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How Do International Financial Flows to Developing Countries Respond to Natural Disasters?

Antonio C. David

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Abstract

This paper uses multivariate dynamic panel analysis to examine the response of international financial flows to natural disasters. The models estimated for a large sample of developing countries point to differentiated responses of specific types of financial flows. The results show that remittance inflows increase significantly in response to shocks to both climatic and geological disasters. The models suggest a nuanced role for foreign aid. While the responses of aid flows to natural disaster shocks in general tend not to be statistically significant, international assistance to low income countries increases following geological disaster shocks. Furthermore, the results show that typically, other private capital flows (bank lending and equity) do not attenuate the effects of disasters and in some specifications, even amplify the negative economic effects of these events. The conclusions of the paper have implications for capital/financial account management policies. In particular, countries should take their vulnerability to natural disasters into account when considering the costs and benefits of the liberalization of private capital flows.

I. INTRODUCTION

There is an emerging consensus in policy circles that climate change is a mounting challenge to economic development. In a recent overview, Hamilton and Fay (2009) argue that even modest increases in global temperatures are likely to lead to increased variability and more frequent and intense extreme weather events and that developing countries are more vulnerable than richer countries to the consequences of the changing climate. In the economics literature, several papers have attempted to quantify the macroeconomic consequences of natural disasters (climatic and otherwise), particularly by looking at the impact of disasters on output growth (Noy, 2009; Raddatz, 2009; and Skidmore and Toya, 2002; among others). Noy's (2009) results suggest that disasters have large adverse macroeconomic effects and that these effects tend to be larger in developing countries. This author finds that a one standard deviation increase in the direct damages attributed to a natural disaster could reduce output growth in a developing country by about 9 percent.

This paper quantifies the response of certain types of capital flows to natural disasters in a panel of countries covering the period from 1970 to 2005. One of the main motivations for studying the response of financial flows is that these flows are likely to constitute an important mechanism through which natural disasters affect the economy, because they are a measure of the country's ability to mobilize resources for reconstruction and consumption smoothing after a shock. Nevertheless, certain characteristics of capital flows to developing countries, namely their volatility and pro-cyclicality, could actually exacerbate the negative economic effects of disasters. This aspect might be even more important given limited fiscal space in many developing countries for countercyclical action against these disasters.

This paper focuses on development aid, migrant remittances inflows, equity flows and bank lending flows. The main objectives are to assess in a systematic way the different responses to natural disaster shocks of different types of capital flows and to examine whether capital flows exacerbate or attenuate the economic effects of natural disasters. The paper outlines whether capital flows are an important channel through which disasters affect the economy and whether public flows such as foreign aid behave differently when compared to private flows.

Because the paper is interested in the dynamics of the response of capital flows to shocks, in additional to standard panel data techniques, it focuses on panel vector autoregression (PVAR) models of different types of capital flows. This methodology allows for the study of the effects of shocks in a convenient and intuitive way through impulse response functions and forecast error variance decompositions.

The conclusions obtained from this analysis are useful to inform policy makers regarding appropriate policy responses to expected movements in capital flows following natural disasters. In addition, this research could highlight circumstances under which private capital flows do not alleviate shocks, and therefore an increase in foreign aid to developing countries would be justified and necessary.

II. The Links Between International Financial Flows and Natural Disasters

A stylized fact of the cross-country growth literature is that growth rates are not very persistent and exhibit significant volatility across time (Chami, Hakura and Montiel, 2009). This observation may be linked to several factors. For example, country size may matter because large countries tend to have a more diversified structure of production and are less vulnerable to industry specific shocks. This paper is closely related to a strand of the literature that has attempted to assess whether international capital flows contribute to output volatility. In particular, the issue of whether greater integration to international financial markets leads to higher macroeconomic volatility in developing countries has received significant attention from economists (see for instance Kose and others, 2006).

It is usually recognized that different types of capital flows have different time series properties and that foreign direct investment (FDI) flows tend to be more resilient than portfolio and bank flows, for example. Nevertheless, there are dissenting views such as Claessens, Dooley and Warner (1995) that look at a limited sample of developing countries and conclude that the time series properties of different types of capital flows do not differ much; in particular capital flows usually labeled as "hot" flows do not seem to be more volatile than FDI.

Regarding overseas development assistance (ODA), there is substantial empirical evidence that aid flows tend to be volatile and procyclical with adverse consequences for macroeconomic management, especially for poor, aid-dependent countries (Bulir and Hamann, 2008). Nevertheless, Hudson and Mosley (2008) show that these conclusions usually depend on the dataset used. In addition, the mix between different components of aid such as program aid and technical assistance seems to be important for aid volatility.

Furthermore, anecdotal and case study evidence suggest that contrary to other types of international capital flows, remittance flows tend to increase or remain stable after the onset of large shocks such as natural disasters, macroeconomic/financial crises and armed conflicts (World Bank, 2005 and Yang and Choi, 2007). Yang (2008) provides cross-country evidence on the response of international flows to hurricanes and concludes that hurricane exposure leads to large increases in remittance flows. Chami and others, (2008) present panel regressions indicating that GDP volatility is negatively affected by worker's remittances when controlling for terms of trade volatility, financial openness, commodity export composition and government consumption to GDP. Furthermore, in countries with more shallow financial systems, remittances could substitute for financial sector development and alleviate credit constraints (Giuliano and Ruiz-Aranz, 2009).

Nevertheless, Neagu and Schiff (2009) by comparing simple coefficients of variation among different types of flows find that official development assistance tends to be more stable than remittance flows, that is, they present a smaller coefficient of variation over the period 1980-2007 for 73 percent of the countries included in their sample. But, according to these authors, remittance flows are more stable than FDI flows.

Overall, the empirical evidence suggests that different capital flows respond in different ways to shocks and therefore may exacerbate or attenuate their economic effects accordingly. In addition, the evidence is at best ambiguous on whether greater financial integration in fact promotes greater consumption smoothing at the macroeconomic level or whether it increases vulnerability to external shocks. This ambiguity in results is certainly related to the fact that this literature is plagued by several empirical difficulties, such as the lack of reliable data and adequate measures of financial integration or financial restrictions, as well as endogeneity problems in econometric estimations, among other shortcomings[2].

For this paper, it is important to outline the expected links between international capital flows and the transmission of the macroeconomic effects of natural disasters. Capital flows could serve as a transmission or amplification (attenuation) channel of such shocks in many ways. In the context of neo-classical growth models, if a disaster causes a destruction in a country's capital stock and the country was already at its steady state level where the marginal product of capital is diminishing, the reduction in the capital stock would increase the marginal product of capital and would therefore attract more capital flows until the steady state capital stock is reached once again.

Nevertheless, if a natural disaster destroys complementary inputs to capital such as public goods, infrastructure and human capital, it is possible that the returns to capital would be affected in a negative way (as opposed to the direct positive effect outlined previously). In this case, one might not observe additional capital inflows, and a country might even experience capital outflows following a disaster. Natural disasters could also negatively affect total factor productivity and, as shown by Loayza and others (2009) in the context of the Solow growth model, if a natural disaster decreases productivity, the average product of capital will decline and so will growth. This reduction in overall growth prospects for the economy is likely to have a negative impact on private capital flows such as equity flows and FDI. In addition, disasters might lead to capital outflows if they are large enough to create political instability and/or a reduction in the capacity of a government to maintain the rule of law.

Furthermore, if international capital markets are characterized by market failures and developing countries are capital constrained (that is if these countries cannot meet their demand for capital), it is likely that the destruction linked to natural disasters will not necessarily lead to larger capital inflows. Moreover, even if returns to investment are not affected by disaster events, countries may wish to increase the amounts that they borrow abroad for consumption smoothing purposes following such events. Governments may wish to resort to foreign finance (either in the form of concessional international aid,additional market-priced bank loans or bond issuance) to pay for temporary increases in social safety net expenditures. Domestic financial intermediaries may increase

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[2] One advantage of focusing on the response of financial flows to natural disasters is that these events can be safely assumed to be weakly exogenous without imposing significant restrictions during model estimation (more on this issue in the sections below).

borrowing in international markets to meet an increase in domestic demand for credit from households seeking to attenuate consumption shocks.

