., 2019). However, migrants can respond to a depreciation of the nominal exchange rate by reducing the amount they transfer in foreign currency if they want to send a regular fixed local amount (Amuedo-Dorantes & Pozo, 2006). A higher nominal exchange rate can also signal inherent instability that ultimately impedes remittances (Boutalby, 2022; El-Sakka & McNabb, 1999). Therefore, the expected coefficient for a nominal exchange rate change is unclear. Inflation is more straightforward, however, as higher inflation typically means that the purchasing power of remittances is reduced, with

[16] These were projects which the dataset classified as emergency response, reconstruction relief, and disaster prevention. A large number of these projects had no dates, instead showing receipt in January or December, and so any projects which were classified as being received in those months were not considered.

[17] However, countries may receive foreign aid to help recover from a natural disaster due to the severity of the disaster making it necessary. This means it could be possible for both remittances and foreign aid to increase together, raising concerns about endogeneity.

[18] Though these variables could have been combined into the real exchange rate, the analysis wanted to isolate the effects of each variable instead of masking inflation and assuming that purchasing power parity holds.

extremely high levels of inflation also signalling instability that discourages remittances (Hagen-Zanker & Siegel, 2007). The expected coefficient is therefore negative – higher inflation should reduce remittances. Concerns about endogeneity for both variables are addressed through a one-month lag. The use of the lag implies that remittance senders make decisions based on historical data, which is not far-fetched as they typically get salaries at month's end, at which point data from the month before should be available.

Similarly, a one-month lag of real GDP growth was included as a control despite endogeneity concerns. As monthly figures for GDP growth are not available, and suitable instruments such as unemployment were not found for the countries and periods considered, the figures for GDP growth were interpolated through reverse compounding annual growth rates. This raises obvious problems as remittances can impact GDP growth throughout the year, skewing the relationship between the variables. Though this is not directly accounted for under the baseline, robustness tests specifically factor in endogeneity later on. Based on the literature and the assumed countercyclical properties of remittances, it is expected that if real GDP declines, remittances should rise in response (Hagen-Zanker & Siegel, 2007; Gupta, 2005).[19]

4. Theoretical Rationale

The countercyclical characteristics of remittances can be understood through the lens of risk sharing and household strategies (Lucas & Stark, 1985). Developing countries are often plagued with broken or missing markets for insurance, and wages are limited by smaller per capita incomes. Households, therefore, use migration for informal insurance whereby migrants move to countries with different economic cycles that typically also have higher per capita GDPs that allow migrants to earn higher salaries. This raises total household income and enables the household to better respond to shocks, including natural disasters.

Once the household decides migration is an optimal strategy, the decision to remit on the migrant's part is based on a combination of altruism and self-interest. The altruistic view is that the migrant cares about their household. Migrants may feel a strong sense of empathy for those at home and may increase remittances to help meet immediate needs arising from events like natural disasters. This altruism can also extend to situations where remittances serve as repayment for loans, such as those taken for education. Migrants also send remittances out of self-interest. In response to disasters, this may include protecting their inheritance by remitting to preserve inheritance rights or rebuilding when a property which might be inherited

[19] Given the desire to understand whether remittances are countercyclical overall, including in response to economic slowdowns, it was deemed important to continue with this variable despite concerns about endogeneity.

is damaged. Sending remittances may also help migrants benefit from higher future household earnings through the household providing reciprocal insurance during downturns.

Both altruistic and self-interest motives for remitting can be simplified into the migrant getting utility from a combination of their consumption and home consumption. Home consumption is contingent on the remittances the migrant sends and home income. The value of remittances the migrant sends depends on home inflation (which can erode the purchasing power of remittances), the nominal exchange rate (which affects the local remittance value), and financial openness and political stability, both of which can facilitate or hinder transfers.[20] Whether a disaster occurs, and the provision of aid, also influence home income and therefore indirectly determine the amount that migrants remit.

5. Empirical Framework

The model capturing the effects of natural disasters on remittances is specified as follows:

$$R_{it} = \alpha_i + \gamma R_{it-1} + \beta_1 D_{it} + \beta_2 D_{it-1} + \beta_3 D_{it-2} + \beta_4 EA_{it} + \beta_5 N_{it-12} + \Sigma\beta_i X_{it} + \Sigma\beta_i Z_{it-1} + \varphi M + \epsilon_{it} \quad (1)$$

where the dependent variable R_{it} is the per capita remittances received by country *i* at time *t* in constant 2010 US$ and R_{it-1} is the lagged dependent variable. The disaster variable D_{it} takes a value of 1 if a disaster hits with an intensity above a certain percentile (either the 25th, 50th, 75th, or 90th) in country *i* in time *t,* taking a value of 0 otherwise. Similarly, D_{it-1} and D_{it-2} are dummy variables capturing whether a country had a disaster of a specified percentile in the month before or two-months before respectively. EA_{it} has a value of 1 if a country receives disaster-related aid in a particular month and 0 otherwise. The 12-month delayed effects of net migration are included as N_{it-12}. $\Sigma\beta_i X_{it}$ are country-specific fundamentals such as political stability and financial openness. One month lagged values of fundamentals are captured by $\Sigma\beta_i Z_{it-1}$ including, the percentage change in the nominal exchange rate, CPI inflation, and real GDP growth. Fixed effects are captured for each country by α_i and month by M.[21]

5.1 Diagnostic Tests

Several diagnostic tests were conducted to determine the appropriate methodology (Appendices 1 – 3). A priori, fixed effects estimation was preferred for a few reasons. Firstly,

[20] Greater outward migration should increase the total migrants as a whole, therefore increasing remittances overall when looking at the entire country if the amount transferred by each migrant remains the same.
[21] Regional and yearly fixed effects are introduced later for robustness.

much of the cross-country literature utilises it. Secondly, the regressors are likely correlated with country-specific effects and including the country effects as a regressor under the random effects model can cause biased estimates. Moreover, the fixed effects method captures the time-invariant omitted variables, including culture, that do not change substantially over the period of study. These beliefs were reinforced by the Hausman test (1978) which showed evidence for systematic differences between the coefficients of the fixed and random effects models.

Though the inclusion of the lagged dependent variable as a regressor introduces the well-known Nickell Bias under the fixed effects model, it is not a major concern given the large sample size. The bias arises due to the correlation of the lagged dependent variable with the error term, which creates endogeneity that is severe under finite time periods. However, given that the bias grows smaller as the time dimension of the panel grows larger, the average continuous monthly observations of this study (235) is large enough to considerably reduce the concern. Therefore, the analysis proceeded with a dynamic fixed effects model.

Additional tests were carried out to confirm the methodology. No evidence of multicollinearity between the explanatory variables was found as the Pearson coefficient matrix had pairwise correlations all less than 0.7 and the values of the Variance Inflation Factor (VIF) were less than 5 (Shrestha, 2020). Fisher-type unit-root tests found that all the variables exhibit stationarity, and hence, cointegration tests were not necessary (Jalil & Rao, 2019).[22] The Wooldridge test (2002) nonetheless found first-order autocorrelation (Drukker, 2003), and a Modified Wald test rejected constant variance, finding heteroskedasticity (Baum, 2000). Further, the Pesaran (2004) test rejected that residuals are uncorrelated across countries, confirming cross-sectional dependence (Pesaran, 2004).[23] Therefore, Driscoll and Kraay (DK) (1998) standard errors robust to autocorrelation, heteroskedasticity, and cross-sectional dependence were preferred to cluster robust standard errors (Hoechle, 2007).