The available empirical evidence also suggests that capital flows may play a role in determining the extent of the macroeconomic consequences of natural disasters. Noy (2009) uses the Hausman-Taylor panel IV methodology and presents results indicating that countries with a less open capital account are better able to endure natural disasters. In other words, in these countries natural disasters have less of an effect on output growth. This paper argues that this result probably stems from the fact that countries with capital account restrictions are less vulnerable to capital flight following a natural disaster event. In addition, Raddatz (2009) using a panel vector autoregressive model finds that foreign aid flows have not attenuated the output consequences of natural disasters in a significant way in his sample of developing countries.

Earlier papers on the direct effects of disasters on financial flows indicate that responses can be quite different. Yang (2008) uses the incidence of hurricanes to examine the consumption smoothing role of international financial flows and concludes that foreign aid and foreign remittance flows seem to increase following hurricanes, whereas private flows turn negative ("capital flight"). Raddatz (2007) using a panel VAR methodology, similar to the one that will be adopted below, finds that aid flows do not respond significantly to the occurrence of natural disasters. Mohapatra, Joseph and Ratha (2009) present micro evidence from household surveys and some macroeconomic results indicating that remittances have a positive role in preparing households against natural disasters and in mitigating economics losses afterwards. These authors find that remittances increase in the aftermath of natural disasters in countries that have a large number of migrants abroad.

This paper departs from the literature surveyed above by considering the response of remittances, international aid and some types of private capital flows to exogenous non-economic shocks within a multivariate dynamic panel framework. The paper uses a large set of developing countries for which data is available. It adds to the analysis of the response of international financial flows undertaken by Yang (2008) by considering a larger set of natural disasters[3] and by explicitly modeling the dynamics of financial flows controlling for a number of determinants of these flows, such as interest rate differentials and real exchange rate movements. Although Raddatz (2007) and (2009) also use the panel VAR methodology, these papers focus on the links between economic growth and international aid flows rather than the response of capital flows to disasters.

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[3] As noted previously, Yang's paper considers only hurricanes.

III. A FRAMEWORK FOR ANALYZING THE RESPONSE OF FINANCIAL FLOWS TO NATURAL DISASTER SHOCKS

The analysis of this paper will focus on a number of natural disaster shocks and their impact on capital flows. Following Raddatz (2007) we divided natural disasters into geological, climatic and human disasters (this categorization is further explained below). Moreover, the other main variables of interest in the analysis comprise the different types of capital flows (namely migrant remittances, foreign aid, bank loans and equity flows) and a small number of additional variables deemed relevant determinants of capital flows such as interest rate differentials. Section IV below presents a detailed description of all the variables and the relevant data sources.

In this context, the empirical models estimated will take the following form for country i (t denotes time):

$$A_0 z_{i,t} = \sum_{j=1}^{q} A_j z_{i,t-j} + \theta_i + \varepsilon_{it} \qquad \textbf{(1)}$$

Where the matrix A_0 is the matrix of contemporaneous coefficients of the vector of variables z_{it} that comprises both endogenous (y_{it}) and weakly exogenous variables (x_{it}) such that $z_{it}' = \left(y_{it}' ; x_{it}' \right)'$. The remaining variables represent country fixed-effects and the error term respectively. In this framework, the structural identification of results requires assumptions about the matrix A_0. Following Raddatz (2007 and 2009), this paper assumes that natural disaster shocks are weakly exogenous and do not respond contemporaneously to shocks in other variables.

It is a well known problem in the econometric literature that the number of coefficients to be estimated in a VAR model increases proportionately to the number of variables included in the system, thus increasing the amount of estimation error entering forecasts obtained from the model. Given the limitations in availability for long and high frequency cross-country time series on the types of capital flows of interest for this research and the need to avoid problems of overparametrization and restriction in the degrees of freedom in the estimation, the number of endogenous variables included in each model was limited and models for each type of capital flow were estimated separately[4].

In this context, the matrices in the VAR models take the form below, where for simplicity of exposition the systems are expressed at the country level. Section IV outlines the rationale for the inclusion of certain variables as determinants of capital flows. *CF* refers to the specific type of capital flow of interest (remittances, aid, equity flows or bank

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[4] The issue of substitutability and fungibility of the different types of capital flows considered is not addressed here. The interpretation of the results presented in this paper remains subject to this caveat.

loans); *idiff* is the real interest rate differential; ΔRER is the change in the real effective exchange rate; *Ydiff* is the output differential and *Nat* is the natural disaster variable.

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \begin{bmatrix} Nat \\ Ydiff \\ \Delta RER \\ idiff \\ CF \end{bmatrix}_t ; A_j = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & b_{33} & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{bmatrix} Nat \\ Ydiff \\ \Delta RER \\ idiff \\ CF \end{bmatrix}_{t-j}$$

This system can be estimated by standard panel techniques, but because some of the explanatory variables are likely not to be strictly exogenous, might be correlated with the fixed effects and might present significant measurement errors, there are considerable advantages in using the Generalized Method of Moments (GMM) estimator. In the models presented in Section V, lagged values of the variables are used as instruments. Panel VAR models estimated by GMM have had diverse applications in the economics literature, Love and Zicchino (2006), for example, used this framework to analyze the dynamics of investment behavior with firm-level data. Nevertheless, it is important to bear in mind that the GMM estimator is less efficient than some of the alternatives and it could be biased if the instruments used are weak (for a discussion see Baltagi, 2005).

As previously discussed, this paper is particularly interested in the dynamics of capital flows to developing countries. In this context, the paper looks at impulse response functions to simulate the dynamic effects of specific natural disaster shocks on capital flows. The paper also uses forecast error variance decompositions to assess how much of the underlying variability of the different types of capital flows can be attributed to the different types of shocks of interest at specific time horizons.

IV. DATA DESCRIPTION AND PRELIMINARY RESULTS

The econometric analysis is based on annual data for international financial flows (overseas development assistance, and bank and equity flows) from the World Bank's Global Development Finance database as well as remittance inflows data to developing countries compiled by the World Bank's Development Prospects Group. In addition, information on the incidence of natural disasters data from the OFDA/CRED International Emergency Disasters Database (EM-DAT) is also included. The data covers the period 1970-2005. Annex Table 1 provides a detailed description of the variables included and their construction as well as the respective primary sources. Annex Table 2 presents a set of descriptive statistics for the different variables included in the analysis. The table includes statistics for the entire sample of developing countries as well as a sub-sample comprising only low-income countries.

The EM-DAT database has worldwide coverage and contains data on the occurrence of natural disasters since 1900 based on several sources such as UN agencies, press reports, and insurance companies, among others. A disaster is defined as an event that

overwhelms local capacity and prompts governments to request external assistance[5]. We will follow Raddatz (2007) and divide natural disasters into three broad categories, namely, *Climatic* events (which comprise floods, droughts, extreme temperatures and hurricanes); *Geological* events (which comprise earthquakes, landslides, volcano eruptions and tidal waves); and *Human* disasters (which comprise famines and epidemics). Geological disasters tend to be relatively more difficult to predict compared to climatic or human disasters.

The data on the incidence of climatic disasters over the period 1970-2005 indicates that these types of events occur throughout the world, but tend to be more concentrated in countries located in the Indian and Pacific oceans (see also Raddatz, 2009). Furthermore, geological disasters are more pervasive in countries in East Asia and Eastern Europe and Central Asia (with more than one event per year on average) and are less frequent for countries in Sub-Saharan Africa. Famines and epidemics are also widely distributed geographically with some concentration in countries in South Asia and sub-Saharan Africa, but less frequent in Middle-East and North Africa.

The data on capital flows are expressed in real dollar terms (deflated by the US CPI index). In addition, we include a small number of determinants of capital flows. The log of the real interest rate differential between the domestic interest rate in each of the developing countries and international rates (such as the three-month U.S. treasury bill rate) was included to capture the "investment" motive in international financial flows and is a proxy for the relative return obtained from investing in the specific country. Real ex-post interest rates were calculated as the difference between the nominal interest rate and the actual inflation rate observed in the year.