The cross-country studies suggest the need to account for endogeneity which mainly arises from the use of annual data. Examining the response of remittances against controls such as GDP growth, the nominal exchange rate, and inflation raise obvious concerns as remittances can influence all, especially over a year. However, the use of high-frequency monthly data, lagged values, and percentage changes reduced potential endogeneity for the nominal exchange rate and inflation, though concerns exist for GDP growth which although lagged, was interpolated from annual figures. The main natural disaster variables are assumed as exogenous

[22] The Fisher test was preferred over the Im-Pesaran-Shin (1997) as it can be used in the unbalanced panel.
[23] The Pesaran test was carried out over individual variables as it could not work in the highly unbalanced panel.

due to the monthly timeframe. In annual studies, countries can use remittances to improve infrastructure which, although it does not stop a natural disaster, might diminish its harm. Remittances are far less likely to distort the impact on a monthly basis.

Despite minimal concerns surrounding Nickell Bias and endogeneity, System GMM (SGMM) estimation was used for robustness. The estimates and tests are shown in Section 7. SGMM was preferred to Difference GMM as the latter magnifies gaps in unbalanced panels and removes fixed effects which captures important country-specific factors such as culture that influence remittances.[24] Though the panel is unbalanced, orthogonal deviations were not used as timeseries were continuous once countries started recording data. One-step analysis was used as there was no second-order autocorrelation based on the Arellano-Bond (AB) AR(2) test when the nominal exchange rate, inflation, and GDP growth were treated as endogenous alongside the lagged dependent (Table 8).[25] However, SGMM is designed for panel data with large cross-sections and short timeseries.[26] The perfect score of the Hansen test suggests that even after collapsing the instruments into a single moment condition, there are too many instruments, and the model may be overidentified (Roodman, 2009).[27] The failure confirms that the dynamic fixed effects method is more appropriate given the timeseries length.[28]

6. Empirical Results

6.1 Baseline Regressions

The baseline results are reported for dynamic fixed effects with Driscoll Kraay (1998) standard errors. Both short-run (1-4) and long-run coefficients (5-8) are shown, where the long-run coefficients are determined by dividing the short-run coefficient by 1 minus the coefficient of the lagged dependent variable (Table 4).[29] The disaster variables for the 25th, 50th, 75th, and 90th percentile disasters are significant and positive across the baseline. All controls are significant at the 10% level with expected signs, with the exception of financial openness.

Across both short-run and long-run, the lagged dependent variable is highly significant showing a large degree of persistence in remittances. This is expected as countries which have very high remittance flows tend to have a strong culture of relying on remittances, meaning

[24] Bettin & Zazzaro (2018) use System GMM whilst Naudé & Bezuidenhout (2012) use Difference GMM.
[25] Given the large sample size, Windmeijer-corrected errors were not used.
[26] This problem arises due to the large timespan of the analysis where the average value of T is 235.
[27] The instruments in the System GMM are collapsed into a single moment condition to reduce overfitting and the computational burden. Collapsing the dataset into years was not used as it defeats the benefit of the study (exploring the immediate *monthly* reaction of remittances to disasters).
[28] Other estimation techniques could be used, such as Panel VAR models, to counteract these problems.
[29] The monthly dummies capturing the seasonality of remittances were also all significant as expected.

past flows should strongly influence future ones. It is also anticipated under the timeframe where month-to-month changes both in remittances and the controls are not particularly large. In the short-run, an increase in the previous month's remittances by US$1.00 per capita would result in an increase of US$0.828 per capita in the current month.[30] This dominance short-run means that the effects of most control variables emerge in the long-run.

Dependent Variable: Remittances per Capita (Constant 2010 US$)	*Short-Run*				*Long-Run*			
	DFE 25th (1)	DFE 50th (2)	DFE 75th (3)	DFE 90th (4)	DFE 25th (5)	DFE 50th (6)	DFE 75th (7)	DFE 90th (8)
Lag Remittances Per Capita	0.828***	0.828***	0.828***	0.828***	4.818***	4.814***	4.820***	4.818***
	(0.0252)	(0.0252)	(0.0253)	(0.0253)	(0.853)	(0.852)	(0.856)	(0.855)
Financial Openness	-0.987***	-0.981***	-0.984***	-1.000***	-5.740**	-5.706***	-5.729***	-5.817***
	(0.369)	(0.367)	(0.368)	(0.370)	(2.065)	(2.054)	(2.059)	(2.068)
Political Stability	0.372*	0.373*	0.367*	0.357*	2.162**	2.166**	2.136**	2.076*
	(0.200)	(0.200)	(0.201)	(0.203)	(0.981)	(0.980)	(0.984)	(1.004)
Net Migration Rate	-0.413*	-0.418*	-0.421*	-0.422*	-2.402*	-2.431*	-2.448*	-2.454*
	(0.232)	(0.232)	(0.233)	(0.233)	(1.375)	(1.376)	(1.379)	(1.381)
Lag Inflation	-18.95**	-19.14**	-19.16**	-19.01**	-110.220**	-111.264**	-111.510**	-110.607**
	(7.871)	(7.894)	(7.898)	(7.884)	(46.989)	(47.121)	(47.162)	(47.165)
Lag Exchange Rate Change	-5.533***	-5.517***	-5.695***	-5.680***	-32.192**	-32.077**	-33.147**	-33.049***
	(2.109)	(2.122)	(2.123)	(2.115)	(12.695)	(12.770)	(12.831)	(12.740)
Lag GDP Growth	-86.12*	-86.03*	-87.92*	-88.95*	-501.022*	-500.231*	-511.690*	-517.550*
	(45.32)	(45.48)	(45.56)	(45.47)	(277.664)	(278.24)	(279.199)	(278.672)
Disaster Aid Programme	-0.359**	-0.368**	-0.375**	-0.360*	-2.090**	-2.138**	-2.181**	-2.097**
	(0.180)	(0.180)	(0.184)	(0.184)	(1.007)	(1.001)	(1.024)	(1.027)
Natural Disaster (ND)	0.341**	0.453***	0.410**	0.636**	1.981**	2.637***	2.388**	3.700**
	(0.132)	(0.162)	(0.187)	(0.284)	(0.779)	(0.964)	(1.033)	(1.572)
One Period Lag ND	0.429**	0.599**	0.657***	0.699***	2.498**	3.484**	3.825***	4.069**
	(0.195)	(0.241)	(0.238)	(0.267)	(1.178)	(1.435)	(1.400)	(1.584)
Two Period Lag ND	-0.184	-0.172	-0.00124	-0.0514	-1.073	-1.002	-0.007	-0.299
	(0.132)	(0.149)	(0.200)	(0.272)	(0.786)	(0.876)	(1.164)	(1.584)
Constant	6.354***	6.363***	6.389***	6.417***	36.967***	36.998***	37.183***	37.336***
	(0.926)	(0.927)	(0.927)	(0.935)	(3.554)	(3.555)	(3.560)	(3.611)
Observations	5655	5655	5655	5655	5655	5655	5655	5655
Within R-Squared	0.7100	0.7100	0.7098	0.7096	0.7100	0.7100	0.7098	0.7096

Driscoll-Kraay robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 4 - Baseline Dynamic Fixed Effects Results

Both inflation and the change in the nominal exchange rate have significant effects on remittances per capita.[31] Inflation, significant at the 5% level, has a negative impact on

[30] This and all other discussions refer to constant 2010 US$ unless otherwise specified.
[31] All figures were calculated using the 50th percentile short-run and long-run coefficients. The calculations for inflation, the exchange rate change, and GDP growth consider that elasticities are constant away from the mean. The values were obtained by multiplying the mean values for these change variables by 1%, using that output to divide 1%, and multiplying the corresponding figure by the elasticities. This gave the representative changes to remittances per capita under 1 percentage point higher inflation, exchange rate, and growth figures.

remittances in-line with expectations. The elasticity suggests that if monthly inflation becomes 1 percentage point higher, it leads to a 0.90% decrease in remittances in the next month in the short-run, with the decrease amounting to 5.22% in the long-run (Table 5). The nominal exchange rate change is also significant at the 1% and 5% levels, with the elasticity suggesting a 1 percentage point increase or depreciation of the exchange rate decreases remittances per capita in the following month by 0.26% in the short-run, amounting to 1.50% in the long-run. This is in line with the idea that higher nominal exchange rates signal instability that reduces remittances or that migrants try to send a fixed value of remittances in local currency.

	50th Percentile Elasticities		*1 Percentage Point Increase*	
Variables	Short-Run	Long-Run	Short-Run	Long-Run
Political Stability	-0.006	-0.037		
Net Migration Rate	0.092	-0.524		
Lag GDP Growth	-0.010	-0.060	-4.03	-23.45
Lag Inflation	-0.005	-0.030	-0.90	-5.22
Lag Exchange Rate Change	-0.001	-0.006	-0.26	-1.50
Financial Openness	-0.024	-0.139		

Table 5 - Elasticities for Control Variables

Remittances also increase when GDP falls but decrease in response to disaster-related aid and net migration. In line with theory, the model finds that GDP growth decreases remittances, significant at the 10% level across disasters. If GDP growth falls 1 percentage point in a month, the remittances per capita are expected to increase by 4.03% the following month, amounting to 23.45% in the long-run. This reinforces that remittances are countercyclical. Disaster-related aid is also found to negatively impact or crowd out remittances, as the coefficient is significant at the 5% and 10% levels across the disaster intensities. Disaster-related aid programmes cause remittances per capita to decline by US$0.368 in the short-run, with a total decrease of US$2.181 in the long-run. This suggests that migrants may reduce their remittances if they know that the household is getting other short-term income to help recovery. Decreasing net migration from the same month one year earlier, that is inward migration relative to outward migration by 1%, increases remittances per capita by 0.53% in the long-run, significant at the 10% level across the baseline.[32]

Political stability is statistically significant at the 10% level in the short-run and the 5% level in the long-run, but it is not economically significant as a 1% increase only corresponds to a minimal 0.037% increase in remittances in the long-run. Similarly, though financial openness is significant at the 1% level across the baselines, its coefficient is negative which

[32] This variable was lagged by a year as it is assumed that individuals who migrate need to time to organise their lives abroad, including through finding a job, before they can start remitting.

suggests an inverse relationship to remittances, contrary to the expectation. A 1% increase in openness is associated with a 0.024% decrease in remittances in the short-run and a 0.139% decrease in the long-run. The negative coefficient may be due to remittances flowing to places with underdeveloped financial sectors that are more closed to capital flows, suggesting financial development might be a pertinent omitted variable that biases this coefficient.[33]

The disaster variables are positive and significant at least at the 5% level for the month of the disaster and the month following the disaster across all percentiles, though they are insignificant and negative across the two-month lag. The coefficients across the month of the disaster and the month following increase with more intense disasters. In the short-run, remittances per capita rise by US$0.341 in the month of a 25th percentile disaster against US$0.636 for a 90th percentile disaster. Similarly, a 25th percentile disaster corresponds to a further increase in the following month of US$0.429 while a 90th percentile disaster sees an increase of US$0.699. This increase is quite substantial if one considers that it goes mainly to those affected in local currency and current prices. However, the effect in the two-month lag is unclear and not statistically significant under any percentile. The negative coefficients for this lag may nonetheless imply some intertemporal smoothing occurs, whereby migrants advance future remittances to the household to help with immediate recovery and consumption i.e., the migrants decrease remittances in this month to offset the increase in the two months prior.

The effects of the disaster become more substantial in the long-run, with increases between US$1.981-US$3.700 in the disaster month depending on intensity, and between US$2.398-US$4.069 in the month after. Overall, the month after registers the largest increase among all months, which may happen due to a few reasons. Firstly, it is likely that migrants withdraw remittances from their salary which is received at month's end. Therefore, the largest increases may occur in the month following the disaster when migrants have the budgetary space to make a larger allocation. Secondly, disasters can happen at any point in the month, including on later days. The effects and response may therefore spill over into the month after the disaster. Thirdly, severe disasters damage infrastructure, including those for receiving remittances. Infrastructure may need time to be rebuilt, and this may delay remittance sending to the following month.

[33] For instance, both Samoa and Tonga, two of the four countries with the largest capita remittances, have financial openness scores in the bottom 10 countries of the sample.

6.2 Different Disaster Types

Analysis was conducted to determine whether different types of disasters had different effects on remittances per capita (Table 6).[34] The metrological disasters noticed an increase in the month after the disaster. This is likely due to the severity of this type, which was dominated by cyclones, making it likely that heavy damage delayed rebuilding post-disaster ultimately slowing down remittances. Hydrological disasters had smaller coefficients under the month after than the meteorological disasters, but it's coefficients were significant in at least one of period across all percentiles, with strong effects in the month of the impact and the month immediately after. Finally, the largest coefficient was under the geophysical category at the 90th percentile disaster, while all other geophysical disasters were found to have insignificant effects on remittances per capita. Potential remittance smoothing was also noticed as negative coefficients were encountered under 9 out of 12 two-month lags, with statistical significance noted at conventional levels for negative coefficients for 25th and 50th hydrological disasters.

DV: Remittances per	*Metereological*				*Hydrological*				*Geophysical*			
Capita (Constant 2010 US$)	25th (9)	50th (10)	75th (11)	90th (12)	25th (9)	50th (10)	75th (11)	90th (12)	25th (9)	50th (10)	75th (11)	90th (12)
ND	0.209	0.389	0.246	0.415	0.449***	0.545***	0.404*	0.710**	0.108	0.103	0.640	0.730
	(0.245)	(0.240)	(0.306)	(0.427)	(0.127)	(0.159)	(0.219)	(0.315)	(0.274)	(0.416)	(0.424)	(0.516)
One Period ND Lag	0.742*	0.953**	0.923*	0.666	0.191	0.320**	0.593**	0.485*	0.443	0.650	0.302	1.239***
	(0.383)	(0.460)	(0.472)	(0.404)	(0.144)	(0.154)	(0.230)	(0.261)	(0.425)	(0.612)	(0.315)	(0.408)
Two Period ND Lag	-0.124	-0.0316	0.0225	-0.106	-0.265**	-0.291*	-0.0897	-0.247	-0.0296	-0.154	0.00412	0.120
	(0.247)	(0.285)	(0.384)	(0.456)	(0.123)	(0.151)	(0.254)	(0.369)	(0.265)	(0.348)	(0.465)	(0.882)

Driscoll-Kraay robust standard errors in parentheses. All coeffients and errors are calculated for the short-run.
* p<0.1, ** p<0.05, *** p<0.01

Table 6 - Remittances Response to Disaster Types

6.3 Different Regions

Table 7 shows differences in disaster intensity across regions in the short-run.[35] Disasters are found to increase remittances per capita in Asia, Central America, and South America, while Africa only had significance for one lag at the 75th intensity. No evidence of disasters having an effect was found for Europe. Central American countries show a strong response in the month following the natural disaster, as theorised in the previous section, with the coefficients generally increasing relative to the intensity and significant at 10%. Asian countries follow, with higher coefficients in the month after the natural disaster, though the coefficients

[34] These disasters were easier to isolate the effects of as they were more immediate and short-lasting. Disasters such as the pandemic and droughts, though they have a known start date, are difficult to isolate due to their length and varying intensities

[35] Results were included only for countries and percentiles which showed significance. The short-run focus was deemed more appropriate as the speed at which remittances adjust matters more to natural disaster recovery. The tables presented for both the disaster types and regions did not show the other controls as they were largely similar to the coefficients described under the baseline results. The findings for both the regions and disasters were derived by utilising dummy variables to isolate the effects of each under the main sample.

decreased with larger intensities. In South America on the other hand, there is a strong increase in the disaster month, significant at the 1% level, with no increase in the month after. There is also evidence of intertemporal smoothing in the second months after the disaster across the 25th and 50th percentiles in South America. The coefficients are negative and significant at the 5% and 1% levels, with the coefficients under other disaster variables also remaining negative. Further evidence of smoothing is in Africa, with all intensities showing a degree of smoothing by the negative coefficients, but the 25th in particular confirming this at 10% significance.