In addition, the change in the real effective exchange rate (the first difference of the log of the real trade-weighted effective exchange rate) was also included. It seems intuitive that foreign investors (including migrants who send remittances to their home countries) care about the effects of fluctuations in exchange rates on the returns for their investment and hence would rebalance their portfolios as a response. For example, an appreciation of the currency in the financial-flows-receiving-country could increase incentives for foreign investors to enter as the foreign currency ("dollar-denominated") value of the cash flows linked to the investment increase. In the case of remittance flows, the response to exchange rate movements is more ambiguous and may depend on whether "compensatory" or "investment" motives to remit dominate (see Chami and others, 2008).

Furthermore, we also consider the log of income differentials between the specific developing countries and the United States (difference between real GDP per capita PPP adjusted, which is obtainable from the Penn World tables). This variable is included to

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[5] For a disaster to enter the database it needs to fulfill at least one of the following criteria: (a) 10 or more people are reported killed; (b) 100 or more people are reported to be affected; (c) a state of emergency is declared and; (d) a call for international assistance is made.

capture the compensatory nature of certain types of capital flows, such as remittances and foreign aid. In this context, it is expected that capital flows would increase as the differential increases and conversely decelerate as the income differential narrows. Furthermore, in a context of underdeveloped domestic financial markets, the real income differential might constitute an alternative measure of the returns on real investment not captured by interest rates (for example the exploitation of natural resources).

Firstly, the paper tests whether the main variables of interest are stationary by examining three different panel unit root tests: the Levin, Lin & Chu (2002) test (denoted LLC), the Breitung (2000) test and the Im, Pesaran & Shin (2003) test (denoted IPS). The unit root tests are reported in Table 1. The tests strongly suggest that remittance flows, net development aid, net bank loans, net equity flows, the interest rate differential and the first difference of the real effective exchange rate do not follow unit root processes. Nevertheless, the tests for the income differential series present somewhat ambiguous results, with both the LLC and IPS test indicating that the series are stationary, whereas the Breitung test suggests the presence of unit roots. Overall, the tests results indicate that non-stationarity is not a major concern for the variables included in the analysis and therefore the estimation of the Panel VAR models in levels seems appropriate.

Table 1
Panel Unit Root Tests

	Remittances	ODA	Bank	Equity	Income Differential	Δ Real Exchange Rate	Interest Differential
Levin-Lin-Chu unit-root test							
Adjusted t*	-13.31	-10.08	-18.28	-3.35	-5.17	-22.01	-13.23
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Ho: Panels contain unit roots Ha: Panels are stationary
Number of panels=78   Number of periods=36
Time trends and panel means were included. Lag-length chosen by AIC.

	Remittances	ODA	Bank	Equity	Income Differential	Δ Real Exchange Rate	Interest Differential
Breitung unit-root test							
lambda	-2.93	-4.55	-18.60	-6.93	2.66	-14.62	-8.41
p-value	0.00	0.00	0.00	0.00	0.99	0.00	0.00

Ho: Panels contain unit roots Ha: Panels are stationary
Number of panels=78   Number of periods=36
Time trends and panel means were included. Common AR parameter.

	Remittances	ODA	Bank	Equity	Income Differential	Δ Real Exchange Rate	Interest Differential
Im-Pesaran-Shin unit-root test							
Z-t-tilde-bar	n.a.	n.a.	n.a.	n.a.	-5.27	-18.79	-14.93
p-value	n.a.	n.a.	n.a.	n.a.	0.00	0.00	0.00

Ho: All panels contain unit roots Ha: Some panels are stationary
Number of panels=78   Number of periods=36
Time trends and panel means were included. Panel specific AR parameter.

A. Fixed-effects regression results

This section presents preliminary results obtained from estimating a more conventional dynamic panel model in which the specific type of financial flow is included as the endogenous variable and the incidence of natural disasters and other determinants of capital flows are included as explanatory variables. Therefore, the following equation is estimated by the standard fixed-effect panel estimator:

$$CF_{i,t} = \theta_i + \sum_{l=0}^{1} \varphi_l CF_{i,t-1-l} + \sum_{j=0}^{2} \beta_j' X_{i,t-j} + \sum_{j=0}^{2} \phi_j Nat_{i,t-j} + \varepsilon_{i,t} \quad (2)$$

It is well known in the econometrics literature that the fixed effect estimator is biased when lagged endogenous variables are included in the panel model. Nevertheless, this bias depends negatively on the number of time series observations included. Furthermore, it is important to bear in mind that alternative estimators, such GMM or instrumental variables estimators also have drawbacks, as emphasized by Goodhart and Hofman (2008). In particular, instrumental variables estimators are less efficient and, more importantly, instrumental variable coefficient estimates will also be biased if instruments are weak.

In addition, there are other important caveats concerning the interpretation of the preliminary results. Perhaps the most significant one is the endogeneity of some of the macroeconomic variables included on the right-hand-side, such as interest rate and output differentials. Nevertheless, this issue is less of a concern for our main coefficients of interest, the ones of natural disaster variables, which can be safely assumed to be weakly exogenous with the possible exception of the variables capturing the incidence of human disasters such as famines and epidemics. Note that we report robust standard errors clustered by countries for all models estimated.

Table 2 presents estimation results for several models where remittance inflows are included as the dependent variable. The coefficients for natural disasters presented in the tables can be interpreted as semi-elasticities, such that the impact elasticity of remittances (or other types of capital flows) to a natural disaster event is given by the semi-elasticity multiplied by the level of the disaster variable as stated more formally in equation 3:

$$\frac{\partial Log(CF)}{\partial Log(Nat)} = \frac{\frac{dCF}{CF}}{\frac{dNat}{Nat}} = \frac{\partial Log(CF)}{dNat} * Nat \quad (3)$$

The coefficient estimates presented in Table 2 suggest that remittances inflows tend to increase following climatic and geological disasters. In fact, remittance inflows typically increase by 0.1 percent in the same time period of an increase of one standard deviation in the incidence of climatic disasters given the mean value of the climatic disaster variable across the sample period and countries. When performing a thought experiment for the case of a country with high incidence of climatic disasters (a country in the 95th percentile in terms of incidence of climatic disasters across countries and across time),

the contemporaneous elasticity to a standard deviation increase would amount to approximately 0.2 percent. An even smaller elasticity is estimated for geological disasters, for a one standard deviation increase when disasters are evaluated at their (within and between) mean and the elasticity of remittance flows for a country in the 95th percentile in terms of the incidence of geological disasters would amount to 0.1 percent.

This evidence confirms the compensatory nature of remittance inflows and its effects in terms of mitigating the impact of shocks referred to elsewhere in the literature (see for instance, Chami and others, 2008, Mohapatra, Joseph and Ratha 2009). These results hold when additional lags are included in the models, but the additional lags of the disaster variables are typically not statistically significant at conventional levels. When a deterministic time trend is included remittances seem to respond only to climatic disasters in a statistically significant way.

When the trend and the first difference of the real effective exchange rate are included simultaneously in the model the disaster variables are no longer statistically significant. Nevertheless, it is important to note the substantial reduction in the number of observations because of the introduction of the real exchange rate variable, which only covers shorter time spans. There is no evidence that remittances respond to human disasters such as famines and epidemics in any of the specifications that were attempted. This result might be linked to the fact that famine and epidemics might be related to political instability and poor governance in the remittance receiving country, which are factors that may discourage additional remittances from migrants living abroad. Models for specific types of disasters (earthquakes, floods, droughts, among others) were also estimated with qualitatively similar conclusions. These results are not reported in order to save space.

The estimation results for foreign development aid are presented in Table 3. In most specifications development aid does not seem to respond to disasters in a statistical significant way and when it does, the results indicate that it responds more slowly relative to other types of financial flows. The estimated coefficients are only significant for the response of aid flows to geological disasters with a two-year lag, and there is no evidence in any of the specifications that aid responds to climatic or human disasters. Aid increases by around 0.3 percent two years after a one standard deviation increase in geological disasters, for a country in the 95th percentile in terms of incidence of geological disasters. The results obtained are generally robust to the inclusion of a deterministic trend and the real effective exchange rate in the models. Overall, these results are consistent with the literature that argues that development aid has been ineffective in terms of reducing macroeconomic volatility (see Bulir and Haman, 2008).