DV: Remittances	*Asia*				*Central America*				*South America*				*Africa*	
per Capita (Constant 2010 US$)	25th (13)	50th (14)	75th (15)	90th (16)	25th (13)	50th (14)	75th (15)	90th (16)	25th (13)	50th (14)	75th (15)	90th (16)	25th (13)	75th (15)
ND	0.295	0.385	0.236	0.427	-0.0386	0.166	0.318	0.329	0.798***	1.057***	1.467***	1.999***	-0.0741	-0.112
	(0.320)	(0.351)	(0.246)	(0.265)	(0.320)	(0.369)	(0.435)	(0.884)	(0.200)	(0.261)	(0.458)	(0.699)	(0.471)	(0.746)
One Period ND Lag	1.084**	1.257**	0.819**	0.546*	0.664*	0.769*	1.800**	2.459*	0.0203	0.114	0.271	0.191	0.495	0.851*
	(0.435)	(0.521)	(0.368)	(0.295)	(0.356)	(0.420)	(0.762)	(1.256)	(0.170)	(0.189)	(0.346)	(0.476)	(0.383)	(0.480)
Two Period ND Lag	-0.272	-0.212	0.263	0.267	0.00889	0.384	1.184	0.255	-0.377**	-0.532***	-0.299	-0.346	-0.605*	-0.650
	(0.291)	(0.287)	(0.309)	(0.287)	(0.355)	(0.466)	(0.901)	(1.423)	(0.164)	(0.189)	(0.266)	(0.607)	(0.320)	(0.462)

DK standard errors included in parentheses. All coeffients and errors are calculated for the short-run.
* p<0.1, ** p<0.05, *** p<0.01

Table 7 - Remittances Response by Region

7. Robustness Checks

Macroeconomic analyses, especially cross-country studies of this scale, are highly contingent on the underlying estimation methods. [36] To gauge the legitimacy of the baseline results, a few robustness checks were conducted to understand the differences that change to the models have. The coefficients for the disaster variables remain positive and significant across estimations including regional and yearly fixed effects, the removal of monthly effects, different periods and dependent variables, and System GMM to account for endogeneity.

Robustness was examined to different regional, yearly, and monthly fixed effects (Addendum D1). With the inclusion of regional fixed effects, the disaster variables are significant at the 5% level in the month of the disaster and the month after, with the two-month lag showing a negative coefficient throughout. With yearly fixed effects, the disaster variable was significant at the 5% level in the month after the disaster across all percentiles, but in the month of the disaster only under the 25th and 50th percentiles. Yearly fixed effects also rendered GDP growth, disaster aid, and inflation insignificant though with their expected signs, suggesting that some of the explanatory power of these variables under the baseline might be due to their changes over time and not their interaction with remittances. Removing the monthly effects had a larger impact on the disaster results given the seasonality of remittances.

[36] Given that the robustness checks were relatively long, including through the use of an entirely different estimator, they were relegated to a separate section from the main results.

Remittances are at their lowest in January, the month with the most disasters. Without monthly fixed effects, the analysis may attribute more of the decrease in remittances in January to natural disasters. The inclusion of monthly dummies is therefore warranted if the decrease in remittances in January occurs not because disasters happen more regularly but because of other seasonal factors such as smoothing remittance transfers after Christmas. Nonetheless, even though the lack of monthly dummies reduces the coefficients for the disaster variables, they remain positive and significant for at least one period across all percentiles.

Robustness was also examined against the use of different dependent variables (Addendum D2). With logged remittances as a dependent variable, most control variables are insignificant except the exchange rate which has a negative coefficient. The disaster variables are also insignificant except under the one-period lag for 90th percentile natural disasters. This may be due to the log transformation compressing much of the small changes which occur on a monthly basis, further distorting the relatively weak statistical capacities of these developing countries. Using remittances per GDP on the other hand shows significance across many of the variables and periods, yielding similar results to the baseline model, with the disaster variables remaining significant across all percentiles in the two lagged months.

Splitting the sample into before and after the global financial crisis affected the sample countries as the panel is unbalanced, but it was done to analyse the trend of increasing remittances from 2000 to 2008 and the growth in the years afterwards (Addendum D2).[37] The former comprised countries which have longer records for monthly remittances, which may indicate that they rely on remittances more than other nations. The natural disaster variables before the financial crisis remained significant from the 25th to the 75th percentile, though the 90th percentile was insignificant. The control variables are also mostly insignificant except for the lag of the exchange rate change, financial stability which has its expected positive sign, and political stability which has an unanticipated negative coefficient. After the crisis, the disaster variable is significant for one month at least across all percentiles, with two-month lag coefficients having negative signs. Most variables in this period are significant with their expected coefficients, except for the lag of the real exchange rate and financial openness.

The baseline estimation accounts for endogeneity problems expressed in the literature through lags and variable transformation. The long timeseries also sufficiently reduces Nickell Bias given the average observations of 235. Nonetheless, SGMM was used for robustness by considering the lagged dependent variable, the lag of real GDP growth, the change in the

[37] The periods both before and after the crisis were long enough to not warrant concern about the Nickell Bias.

nominal exchange rate, and CPI inflation as endogenous.[38] The results support that remittances increase in response to natural disasters, with the variables showing significance at conventional levels from 50th to the 90th percentile disasters, this time under the one-period and two-period lags for the disaster variables. Though all the variables have their expected signs in-line with the literature, financial openness, real GDP growth, and disaster-related aid are insignificant at conventional levels across all the models. The perfect score for the Hansen test also suggests that the model suffers from overidentification, implying that the dynamic fixed effects model is better suited for the long timeseries (Roodman, 2009). This is further shown by the coefficient on the dependent variable under SGMM which is significantly lower than the fixed effects model. If Nickell Bias exists, which is unlikely given the long timeseries, the coefficient is already supposed to be biased downwards (Beck, et al., 2014).