Table 2
Fixed Effects Panel Regressions for Remittance Inflows

VARIABLES	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Climatic Disasters	0.038***			0.023***			0.024**			0.026**			0.024**			0.009	
	[0.010]			[0.008]			[0.009]			[0.011]			[0.011]			[0.008]	
Income Differential	0.361**	0.364*	0.388**	0.299**	0.316**	0.330**	0.394**	0.418**	0.433***	0.424**	0.425**	0.442**	0.433**	0.435**	0.447**	0.273*	0.277*
	[0.179]	[0.184]	[0.183]	[0.146]	[0.149]	[0.151]	[0.156]	[0.159]	[0.161]	[0.188]	[0.191]	[0.192]	[0.191]	[0.195]	[0.195]	[0.162]	[0.164]
Real Interest Rate Differential	0.086	0.076	0.074	-0.012	-0.015	-0.014	-0.033	-0.038	-0.035	0.077	0.068	0.070	0.063	0.053	0.058	-0.030	-0.030
	[0.112]	[0.113]	[0.116]	[0.119]	[0.120]	[0.123]	[0.118]	[0.120]	[0.120]	[0.108]	[0.108]	[0.110]	[0.110]	[0.112]	[0.111]	[0.112]	[0.111]
Remittances (t-1)	0.867***	0.870***	0.874***	0.887***	0.893***	0.895***	0.817***	0.823***	0.825***	0.839***	0.839***	0.840***	0.845***	0.846***	0.847***	0.846***	0.847***
	[0.013]	[0.012]	[0.012]	[0.018]	[0.018]	[0.017]	[0.048]	[0.049]	[0.049]	[0.012]	[0.012]	[0.012]	[0.027]	[0.027]	[0.027]	[0.020]	[0.020]
Climatic Disasters (t-1)	0.013			0.022**			0.017*			0.001			0.004			0.008	
	[0.011]			[0.010]			[0.009]			[0.011]			[0.012]			[0.010]	
Income Differential (t-1)	-0.590***	-0.614***	-0.599***	-0.521***	-0.554***	-0.549***	-0.369	-0.389	-0.397	-0.487**	-0.497**	-0.487**	-0.633**	-0.639**	-0.642**	-0.309*	-0.315*
	[0.186]	[0.188]	[0.190]	[0.180]	[0.184]	[0.188]	[0.247]	[0.248]	[0.246]	[0.193]	[0.192]	[0.194]	[0.287]	[0.285]	[0.286]	[0.178]	[0.178]
Real Interest Rate Differential(t-1)	-0.028	-0.017	-0.021	0.042	0.046	0.044	-0.063	-0.052	-0.067	-0.041	-0.033	-0.035	0.001	0.013	0.004	0.017	0.017
	[0.059]	[0.059]	[0.058]	[0.063]	[0.063]	[0.063]	[0.072]	[0.071]	[0.073]	[0.062]	[0.062]	[0.062]	[0.092]	[0.092]	[0.092]	[0.067]	[0.067]
Geological Disasters		0.038*			0.036**			0.036**			0.023			0.021			0.020
		[0.020]			[0.016]			[0.015]			[0.020]			[0.020]			[0.016]
Geological Disasters(t-1)		0.054**			0.027			0.025			0.037			0.036			0.008
		[0.024]			[0.022]			[0.020]			[0.024]			[0.023]			[0.021]
Human Disasters		0.041				0.011			0.005			0.024			0.020		
		[0.027]				[0.018]			[0.018]			[0.026]			[0.025]		
Human Disasters(t-1)		0.001				0.001			-0.015			-0.017			-0.024		
		[0.018]				[0.017]			[0.016]			[0.017]			[0.018]		
Remittances (t-2)							0.063	0.066	0.064				-0.026	-0.025	-0.026		
							[0.044]	[0.044]	[0.045]				[0.025]	[0.025]	[0.025]		
Climatic Disasters (t-2)							0.013						-0.003				
							[0.010]						[0.014]				
Income Differential (t-2)							-0.262	-0.281	-0.249				0.127	0.131	0.145		
							[0.178]	[0.177]	[0.178]				[0.222]	[0.221]	[0.220]		
Real Interest Rate Differential(t-2)							0.125	0.120	0.122				-0.017	-0.020	-0.020		
							[0.084]	[0.082]	[0.084]				[0.085]	[0.084]	[0.085]		
Geological Disasters(t-2)								-0.011						-0.020			
								[0.018]						[0.019]			
Human Disasters(t-2)									0.050*						0.029		
									[0.025]						[0.025]		
Real Exchange Rate				0.001	-0.001	0.008	0.043	0.038	0.041							-0.052	-0.054
				[0.094]	[0.095]	[0.096]	[0.098]	[0.099]	[0.096]							[0.096]	[0.097]
Real Exchange Rate(t-1)				0.084**	0.081**	0.084**	0.133*	0.131*	0.129							0.089***	0.088***
				[0.033]	[0.033]	[0.034]	[0.079]	[0.078]	[0.078]							[0.030]	[0.030]
Real Exchange Rate(t-2)							0.141***	0.139***	0.145***								
							[0.047]	[0.049]	[0.049]								
Deterministic Trend										0.012***	0.012***	0.013***	0.013***	0.013***	0.013***	0.018***	0.019***
										[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Constant	1.046***	1.112***	1.028***	0.966***	1.016***	0.986***	1.036***	1.086***	1.010***	0.545***	0.572***	0.507**	0.625***	0.627***	0.576***	0.295	0.297
	[0.157]	[0.150]	[0.182]	[0.173]	[0.183]	[0.206]	[0.180]	[0.196]	[0.225]	[0.197]	[0.180]	[0.211]	[0.200]	[0.181]	[0.213]	[0.182]	[0.183]
Observations	2450	2450	2450	1772	1772	1772	1696	1696	1696	2450	2450	2450	2371	2371	2371	1772	1772
R-squared	0.833	0.833	0.833	0.800	0.799	0.798	0.797	0.797	0.797	0.835	0.835	0.835	0.819	0.819	0.819	0.806	0.806
Number of Countries	78	78	78	76	76	76	76	76	76	78	78	78	78	78	78	76	76

Dependent variable is the log of remittance inflows. Robust standard errors clustered by countries in brackets. *** p<0.01, ** p<0.05, * p<0.1. All macroeconomic variables are expressed in logs. The real exchange rate is the first difference of the log of the real exchange rate index.

Table 3

Fixed Effects Panel Regressions for Net Foreign Aid Flows

VARIABLES	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Climatic Disasters	-0.054 [0.042]			-0.039 [0.035]			-0.074 [0.053]			-0.058 [0.046]			-0.022 [0.039]			-0.030 [0.046]		
Income Differential	-0.253 [0.346]	-0.249 [0.343]	-0.275 [0.349]	-0.131 [0.340]	-0.117 [0.336]	-0.152 [0.344]	-0.432 [0.771]	-0.452 [0.760]	-0.498 [0.770]	-0.469 [0.705]	-0.505 [0.689]	-0.542 [0.698]	-0.221 [0.380]	-0.198 [0.365]	-0.222 [0.370]	-0.339 [0.681]	-0.337 [0.667]	-0.344 [0.665]
Real Interest Rate Differential	-0.026 [0.074]	0.007 [0.071]	-0.012 [0.075]	-0.006 [0.109]	0.033 [0.105]	0.007 [0.107]	0.069 [0.061]	0.115* [0.059]	0.096 [0.061]	0.164** [0.081]	0.213** [0.083]	0.187** [0.085]	0.023 [0.103]	0.063 [0.099]	0.034 [0.097]	0.220*** [0.072]	0.269*** [0.080]	0.233*** [0.073]
ODA (t-1)	0.458*** [0.068]	0.457*** [0.068]	0.457*** [0.068]	0.358*** [0.064]	0.359*** [0.063]	0.358*** [0.063]	0.368*** [0.079]	0.367*** [0.078]	0.366*** [0.078]	0.277*** [0.082]	0.278*** [0.081]	0.276*** [0.082]	0.356*** [0.065]	0.357*** [0.065]	0.356*** [0.065]	0.270*** [0.083]	0.272*** [0.083]	0.270*** [0.083]
Climatic Disasters(t-1)	0.007 [0.053]			-0.011 [0.047]			-0.010 [0.051]			-0.031 [0.051]			0.005 [0.042]			-0.008 [0.048]		
Income Differential (t-1)	-0.104 [0.329]	-0.077 [0.329]	-0.101 [0.333]	-0.788** [0.332]	-0.773** [0.334]	-0.767** [0.329]	0.275 [0.767]	0.354 [0.762]	0.292 [0.773]	-0.478 [0.341]	-0.413 [0.345]	-0.428 [0.344]	-0.809** [0.335]	-0.802** [0.340]	-0.790** [0.333]	-0.599* [0.343]	-0.560 [0.351]	-0.573 [0.345]
Real Interest Rate Differential(t-1)	-0.136 [0.125]	-0.162 [0.131]	-0.143 [0.127]	0.112 [0.186]	0.064 [0.171]	0.107 [0.181]	-0.073 [0.111]	-0.111 [0.119]	-0.084 [0.112]	0.226 [0.254]	0.163 [0.238]	0.228 [0.252]	0.120 [0.185]	0.073 [0.170]	0.114 [0.180]	0.246 [0.252]	0.186 [0.235]	0.244 [0.250]
Geological Disasters		0.019 [0.072]			0.002 [0.063]			0.017 [0.084]			-0.003 [0.071]			0.021 [0.066]			0.020 [0.076]	
Geological Disasters(t-1)		-0.148 [0.101]			-0.165 [0.102]			-0.195 [0.123]			-0.209* [0.123]			-0.143 [0.099]			-0.178 [0.121]	
Human Disasters		-0.015 [0.054]				-0.033 [0.058]			-0.035 [0.062]			-0.049 [0.065]			-0.014 [0.055]			-0.020 [0.064]
Human Disasters(t-1)		-0.045 [0.054]				-0.042 [0.055]			-0.072 [0.067]			-0.072 [0.066]			-0.025 [0.052]			-0.043 [0.062]
ODA (t-2)				0.215** [0.082]	0.215*** [0.081]	0.216*** [0.082]				0.198** [0.091]	0.198** [0.090]	0.199** [0.091]	0.214** [0.082]	0.213** [0.081]	0.214** [0.081]	0.194** [0.092]	0.192** [0.090]	0.194** [0.091]
Climatic Disasters(t-2)				0.012 [0.046]						0.009 [0.054]			0.029 [0.050]			0.035 [0.055]		
Income Differential (t-2)				0.661 [0.495]	0.652 [0.489]	0.661 [0.492]				0.808 [0.641]	0.823 [0.623]	0.791 [0.636]	0.535 [0.458]	0.508 [0.452]	0.536 [0.462]	0.428 [0.547]	0.393 [0.546]	0.406 [0.557]
Real Interest Rate Differential(t-2)				-0.422 [0.415]	-0.414 [0.407]	-0.439 [0.415]				-0.428 [0.470]	-0.421 [0.456]	-0.451 [0.467]	-0.393 [0.414]	-0.382 [0.407]	-0.407 [0.413]	-0.354 [0.464]	-0.339 [0.453]	-0.370 [0.462]
Geological Disasters(t-2)					0.111** [0.051]						0.111** [0.054]			0.135** [0.056]			0.146** [0.063]	
Human Disasters (t-2)						0.049 [0.060]						0.028 [0.065]			0.071 [0.066]			0.064 [0.070]
Real Exchange Rate							0.036 [0.191]	0.048 [0.188]	0.026 [0.196]	-0.142 [0.173]	-0.129 [0.169]	-0.161 [0.182]				-0.003 [0.175]	0.007 [0.177]	-0.013 [0.185]
Real Exchange Rate(t-1)							-0.014 [0.050]	-0.020 [0.046]	-0.028 [0.051]	0.006 [0.270]	0.001 [0.265]	-0.018 [0.271]				0.100 [0.261]	0.096 [0.257]	0.086 [0.261]
Real Exchange Rate(t-2)										-0.229 [0.148]	-0.223 [0.148]	-0.236 [0.146]				-0.213 [0.136]	-0.208 [0.136]	-0.213 [0.133]
Deterministic Trend													-0.013 [0.011]	-0.013 [0.011]	-0.013 [0.010]	-0.032** [0.014]	-0.032** [0.016]	-0.032** [0.015]
Constant	7.287*** [0.789]	7.215*** [0.699]	7.305*** [0.761]	5.672*** [0.898]	5.604*** [0.855]	5.636*** [0.868]	7.987*** [0.835]	7.824*** [0.733]	8.035*** [0.810]	6.635*** [1.212]	6.470*** [1.140]	6.655*** [1.165]	6.481*** [1.164]	6.472*** [1.170]	6.440*** [1.163]	8.314*** [1.532]	8.304*** [1.595]	8.325*** [1.569]
Observations	2449	2449	2449	2370	2370	2370	1772	1772	1772	1696	1696	1696	2370	2370	2370	1696	1696	1696
R-squared	0.200	0.201	0.199	0.230	0.232	0.230	0.132	0.134	0.131	0.155	0.158	0.155	0.231	0.234	0.232	0.160	0.163	0.160
Number of countries	78	78	78	78	78	78	76	76	76	76	76	76	78	78	78	76	76	76

Dependent variable is the log of net international development assistance inflows. Robust standard errors clustered by countries in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All macroeconomic variables are expressed in logs. The real exchange rate is the first difference of the log of the real exchange rate index.

The estimated results for the response of bank lending flows to natural disaster events are reported in Table 4. The estimated coefficients indicate that bank lending flows respond negatively to climatic and to human disasters and that this response tends to occur relatively rapidly. This conclusion is consistent with the evidence presented by Yang (2008) regarding the response of private capital flows to hurricanes. Typically net bank lending flows decrease by around 0.8 percent within the same time period (one year) following a one standard deviation increase in climatic disasters. As far as human disasters are concerned, bank flows decrease by about 0.1 percent following an increase of one unit in the incidence of disasters. Although generally bank flows do not present a statistical significant response to geological disasters, when one considers landslides, these types of financial flows have a high negative semi-elasticity.

Overall, these results hold when additional time lags are included in the models, but the negative effects are only statistically significant contemporaneously, suggesting that the effects of disasters on bank flows are not persistent. It is also interesting to note that the response of bank flows to large human disasters (see Annex Table 1 for a definition of large disasters) is more pronounced, which could be evidence of the presence of non-linearities. The negative effect of climatic and human disasters on bank lending flows is also observed when one includes the effective real exchange rate in the model. Nevertheless, these results do not appear to be robust when a deterministic trend and the real exchange rate are both included in the models. In any case, our preliminary results indicate that bank flows either respond negatively to disaster events or do not respond at all. Under no specification did we observe a positive response, which suggests that these flows do not play a role in mitigating these types of shocks.

The estimation results for net equity flows are presented in Table 5. The results show that net equity flows increase following climatic and geological disasters, but only with a one-year lag. Equity flows also respond positively to human disasters with a lag, but results are only statistically significant for the models in which two lags of the variables are included. Net equity flows increase by around 0.5 percent one year after a one standard deviation increase in the incidence of climatic disasters (1.3 percent for a country in the 95th percentile in terms of incidence of climatic disasters) and by 0.1 percent one year after a one standard deviation increase in the incidence of geological disasters. Equity flows increase by about 0.1 percent two years after a one standard deviation increase in human disaster events. Nevertheless, it is important to bear in mind when interpreting these results that many of the developing countries included in our sample do not have access to international equity markets.

Only the results for geological disasters and human disasters are robust to the inclusion of the real effective exchange rate in the specifications, and the conclusions previously obtained do not change much in qualitative terms. In addition, it seems that equity flows also present a statistically significant response when more specific types of natural disasters, such as earthquakes are considered. Nevertheless, when both a time trend and the real exchange rate are included in the models, only the response of equity flows to geological disasters remains statistically significant. Overall, there is some evidence that

equity flows behave differently from other types of private flows in terms of their responses to natural disasters and that these flows might mitigate the macroeconomic consequences of certain types of disaster events.