Dependent Variable: Remittances per Capita (Constant 2010 US$)	Short-Run				Long-Run			
	SGMM (17)	SGMM (18)	SGMM (19)	SGMM (20)	SGMM (21)	SGMM (22)	SGMM (23)	SGMM (24)
Lag Remittances Per Capita	0.267***	0.265***	0.265***	0.266***	0.364***	0.361***	0.361***	0.362***
	-0.0686	-0.0686	-0.068	-0.068	(0.128)	(0.127)	(0.126)	(0.126)
Financial Openness	6.739	6.834	6.836	6.801	9.195	9.301	9.307	9.266
	-4.229	-4.232	-4.242	-4.238	(5.667)	(5.656)	(5.670)	(5.671)
Political Stability	4.450***	4.494***	4.495***	4.473***	6.071***	6.117***	6.119***	6.094***
	-1.55	-1.552	-1.56	-1.576	(1.993)	(1.994)	(2.007)	(2.033)
Net Migration Rate	-1.564***	-1.571***	-1.566***	-1.563***	-2.134***	-2.138***	-2.132***	-2.129***
	-0.33	-0.33	-0.33	-0.329	(0.425)	(0.425)	(0.425)	(0.424)
Lag Inflation	-296.9***	-298.0***	-298.6***	-297.1***	-405.162**	-405.568**	-406.514**	-404.725**
	-98.31	-98.36	-98.68	-98.39	(167.027)	(166.645)	(166.977)	(166.613)
Lag Exchange Rate Change	-64.98***	-65.39***	-66.09***	-65.16***	-88.667***	-88.996***	-89.984***	-88.783***
	-22.39	-22.53	-22.89	-22.72	(29.800)	(29.976)	(30.369)	(30.075)
Lag GDP Growth	-827.2	-835.5	-837.1	-840.2	-1128.69	-1137.16	-1139.74	-1144.75
	-536.7	-537.2	-537.9	-536.9	(723.683)	(722.725)	(723.497)	(723.064)
Disaster Aid Programme	0.85	0.816	0.774	0.78	1.159	1.111	1.054	1.063
	-0.649	-0.653	-0.651	-0.652	(0.897)	(0.900)	(0.896)	(0.898)
Natural Disaster (ND)	0.184	0.597	0.975	2.046**	0.252	0.813	1.327	2.788**
	-0.578	-0.625	-0.801	-0.833	(0.783)	(0.840)	(1.087)	(1.109)
One Period Lag ND	0.855	1.293*	1.642**	2.396**	1.166	1.759*	2.236**	3.264**
	-0.746	-0.752	-0.774	-1.038	(1.010)	(1.012)	(1.020)	(1.358)
Two Period Lag ND	0.587	1.060*	1.680**	2.426***	0.801	1.443*	2.287**	3.306***
	-0.631	-0.623	-0.687	-0.754	(0.864)	(0.855)	(0.958)	(1.104)
Constant	12.47***	12.36***	12.44***	12.53***	17.009***	16.820***	16.936***	17.067***
	-3.138	-3.171	-3.208	-3.21	(4.158)	(4.193)	(4.250)	(4.244)
Sargan Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen Test	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AB AR(1) Test	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
AB AR(2) Test	0.143	0.148	0.145	0.146	0.143	0.148	0.145	0.146
Observations	5615	5615	5615	5615	5615	5615	5615	5615

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

Table 8 - Disaster Variables Under SGMM Estimation

[38] Both yearly and monthly dummies were used in this estimation method as the corresponding AB AR2 tests for the SGMM benefitted from having significantly higher values with their inclusion.

8. Conclusion

This paper is perhaps the first to examine the response of monthly remittances to natural disasters across countries. The findings in a dynamic fixed effects model suggest remittances rise in response to natural disaster shocks, with larger increases occurring with more intense disasters. Under the baseline, the increase was largest in the month after the disaster potentially due to spillovers and migrants needing time for salaries, with decreases two months after the shock suggesting migrants may smooth and advance remittances when needed. Hydrological and meteorological disasters tend to have the strongest effects, while Asia, Central America, and South America show the largest and most consistent rises in remittances following disasters.

Generally, remittances are quite persistent in the short-run, but the effect of natural disasters and other controls rise in the long-run. The baseline results suggest that remittances increase during economic downturns and in response to greater outward migration, though they fall against increases in inflation, nominal exchange rate depreciation, and in response to disaster aid. These findings are robust to a few specifications including regional dummies, monthly effects, splitting the sample, and a different dependent variable (remittances as a percentage of GDP). Even under yearly fixed effects when GDP, emergency aid, and inflation are insignificant, the disaster variables are still positive and significant across intensities.

Despite the results, the analysis has a few shortcomings which future research should address. Though the study reduces endogeneity concerns through variable lags and transformations, analysing the monthly data required interpolating some annual regressors which may have induced endogeneity. In using System GMM to account for this and eliminate any Nickell Bias, which should be small under the large timeseries, remittances are still found to increase after natural disasters across intensities, with larger increases registered against larger shocks. Further studies analysing monthly remittances should test alternative methods to deal with endogeneity in large timeseries, such as Panel VAR models. Research should also expand controls to ones with limited interpolation while including potentially pertinent omitted variables such as financial depth, interest rates, and unemployment.[39] Though the paper already helps disentangle the effects of natural disasters on remittances in comparison to annual studies which grouped all disasters together for the year, research should further separate overlapping disasters and their lags, including slow-onset disasters and ones which damage infrastructure.

[39] Financial depth, interest rate differentials, and unemployment were difficult to find for the number of countries and time periods under consideration, and so were not included as regressors.

Further analysis also needs to isolate the supply side of remittances, for instance through a two-way fixed effects model tracking high-frequency inflow and outflow data.[40]

Nonetheless, the findings that remittances increase immediately after natural disasters enabling receivers to smooth consumption intertemporally suggests that it plays an important role in filling the financing gap left after capital flight and possibly aiding the individual recovery process. Countries which suffer from frequent disasters, or large external shocks, should therefore consider policies which promote the inflow of remittances, including reducing associated transaction costs, robust financial infrastructure that can withstand disasters, and encouraging diaspora engagement and support (UNCDF, 2022). Such actions may require a coherent policy and institutional framework, including regulation governing remittance companies to encourage competition within the industry and regulate the fee structures (Ratha & Mohieldin, 2020). If sufficiently encouraged, remittances can be a powerful tool that helps individuals and countries recover after natural disasters.

[40] Though such data is scarce, it can be obtained for countries such as Italy, Japan, and Korea.

References

Agbegha, V. O., 2006. *Does Political Instability Affect Remittance Flows?,* s.l.: Vanderbilt University.

Amuedo-Dorantes, C. & Pozo, S., 2006. Remittances as Insurance: Evidence from Mexican Immigrants. *Journal of Population Economics,* 19(2), pp. 227 - 254.

Amuedo-Dorantes, C., Pozo, S. & Vargas-Silva, C., 2010. Remittances in Small Island Developing States. *The Journal of Development Studies,* 46(5), pp. 941-960.

Arezki, R. & Brückner, M., 2011. *Rainfall, Financial Development, and Remittances: Evidence from Sub-Saharan Africa,* s.l.: IMF.

Baltagi, 2014. Panel Data and Difference-in-Differences Estimation. *Encyclopedia of Health Economics,* pp. 425-433.

Bank of Zambia, 2012. *Currency Rebasing Guidelines,* Lusaka: Bank of Zambia.

Baum, 2000. *XTTEST3: Stata module to compute Modified Wald statistic for groupwise heteroskedasticity,* s.l.: Boston College Department of Economics.

Beck, N. L., Katz, N. & Mignozzetti, U., 2014. Of Nickell Bias and its Cures: Comment on Gaibulloev, Sandler, and Sul. *Political Analysis,* 22(2), pp. 274-278.

Beine, Lodigiani & Vermuelen, 2012. Remittances and financial openness. *Regional Science and Urban Economics,* 42(5), pp. 844-857.

Benson, C. & Clay, E. J., 2004. *Understanding the Economic and Financial Impacts of Natural Disasters,* Washington D.C.: The World Bank.

Bettin, G., Presbitero, A. & Spatafora, N., 2014. Remittances and vulnerability in developing countries. *Policy Research Working Paper Series,* Volume 6812.

Bettin & Zazzaro, 2018. The Impact of Natural Disasters on Remittances to Low- and Middle-Income Countries. *The Journal of Development Studies,* 54(3), pp. 481-500.

Boutalby, H., 2022. The Impact of Parallel Exchange Rate's Premium on the Flow of Remittances for Algerian Migrants: An Analytical and Empirical Study During 1980-2018. *Algerian Scientific Journal,* 18(1).

Bragg, C. et al., 2018. Remittances as aid following major sudden-onset natural disasters. *Disasters,* 42(1), pp. 3 - 18.

Cazachevici, A., Havranek, T. & Horvath, R., 2020. Remittances and economic growth: A meta-analysis. *World Development.*

Chinn, M. & Ito, H., 2022. What Matters for Financial Development? Capital Controls, Institutions, and Interactions (The Chinn-Ito Index: A De Jure Measure of Financial Openness). *Journal of Development Economics,* 81(1), pp. 163-192.

Clarke, G. R. G. & Wallsten, S., 2003. *Do Remittances Act Like Insurance? Evidence from a Natural Disaster in Jamaica,* Washington, D.C.: The World Bank.

Combes, J.-L. & Ebeke, C., 2011. Remittances and Household Consumption Instability in Developing Countries. *World Development,* 39(7), pp. 1076-1089.

David, A., 2010. How do International Financial Flows to Developing Countries Respond to Natural Disasters? *IMF Working Paper,* 2010(166).

De, L. L., Gaillard, J., Friesen, W. & Smith, F. M., 2014. Remittances in the face of disaster: a case study of rural Samoa. *Environment Development and Sustainability,* 17(3).

Drukker, D. M., 2003. Testing for serial correlation in linear panel-data models. *The Stata Journal,* 3(2), pp. 168-177.

Ekanayake, E. & Moslares, C., 2020. Do Remittances Promote Economic Growth and Reduce Poverty? Evidence from Latin American Countries. *Economies,* 8(35).

El-Sakka & McNabb, 1999. The Macroeconomic Determinants of Emigrant Remittances. *World Development,* 27(8).

Fankhauser, S. & McDermott, T. K., 2013. *Understanding the Adaptation Deficit,* London: Grantham Research Institute on Climate Change and the Environment.

Frankel, J., 2010. *Are Bilateral Remittances Countercyclical?,* Boston: HKS Faculty Research Working Paper Series.

Ghosh, B., 2006. *Migrants' Remittances and Development: Myths, Rhetoric, and Realities,* The Hague: International Organisation for Migration.

Giannelli, G. C. & Canessa, E., 2022. After the Flood: Migration and Remittances as Coping Strategies of Rural Bangladeshi Households. *Economic Development and Cultural Change,* 70(3).

Gu, D., 2019. *Exposure and vulnerability to natural disasters for world's cities,* New York: United Nations (UN) Department of Economic and Social Affairs.

Gupta, P., 2005. *Macroeconomic Determinants of Remittances: Evidence from India,* s.l.: International Monetary Fund (IMF).

Hagen-Zanker, J. & Siegel, M., 2007. *The determinants of remittances: A review of the literature,* Maastricht: Maastricht University.

Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectionaldependence. *The Stata Journal,* 7(3), pp. 281 - 312.

IMF, 2019. *Building Resilience in Developing Countries Vulnerable to Large Natural Disasters,* Washington, D.C.: International Monetary Fund (IMF) Policy Paper.

IMF, 2023. *International Financial Statistics,* Washington, D.C.: International Monetary Fund (IMF).

Jalil, A. & Rao, N. H., 2019. Chapter 8 - Time Series Analysis (Stationarity, Cointegration, and Causality). In: *Environmental Kuznets Curve (EKC): A Manual.* s.l.:Elsevier, pp. 85-99.

Kaufmann & Kraay, 2022. *World Governance Indicators (WGI),* Washington, D.C.: World Bank.

Kpodar, K. & Goff, M. L., 2012. *Do Remittances Reduce Aid Dependency? ,* s.l.: FERDI.

Kpodar, Mlachlia, Quayyum & Gammadigbe, 2021. *Defying the Odds: Remittances During the COVID-19 Pandemic,* Washington, D.C.: International Monetary Fund (IMF) Working Paper.

Lopez, H., Molina, L. & Bussolo*, M., 2007. *Remittances and the real exchange rate,* Washington DC: World Bank.

Lucas, R. & Stark, O., 1985. Motivations to Remit: Evidence from Botswana. *Journal of Political Economy,* 93(5), pp. 901-918.

Lueth, E. & Ruiz-Arranz, M., 2006. *A Gravity Model of Workers' Remittances,* s.l.: IMF.

Maddala, G. S. & Wu, S., 1999. A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics and Statistics.*

Maghsoudi, A. & Moshtari, M., 2020. Challenges in disaster relief operations: evidence from the 2017 Kermanshah earthquake. *Journal of Humanitarian Logistics and Supply Chain Management,* 11(1).

Maimbo, S. M. & Ratha, D., 2004. *Remittances: Development Impacts and Future Prospects.* Washington, D.C.: The World Bank.

Mbaye & Drabo, 2017. Natural Disasters and Poverty Reduction: Do Remittances Matter? *CESifo Economic Studies,* 63(4), pp. 481-499.

Mitrutt & Wolff, 2014. *Remittances after natural disasters: Evidence from the 2004 Indian tsunami,* s.l.: University of Gothenburg.

Mohapatra, S., Joseph, G. & Ratha, D., 2009. *Remittances and Natural Disasters: Ex-post Response and Contribution to Ex-ante Preparedness,* Washington, D.C.: The World Bank.

Naudé, W. & Bezuidenhout, H., 2012. *Remittances provide resilience against disasters in Africa,* Maastricht: United Nations University.

Noy, Becerra & Cavallo, 2012. Foreign Aid in the Aftermath of Large Natural Disasters. *Review of Development Economics,* 18(3).

Pesaran, M. H., 2004. *General Diagnostic Test for Cross Section Dependence in Panels,* Bonn: Institute for the Study of Labour.

Rahman, M. R. et al., 2019. Examining the Effect of Exchange Rate and Overseas Employment on Remittances: An Evidence from Bangladesh. *Theoretical Economics Letters,* 9(7).

Ratha, D. et al., 2022. *Remittance Brave Global Headwinds: Migration and Development Brief 37,* Washington, D.C.: The World Bank Group.

Ratha & Mohieldin, 2020. *How to keep remittances flowing,* s.l.: Brookings.

Rojas-Suárez, L., 1991. *Risk and Capital Flight in Developing Countries,* Washington, D.C.: International Monetary Fund (IMF).

Roodman, D., 2009. How to do xtabond2: An introduction to Difference and System GMM in Stata. *The Stata Journal,* 9(1), pp. 86-136.

Seneviratne, S. et al., 2012. Changes in climate extremes and their impacts on the natural physical environment. In: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.* Cambridge; New York: Cambridge University Press, pp. 109-230.

Shrestha, N., 2020. Detecting Multicollinearity in Regression Analysis. *American Journal of Applied Mathematics and Statistics,* 8(2), pp. 39-42.

Stojanov & Strielkowski, 2013. The Role of Remittances as More Efficient Tool of Development Aid in Developing Countries. *Prague Economic Papers,* 22(4), pp. 487-503.

Suleri, A. Q. & Savage, K., 2006. *Remittances in crises: a case study from Pakistan,* s.l.: Overseas Development Institute (ODI).

Tierney, M. J. et al., 2016. *AidData Core Research Release 3.1: More Dollars than Sense: Refining Our Knowledge of Development Finance Using AidData,* s.l.: World Development.

UN, 2020. *How developing countries are addressing hazards, focusing on relevant lessons learned and good practices,* Bonn: United Nations (UN) Climate Change Secretariat.

UN, 2022. *World Population Prospects (WPP),* s.l.: United Nations (UN).

UNCDF, 2022. *Assess the National Remittance Policy and Regulatory Framework,* New York: United Nations Capital Development Fund.