In conclusion, the preliminary results indicate that remittances are responsive to natural disasters (both geological and climatic), but not to human disasters. The elasticities calculated based on the estimated semi-elasticities suggest that the economic importance of these responses is typically small. In general, aid flows do not present statistically significant responses to natural or human disasters, except for geological disasters, where international aid flows seem to respond with substantial delay. There is evidence that bank flows respond negatively to disasters and that the effects of disasters on these flows are not persistent. Nevertheless, the fixed effects results for the bank flow models are not very robust. Equity flows increase after geological and climatic disasters with a one-year lag and after human disasters with a two-year lag. Nevertheless, the response of equity flows to geological disasters is more robust than the response of these flows to climatic disasters or human disasters. It is also interesting to note that the problem of omitted variables seems to be more prominent for the models for bank and equity flows, as these models present relatively poorer measures of goodness of fit.

Table 4
Fixed Effects Panel Regressions for Bank Lending Flows

VARIABLES	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56
Climatic Disasters	-0.355**			-0.256*					-0.320**			-0.267*			-0.101				-0.224		
	[0.151]			[0.138]					[0.146]			[0.134]			[0.144]				[0.144]		
Income Differential	1.984	1.859	1.588	1.950	1.833	1.594	1.718	1.875	0.007	-0.330	-0.543	-0.562	-0.912	-1.128	1.062	0.957	0.844	1.133	-0.367	-0.531	-0.688
	[2.007]	[2.041]	[1.993]	[2.051]	[2.074]	[2.037]	[2.036]	[2.029]	[2.525]	[2.536]	[2.523]	[2.549]	[2.564]	[2.563]	[1.980]	[1.998]	[2.007]	[1.964]	[2.611]	[2.640]	[2.645]
Real Interest Rate Differential	0.805	0.801	0.910	0.110	0.217	0.217	0.747	0.745	0.814	0.780	0.948	0.191	0.138	0.306	0.416	0.427	0.518	1.103	0.284	0.284	0.424
	[1.137]	[1.157]	[1.154]	[1.205]	[1.242]	[1.244]	[1.141]	[1.154]	[1.212]	[1.238]	[1.225]	[1.302]	[1.341]	[1.328]	[1.212]	[1.232]	[1.227]	[1.149]	[1.330]	[1.375]	[1.360]
Bank Flows (t-1)	0.386***	0.390***	0.393***	0.350***	0.353***	0.355***	0.396***	0.388***	0.341***	0.344***	0.346***	0.318***	0.321***	0.322***	0.336***	0.336***	0.337***	0.364***	0.315***	0.317***	0.318***
	[0.029]	[0.030]	[0.030]	[0.030]	[0.029]	[0.030]	[0.030]	[0.030]	[0.032]	[0.033]	[0.034]	[0.032]	[0.031]	[0.032]	[0.030]	[0.030]	[0.030]	[0.030]	[0.031]	[0.031]	[0.031]
Climatic Disasters(t-1)	-0.290			-0.201					-0.291			-0.198			-0.057				-0.162		
	[0.217]			[0.208]					[0.215]			[0.213]			[0.202]				[0.213]		
Income Differential(t-1)	0.921	1.307	1.034	3.894*	4.007*	3.944*	1.314	1.281	1.404	1.977	1.620	4.826*	5.040*	4.993*	3.686	3.693	3.714	-0.626	4.633*	4.687*	4.660*
	[2.004]	[2.040]	[2.037]	[2.326]	[2.321]	[2.309]	[2.049]	[2.020]	[2.459]	[2.485]	[2.531]	[2.719]	[2.713]	[2.743]	[2.329]	[2.326]	[2.307]	[1.979]	[2.734]	[2.714]	[2.733]
Real Interest Rate Differential(t-1)	-0.340	-0.447	-0.430	0.694	0.651	0.602	-0.518	-0.334	-0.160	-0.250	-0.268	0.185	0.161	0.091	0.803	0.780	0.713	0.063	0.219	0.220	0.135
	[1.157]	[1.165]	[1.169]	[1.257]	[1.270]	[1.275]	[1.100]	[1.191]	[1.278]	[1.294]	[1.288]	[1.280]	[1.290]	[1.298]	[1.229]	[1.235]	[1.241]	[1.200]	[1.273]	[1.278]	[1.286]
Geological Disasters		-0.312			-0.247					-0.438			-0.317			-0.072				-0.270	
		[0.263]			[0.290]					[0.293]			[0.294]			[0.289]				[0.299]	
Geological Disasters(t-1)		-0.359			-0.257					-0.194			-0.081			-0.032				-0.010	
		[0.265]			[0.260]					[0.312]			[0.332]			[0.266]				[0.323]	
Human Disasters			-0.638**			-0.629**					-0.568*			-0.549*			-0.437*				-0.480
			[0.278]			[0.259]					[0.320]			[0.307]			[0.247]				[0.309]
Human Disasters(t-1)			-0.151			-0.162					-0.143			0.008			-0.105				-0.038
			[0.313]			[0.275]					[0.352]			[0.305]			[0.265]				[0.305]
Bank Flows (t-2)				0.093***	0.097***	0.100***						0.051*	0.056*	0.059*	0.082***	0.083***	0.084***		0.049*	0.052*	0.054*
				[0.027]	[0.028]	[0.027]						[0.029]	[0.030]	[0.030]	[0.026]	[0.027]	[0.026]		[0.029]	[0.030]	[0.029]
Climatic Disasters(t-2)				-0.248								-0.244			-0.085				-0.202		
				[0.224]								[0.228]			[0.227]				[0.236]		
Income Differential(t-2)				-3.427*	-3.140	-3.355						-3.935	-3.516	-3.820	-4.598**	-4.607**	-4.595**		-4.528*	-4.533*	-4.711*
				[1.981]	[1.993]	[2.030]						[2.513]	[2.517]	[2.599]	[1.950]	[1.977]	[1.992]		[2.678]	[2.718]	[2.781]
Real Interest Rate Differential(t-2)				-1.221***	-1.286***	-1.305***						-0.717*	-0.782*	-0.801**	-0.934**	-0.923**	-0.966**		-0.594	-0.572	-0.599
				[0.422]	[0.459]	[0.426]						[0.394]	[0.435]	[0.398]	[0.408]	[0.435]	[0.412]		[0.401]	[0.447]	[0.414]
Geological Disasters(t-2)					-0.256								-0.279			0.009				-0.190	
					[0.292]								[0.389]			[0.297]				[0.389]	
Human Disasters(t-2)						0.098								0.020			0.318				0.105
						[0.313]								[0.350]			[0.303]				[0.339]
Large Human Disasters							-1.563*														
							[0.935]														
Large Human Disasters (t-1)							-0.133														
							[0.852]														
Landslides								-1.388***											-1.046**		
								[0.451]											[0.449]		
Landslides (t-1)								-0.403											0.035		
								[0.516]											[0.528]		
Real Exchange Rate									0.473	0.428	0.308	1.149	1.154	0.982					1.367	1.478	1.327
								[0.933]	[0.925]	[0.934]	[0.997]	[0.981]	[1.005]					[1.027]	[1.022]	[1.040]
Real Exchange Rate(t-1)									0.407	0.423	0.363	-2.092*	-2.097*	-2.180*					-1.942*	-1.868	-1.934*
								[0.550]	[0.563]	[0.565]	[1.108]	[1.112]	[1.131]					[1.116]	[1.122]	[1.139]
Real Exchange Rate(t-2)												1.351**	1.352**	1.334**					1.377**	1.387**	1.387**
											[0.567]	[0.556]	[0.568]					[0.589]	[0.595]	[0.609]
Deterministic Trend															-0.136***	-0.147***	-0.147***	-0.149***	-0.052	-0.079*	-0.079*
														[0.026]	[0.027]	[0.026]	[0.026]	[0.050]	[0.046]	[0.046]
Constant	-5.331**	-6.449***	-5.203**	-4.261**	-5.474***	-4.346**	-6.339***	-6.433***	-2.544	-3.642	-2.368	-0.192	-1.509	-0.287	3.270	3.488	3.674	2.599	2.296	2.649	3.410
	[2.073]	[2.094]	[2.084]	[1.977]	[1.973]	[2.058]	[2.123]	[2.089]	[2.668]	[2.770]	[2.712]	[2.480]	[2.581]	[2.754]	[2.147]	[2.271]	[2.234]	[2.204]	[3.241]	[3.204]	[3.491]
Observations	2450	2450	2450	2371	2371	2371	2450	2450	1772	1772	1772	1696	1696	1696	2371	2371	2371	2450	1696	1696	1696
R-squared	0.177	0.174	0.175	0.186	0.183	0.184	0.173	0.176	0.132	0.129	0.129	0.133	0.130	0.131	0.196	0.196	0.197	0.191	0.134	0.132	0.133
Number of countries	78	78	78	78	78	78	78	78	76	76	76	76	76	76	78	78	78	78	76	76	76

Dependent variable is the log of net bank lending inflows. Robust standard errors clustered by countries in brackets. *** p<0.01, ** p<0.05, * p<0.1. All macroeconomic variables are expressed in logs. The real exchange rate is the first difference of the log of the real exchange rate index.