Yang, D. & Choi, H., 2007. Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *The World Bank Economic Review,* 21(2), pp. 219-248.

Appendix

A1: Pearson Correlation Matrix

Pearson Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Remittances Per Capita	1										
(2) Financial Openness	0.144	1.000									
(3) Political Stability	0.452	-0.056	1.000								
(4) Net Migration Rate	0.067	0.009	0.026	1.000							
(5) Inflation	-0.103	-0.043	-0.094	-0.001	1.000						
(6) Exchange Rate Change	-0.064	-0.037	-0.018	0.001	0.271	1.000					
(7) GDP Growth	-0.166	0.015	-0.144	-0.037	-0.032	-0.074	1.000				
(8) Disaster Aid	-0.083	0.011	-0.239	-0.013	0.020	-0.028	0.049	1.000			
(9) ND	-0.104	-0.013	-0.186	-0.008	-0.006	-0.023	0.006	0.080	1.000		
(10) ND Lag	-0.104	-0.013	-0.186	-0.014	0.009	-0.005	0.007	0.072	0.186	1.000	
(11) ND 2 Lag	-0.105	-0.015	-0.184	-0.011	0.015	0.001	0.011	0.059	0.156	0.186	1.000

A2: Hausman, Wooldridge, and Modified Wald Tests

Test	Test Value	P-Value	H0	Type
Hausman Test (1978) Specification Test	642.23	0.0000	Test of H0: Difference in coefficients not systematic	Chi-Squared
Wooldridge Test (2002) for Autocorrelation	7.356	0.0111	Test of H0: No first-order autocorrelation	F-Test
Modified Wald Test (2000) for Groupwise Heteroskedasticity	23145.05	0.0000	Test of H0: sigma(i)^2 = sigma^2 for all i	Chi-Squared

A3: Fisher Unit Root, VIF, and Pesaran Tests

	Fisher Unit Root		*VIF*		*Pesaran (2004)*	
Variables	Test Value	P-Value	VIF	R-Squared	Test Value	P-Value
Remittances Per Capita	464.97	0.000	1.380	0.277	93.192	0.000
Financial Openness	245.67	0.000	1.030	0.024	7.995	0.000
Political Stability	65.47	0.000	1.490	0.329	24.002	0.000
Net Migration Rate	3559.68	0.000	1.000	0.001	41.795	0.000
Inflation	2247.66	0.000	1.040	0.041	33.423	0.000
Exchange Rate Change	2342.89	0.000	1.040	0.037	40.057	0.000
GDP Growth	198.29	0.000	1.050	0.048	131.494	0.000
Disaster Aid Programme	2400.42	0.000	1.070	0.069	47.705	0.000
ND 25th	3285.9	0.000				
ND 50th	3189.45	0.000				
ND 75th	2452.29	0.000				
ND 90th	1906.77	0.000				
ND			1.070	0.065	2.935	0.003
ND One Period Lag			1.080	0.073	2.907	0.004
ND Two Period Lag			1.070	0.064	2.756	0.006
	Test of H0: Unit Root		Mean VIF: 1.120		H0: Cross-Sectional Dependence	

Addendum

D1: Robustness: Regional, Yearly, and Monthly Effects

Dependent Variable:	*Regional Effects*				*Year Effect*				*No Monthly Effects*			
Remittances per Capita	25th ND	50th ND	75th ND	90th ND	25th ND	50th ND	75th ND	90th ND	25th ND	50th ND	75th ND	90th ND
(Constant 2010 US$)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
Lag Remittances Per Capita	0.828***	0.828***	0.828***	0.828***	0.733***	0.733***	0.733***	0.733***	0.798***	0.798***	0.798***	0.798***
	(0.0252)	(0.0252)	(0.0253)	(0.0253)	(0.0296)	(0.0296)	(0.0296)	(0.0296)	(0.0303)	(0.0303)	(0.0304)	(0.0303)
Financial Openness	-0.987***	-0.981***	-0.984***	-1.000***	-1.640***	-1.637***	-1.639***	-1.653***	-1.184***	-1.179***	-1.179***	-1.195***
	(0.369)	(0.367)	(0.368)	(0.370)	(0.432)	(0.431)	(0.432)	(0.434)	(0.419)	(0.417)	(0.417)	(0.419)
Political Stability	0.372*	0.373*	0.367*	0.357*	0.704***	0.702***	0.697***	0.694***	0.442**	0.445**	0.441**	0.432*
	(0.200)	(0.200)	(0.201)	(0.203)	(0.185)	(0.186)	(0.186)	(0.187)	(0.221)	(0.220)	(0.221)	(0.222)
Net Migration Rate	-0.413*	-0.418*	-0.421*	-0.422*	-0.417*	-0.422*	-0.424*	-0.425*	-0.915***	-0.916***	-0.917***	-0.919***
	(0.232)	(0.232)	(0.233)	(0.233)	(0.224)	(0.224)	(0.224)	(0.224)	(0.351)	(0.353)	(0.352)	(0.353)
Lag Inflation	-18.95**	-19.14**	-19.16**	-19.01**	-4.906	-5.064	-4.938	-4.849	-25.27***	-25.40***	-25.54***	-25.22***
	(7.871)	(7.894)	(7.898)	(7.884)	(7.735)	(7.746)	(7.745)	(7.698)	(8.760)	(8.786)	(8.782)	(8.749)
Lag Exchange Rate Change	-5.533***	-5.517***	-5.695***	-5.680***	-5.037*	-5.047*	-5.179*	-5.166*	-4.377*	-4.382*	-4.463*	-4.459*
	(2.109)	(2.122)	(2.123)	(2.115)	(2.609)	(2.623)	(2.631)	(2.637)	(2.568)	(2.571)	(2.580)	(2.566)
Lag GDP Growth	-86.12*	-86.03*	-87.92*	-88.95*	-28.28	-28.79	-29.02	-29.69	-118.9**	-118.9**	-120.0**	-120.7**
	(45.32)	(45.48)	(45.56)	(45.47)	(36.27)	(36.43)	(36.55)	(36.45)	(54.09)	(54.05)	(54.28)	(54.28)
Disaster Aid Programme	-0.359**	-0.368**	-0.375**	-0.360*	-0.287	-0.285	-0.289	-0.288	-0.196	-0.213	-0.222	-0.207
	(0.180)	(0.180)	(0.184)	(0.184)	(0.202)	(0.200)	(0.202)	(0.206)	(0.178)	(0.178)	(0.180)	(0.180)
Natural Disaster (ND)	0.341**	0.453***	0.410**	0.636**	0.247*	0.295*	0.216	0.488	-0.0393	0.0885	0.0910	0.396**
	(0.132)	(0.162)	(0.187)	(0.284)	(0.132)	(0.164)	(0.188)	(0.301)	(0.122)	(0.143)	(0.149)	(0.195)
One Period Lag ND	0.429**	0.599**	0.699***	0.657***	0.392**	0.503**	0.524**	0.557**	0.363*	0.491*	0.475*	0.449
	(0.195)	(0.241)	(0.267)	(0.238)	(0.189)	(0.234)	(0.265)	(0.255)	(0.208)	(0.251)	(0.272)	(0.293)
Two Period Lag ND	-0.184	-0.172	-0.00124	-0.0514	-0.164	-0.193	-0.0999	-0.0942	0.0435	0.134	0.421**	0.222
	(0.132)	(0.149)	(0.200)	(0.272)	(0.147)	(0.170)	(0.228)	(0.307)	(0.156)	(0.169)	(0.186)	(0.232)
Constant	6.354***	6.363***	6.389***	6.417***	3.929***	3.931***	3.930***	3.940***	5.660***	5.650***	5.667***	5.697***
	(0.926)	(0.927)	(0.927)	(0.935)	(0.481)	(0.482)	(0.483)	(0.492)	(0.884)	(0.884)	(0.883)	(0.887)
Within R-Squared	0.7099	0.7100	0.7098	0.7096	0.7241	0.7242	0.7242	0.724	0.6481	0.6482	0.6481	0.648
Observations	5655	5655	5655	5655	5655	5655	5655	5655	5655	5655	5655	5655

DK standard errors included in parentheses. All coeffients and errors are claculated for the short-run.

* p<0.1, ** p<0.05, *** p<0.01

D2: Robustness: Dependent Variables & Time Periods

Dependent Variable:	*Gross Domestc Product Dependent*				*Log Remittances Dependent*				*Before Financial Crisis*				*After Financial Crisis*			
Remittances per Capita (Constant 2010 US$)	25th ND (37)	50th ND (38)	75th ND (39)	90th ND (40)	25th ND (41)	50th ND (42)	75th ND (43)	90th ND (44)	25th ND (45)	50th ND (46)	75th ND (47)	90th ND (48)	25th ND (49)	50th ND (50)	75th ND (51)	90th ND (52)
Lag Remittances Per Capita	0.795***	0.794***	0.794***	0.794***	0.946***	0.946***	0.946***	0.946***	0.834***	0.834***	0.834***	0.834***	0.622***	0.622***	0.622***	0.622***
	(0.0229)	(0.0229)	(0.0229)	(0.0229)	(0.00810)	(0.00808)	(0.00815)	(0.00812)	(0.0280)	(0.0280)	(0.0281)	(0.0281)	(0.0469)	(0.0469)	(0.0469)	(0.0467)
Financial Openness	-0.000445***	-0.000444***	-0.000445***	-0.000449***	0.000285	0.000437	0.000646	0.000215	1.846*	1.833*	1.783*	1.749*	-1.550***	-1.553***	-1.534***	-1.538***
	(0.000143)	(0.000143)	(0.000143)	(0.000143)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(1.007)	(1.002)	(0.997)	(1.014)	(0.504)	(0.501)	(0.500)	(0.502)
Political Stability	0.0000980*	0.0000987*	0.0000974*	0.0000943*	0.00984	0.00999	0.0100	0.00976	-0.910***	-0.903***	-0.910***	-0.934***	1.641***	1.641***	1.630***	1.637***
	(0.0000563)	(0.0000563)	(0.0000564)	(0.0000569)	(0.00702)	(0.00701)	(0.00704)	(0.00707)	(0.320)	(0.323)	(0.326)	(0.330)	(0.287)	(0.289)	(0.288)	(0.288)
Net Migration Rate	-0.000127	-0.000128	-0.000129	-0.000129	-0.0144	-0.0145	-0.0145	-0.0145	-0.164	-0.162	-0.165	-0.165	-0.566*	-0.563*	-0.565*	-0.565*
	(0.0000954)	(0.0000953)	(0.0000956)	(0.0000957)	(0.00907)	(0.00904)	(0.00908)	(0.00908)	(0.278)	(0.278)	(0.279)	(0.278)	(0.311)	(0.310)	(0.310)	(0.313)
Lag Inflation	-0.00559**	-0.00565**	-0.00566**	-0.00564**	0.00738	0.00117	-0.0108	-0.00553	3.233	3.174	3.059	3.030	-41.99***	-42.36***	-42.51***	-42.20***
	(0.00270)	(0.00271)	(0.00271)	(0.00271)	(0.281)	(0.281)	(0.282)	(0.281)	(9.694)	(9.737)	(9.725)	(9.749)	(9.482)	(9.448)	(9.377)	(9.342)
Lag Exchange Rate Change	-0.00203***	-0.00203***	-0.00207***	-0.00207***	-0.249**	-0.249**	-0.251**	-0.253**	-7.568***	-7.498**	-7.542**	-7.576**	-3.950	-3.944	-4.111	-4.099
	(0.000659)	(0.000663)	(0.000662)	(0.000661)	(0.119)	(0.119)	(0.119)	(0.119)	(2.887)	(2.898)	(2.891)	(2.961)	(3.018)	(3.059)	(3.063)	(3.022)
Lag GDP Growth	0.00214	0.00224	0.00170	0.00142	-0.820	-0.803	-0.839	-0.859	-49.11	-48.97	-49.77	-49.94	-141.0**	-141.0**	-142.6**	-143.7**
	(0.0116)	(0.0116)	(0.0116)	(0.0116)	(1.449)	(1.453)	(1.453)	(1.453)	(52.21)	(52.36)	(52.16)	(52.22)	(65.87)	(66.07)	(66.30)	(66.11)
Disaster Aid Programme	-0.0000307	-0.0000334	-0.0000357	-0.0000322	-0.00794	-0.00809	-0.00868	-0.00823	-0.0798	-0.0959	-0.110	-0.0875	-0.538*	-0.553**	-0.552*	-0.563*
	(0.0000585)	(0.0000583)	(0.0000593)	(0.0000591)	(0.00737)	(0.00737)	(0.00746)	(0.00743)	(0.290)	(0.289)	(0.286)	(0.283)	(0.277)	(0.273)	(0.279)	(0.287)
Natural Disaster (ND)	0.0000942**	0.000134***	0.000137**	0.000195**	0.00810	0.0116	0.0112	0.0242*	-0.0505	0.0971	0.180	0.331	0.393**	0.462**	0.266	0.650
	(0.0000427)	(0.0000474)	(0.0000557)	(0.0000899)	(0.00619)	(0.00754)	(0.00958)	(0.0137)	(0.194)	(0.298)	(0.248)	(0.327)	(0.192)	(0.221)	(0.253)	(0.398)
One Period Lag ND	0.0000973*	0.000140**	0.000157**	0.000143*	0.00439	0.00581	0.00529	-0.00205	0.671***	0.617**	0.444*	0.392	0.210	0.468	0.663*	0.741***
	(0.0000519)	(0.0000607)	(0.0000700)	(0.0000781)	(0.00671)	(0.00776)	(0.0116)	(0.0109)	(0.212)	(0.251)	(0.266)	(0.479)	(0.281)	(0.335)	(0.368)	(0.280)
Two Period Lag ND	-0.0000497	-0.0000374	0.0000126	0.0000328	-0.00946	-0.00607	0.0113	0.00730	-0.355*	-0.234	0.0762	0.0483	-0.173	-0.207	-0.186	-0.264
	(0.0000379)	(0.0000433)	(0.0000475)	(0.0000798)	(0.00655)	(0.00718)	(0.00895)	(0.00996)	(0.201)	(0.225)	(0.289)	(0.449)	(0.178)	(0.211)	(0.277)	(0.348)
Constant	0.00209***	0.00209***	0.00210***	0.00211***	1.066***	1.068***	1.071***	1.070***	2.627***	2.655***	2.697***	2.716***	12.71***	12.72***	12.73***	12.76***
	(0.000232)	(0.000232)	(0.000232)	(0.000234)	(0.158)	(0.157)	(0.159)	(0.158)	(0.841)	(0.841)	(0.836)	(0.845)	(1.287)	(1.291)	(1.288)	(1.297)
Within R-Squared	0.6657	0.6658	0.6657	0.6656	0.9099	0.9099	0.9099	0.9099	0.7222	0.7219	0.7216	0.7216	0.486	0.4863	0.486	0.4859
Observations	5655	5655	5655	5655	5655	5655	5655	5655	2187	2187	2187	2187	3468	3468	3468	3468

DK standard errors included in parentheses. All coeffients and errors are calculated for the short-run.

* p<0.1, ** p<0.05, *** p<0.01