Table 5
Fixed Effects Panel Regressions for Equity Flows

VARIABLES	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82
Climatic Disasters	0.130 [0.123]			0.106 [0.136]				0.041 [0.165]			0.033 [0.179]			0.037 [0.134]				-0.041 [0.172]			-0.033 [0.186]		
Income Differential	-0.165 [0.602]	-0.152 [0.603]	-0.046 [0.611]	-0.016 [0.612]	0.023 [0.623]	0.052 [0.611]	-0.174 [0.597]	0.253 [0.901]	0.279 [0.888]	0.428 [0.896]	0.541 [0.967]	0.382 [0.965]	0.690 [0.983]	0.225 [0.646]	0.200 [0.647]	0.306 [0.669]	0.175 [0.636]	0.011 [0.959]	-0.023 [0.941]	-0.013 [0.943]	0.227 [1.025]	0.080 [1.000]	0.216 [1.017]
Real Interest Rate Differential	0.307 [0.238]	0.245 [0.241]	0.378 [0.234]	0.313 [0.280]	0.294 [0.266]	0.390 [0.284]	0.301 [0.220]	0.285 [0.422]	0.201 [0.438]	0.372 [0.414]	0.226 [0.453]	0.179 [0.443]	0.297 [0.451]	0.176 [0.220]	0.119 [0.222]	0.245 [0.208]	0.161 [0.203]	0.131 [0.404]	0.066 [0.419]	0.235 [0.386]	0.094 [0.426]	0.080 [0.432]	0.193 [0.417]
Equity Flows (t-1)	0.320*** [0.042]	0.320*** [0.042]	0.331*** [0.045]	0.291*** [0.051]	0.279*** [0.050]	0.296*** [0.051]	0.323*** [0.043]	0.283*** [0.048]	0.279*** [0.047]	0.285*** [0.050]	0.256*** [0.055]	0.243*** [0.054]	0.256*** [0.055]	0.308*** [0.044]	0.305*** [0.043]	0.308*** [0.045]	0.306*** [0.044]	0.273*** [0.049]	0.269*** [0.048]	0.270*** [0.050]	0.251*** [0.056]	0.239*** [0.055]	0.248*** [0.055]
Climatic Disasters(t-1)	0.239** [0.102]			0.181* [0.108]				0.182 [0.116]			0.150 [0.128]			0.142 [0.098]				0.096 [0.119]			0.096 [0.134]		
Income Differential(t-1)	-0.106 [0.648]	-0.317 [0.616]	-0.368 [0.672]	0.347 [0.792]	0.204 [0.786]	0.299 [0.790]	-0.326 [0.601]	-0.443 [1.121]	-0.648 [1.028]	-0.774 [1.144]	0.399 [1.226]	0.423 [1.204]	0.266 [1.223]	0.579 [0.695]	0.459 [0.661]	0.505 [0.718]	0.472 [0.656]	0.600 [1.191]	0.600 [1.120]	0.675 [1.229]	0.708 [1.205]	0.700 [1.188]	0.627 [1.204]
Real Interest Rate Differential(t-1)	0.323 [0.353]	0.396 [0.353]	0.344 [0.350]	0.353 [0.283]	0.273 [0.277]	0.291 [0.263]	0.424 [0.355]	0.327 [0.405]	0.392 [0.418]	0.343 [0.403]	0.215 [0.365]	0.112 [0.352]	0.133 [0.349]	0.180 [0.318]	0.229 [0.316]	0.162 [0.321]	0.249 [0.350]	0.121 [0.369]	0.179 [0.350]	0.093 [0.351]	0.169 [0.343]	0.072 [0.342]	0.097 [0.342]
Geological Disasters		0.214 [0.146]			0.148 [0.166]				0.135 [0.210]			0.046 [0.215]			0.112 [0.160]				0.064 [0.214]			0.006 [0.218]	
Geological Disasters (t-1)		0.596** [0.253]			0.446* [0.246]				0.567* [0.292]			0.426 [0.291]			0.470* [0.240]				0.468* [0.276]			0.372 [0.283]	
Human Disasters			-0.045 [0.191]			-0.124 [0.199]				-0.092 [0.207]			-0.153 [0.221]			-0.174 [0.190]				-0.202 [0.209]			-0.225 [0.223]
Human Disasters (t-1)			0.022 [0.160]			-0.100 [0.186]				-0.063 [0.175]			-0.174 [0.208]			-0.118 [0.164]				-0.182 [0.177]			-0.247 [0.206]
Equity Flows (t-2)				0.083 [0.056]	0.083 [0.053]	0.093* [0.054]					0.069 [0.055]	0.069 [0.053]	0.075 [0.053]								0.063 [0.055]	0.063 [0.053]	0.065 [0.053]
Climatic Disasters(t-2)				0.056 [0.174]							-0.008 [0.204]										-0.072 [0.197]		
Income Differential(t-2)				-0.587 [0.577]	-0.707 [0.537]	-0.584 [0.586]					-1.054 [0.982]	-1.186 [0.880]	-1.021 [0.991]								-0.156 [1.087]	-0.433 [0.984]	-0.121 [1.102]
Real Interest Rate Differential (t-2)				-0.130 [0.301]	-0.045 [0.260]	-0.136 [0.296]					-0.050 [0.280]	0.029 [0.236]	-0.069 [0.277]								-0.227 [0.276]	-0.117 [0.223]	-0.261 [0.270]
Geological Disasters (t-2)					0.595** [0.233]							0.630** [0.273]										0.568** [0.271]	
Human Disasters (t-2)						0.455** [0.219]							0.437* [0.226]										0.344 [0.220]
Earthquake							0.885*** [0.172]										0.752*** [0.171]						
Earthquake (t-1)							0.589** [0.237]										0.461** [0.222]						
Real Exchange Rate								1.974*** [0.700]	1.914*** [0.695]	2.021*** [0.712]	2.228*** [0.807]	2.070*** [0.761]	2.187*** [0.802]					1.648** [0.675]	1.612** [0.667]	1.620** [0.677]	1.900** [0.790]	1.831** [0.758]	1.843** [0.792]
Real Exchange Rate(t-1)								-0.147 [0.177]	-0.166 [0.174]	-0.158 [0.179]	0.114 [0.503]	0.022 [0.503]	0.054 [0.514]					-0.154 [0.161]	-0.169 [0.160]	-0.181 [0.157]	-0.094 [0.499]	-0.132 [0.494]	-0.168 [0.505]
Real Exchange Rate(t-2)											0.382 [0.329]	0.341 [0.306]	0.429 [0.356]								0.345 [0.305]	0.315 [0.290]	0.376 [0.328]
Deterministic Trend														0.062*** [0.020]	0.061*** [0.019]	0.076*** [0.020]	0.061*** [0.019]	0.082*** [0.030]	0.074*** [0.027]	0.094*** [0.029]	0.077** [0.031]	0.057* [0.028]	0.078** [0.031]
Constant	1.186 [0.922]	1.789** [0.773]	1.927* [1.152]	1.148 [0.955]	1.676** [0.735]	1.411 [1.137]	1.882** [0.751]	1.439 [1.547]	1.859 [1.180]	2.140 [1.724]	1.345 [1.645]	1.752 [1.074]	1.430 [1.752]	-2.308 [1.435]	-1.932 [1.320]	-2.310 [1.655]	-1.926 [1.331]	-2.546 [2.159]	-2.026 [1.817]	-2.349 [2.360]	-2.362 [2.330]	-1.270 [1.712]	-2.225 [2.475]
Observations	2450	2450	2450	2371	2371	2371	2450	1772	1772	1772	1696	1696	1696	2450	2450	2450	2450	1772	1772	1772	1696	1696	1696
R-squared	0.113	0.117	0.107	0.115	0.125	0.114	0.119	0.085	0.090	0.083	0.086	0.097	0.089	0.123	0.126	0.122	0.129	0.093	0.097	0.094	0.092	0.101	0.095
Number of countries	78	78	78	78	78	78	78	76	76	76	76	76	76	78	78	78	78	76	76	76	76	76	76

Dependent variable is the log of net equity inflows. Robust standard errors clustered by countries in brackets. *** p<0.01, ** p<0.05, * p<0.1. All macroeconomic variables are expressed in logs. The real exchange rate is the first difference of the log of the real exchange rate

V. RESULTS FROM PVAR MODELS

This section follows the framework outlined in Section III and estimates systems of equations using the GMM estimator to assess the dynamic response of financial flows to natural disasters. The main advantage of using a panel-modeling framework is that it increases the efficiency and the power of the analysis, when compared to estimating the models at the individual country level. If vector autoregressive systems were estimated at the country specific level, given the data limitations, it is likely that there would be too few degrees of freedom for meaningful statistical inference.

Following the conclusions obtained from the preliminary estimations presented in Section IV, this Section concentrates its analysis on the response of financial flows to climatic and geological disasters, given that some flows do not seem to respond to human disasters and that human disasters are more likely to be subject to endogeneity problems. PVAR models of one and two lags were estimated, because of the relatively limited time dimension of the data and the potential for overparametrization problems mentioned in previous sections. Furthermore, the variables were transformed by forward mean differencing (Helmert transformation) to tackle the correlation between the country fixed effects and lags of the dependent variables, while preserving the orthogonality between the transformed variables and lagged regressors. We focus the presentation of results on the responses of different flows to the different types of natural disaster shocks (geological and climatic). In addition, we decided to exclude countries with missing data for several years from the estimated VARs. The 10 countries excluded are: Benin, Buthan, Guinea, Guinea-Bissau, Equatorial Guinea, Lebanon, Liberia, Nicaragua, Paraguay and Tunisia

Figure 1 presents impulse response functions for remittance inflows to one standard deviation shocks to climatic and geological disaster variables for the full sample of developing countries and a more restricted sample that considers only low income countries (see Annex Table 3 for country classifications by income groups). The responses are based on the coefficients of one lag PVAR models, unless otherwise specified. The first panel of the figure indicates that remittances increase on impact following a one standard deviation shock in climatic disasters and the effects of the shock persist for a year, but become statistically insignificant thereafter.[6] The forecast error variance decomposition analysis presented in Table 6 suggests that climatic disaster shocks are responsible for about 16 percent of variance of remittance inflows at the 10 year horizon.

In addition, the second panel of Figure 1 shows that the response of remittance inflows to geological disaster shocks is more persistent than its response to climatic shocks. Remittances present a positive, statistically significant response on impact that persists after a year and remains marginally significant even two years after the shock. The

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[6] Throughout this paper, we consider that a "statistically significant" impulse response for each period following a shock means that the interval defined by the error bands does not contain the value zero.

forecast error variance decomposition (FEVD) indicates that geological disasters account for 34 percent of the variance in remittances for this model. Similar conclusions are obtained when one considers only large natural disaster events (both climatic and geological) as defined in Annex Table 1. The impulse responses are not reported to save space.

When the analysis is restricted to a sample of low-income countries (bottom two panels of Figure 1), the previous results are confirmed, with remittances increasing on impact after a climatic shock. Nevertheless the response of remittances in low-income countries seems more persistent than the response observed for the sample as a whole and remains statistically significant even after two periods. For low-income countries, climatic shocks seem to account for over 50 percent of the FEVD. As far as geological shocks are concerned, contrary to the full sample, remittance inflows seem to present a statistically significant increase only on impact. The results from the panel VAR models indicate that the economic significance of the response of remittances to natural disasters is higher than what was suggested by the fixed-effects models.

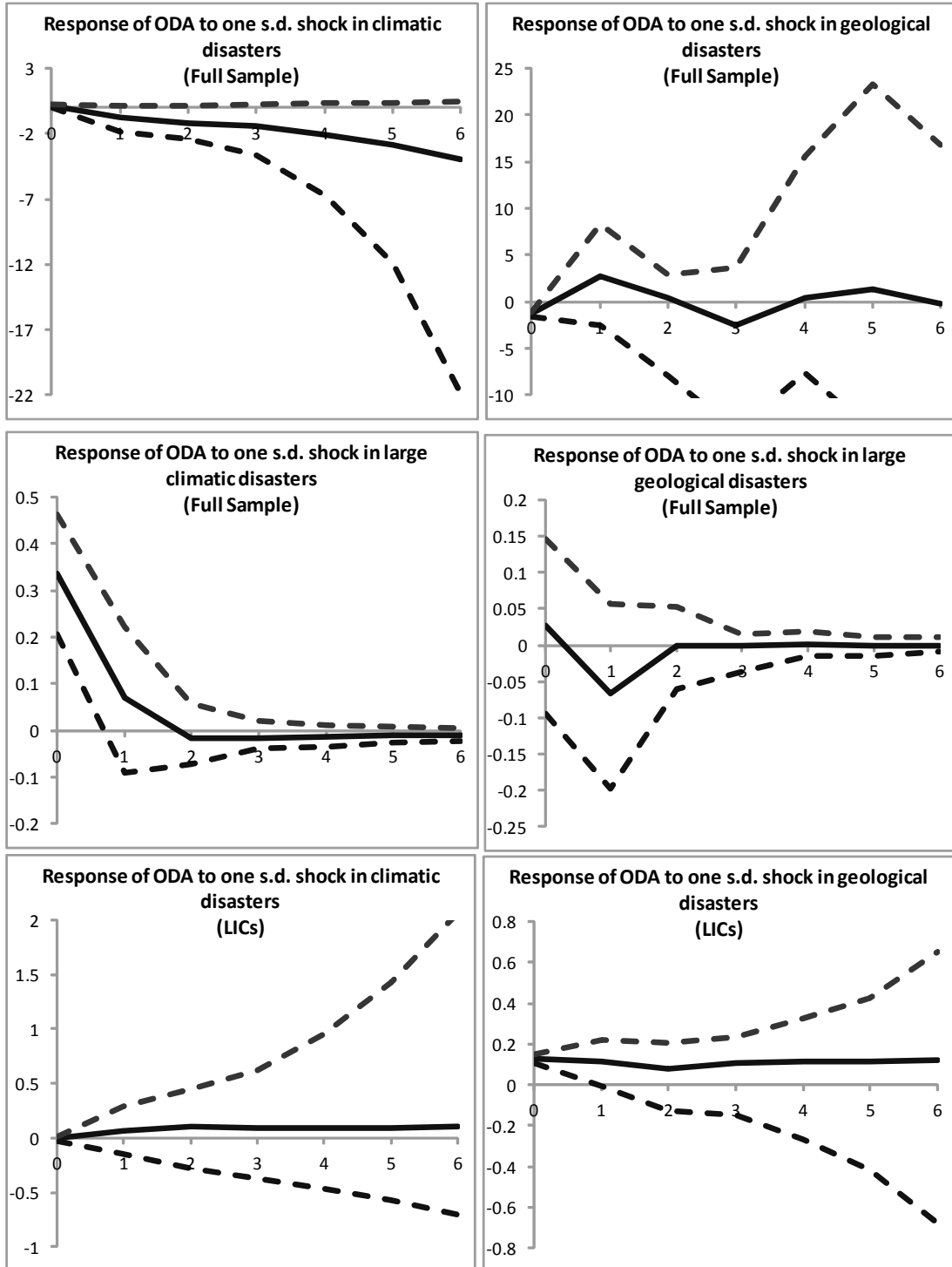**Figure 1: Impulse Response Functions for Remittance Inflows**
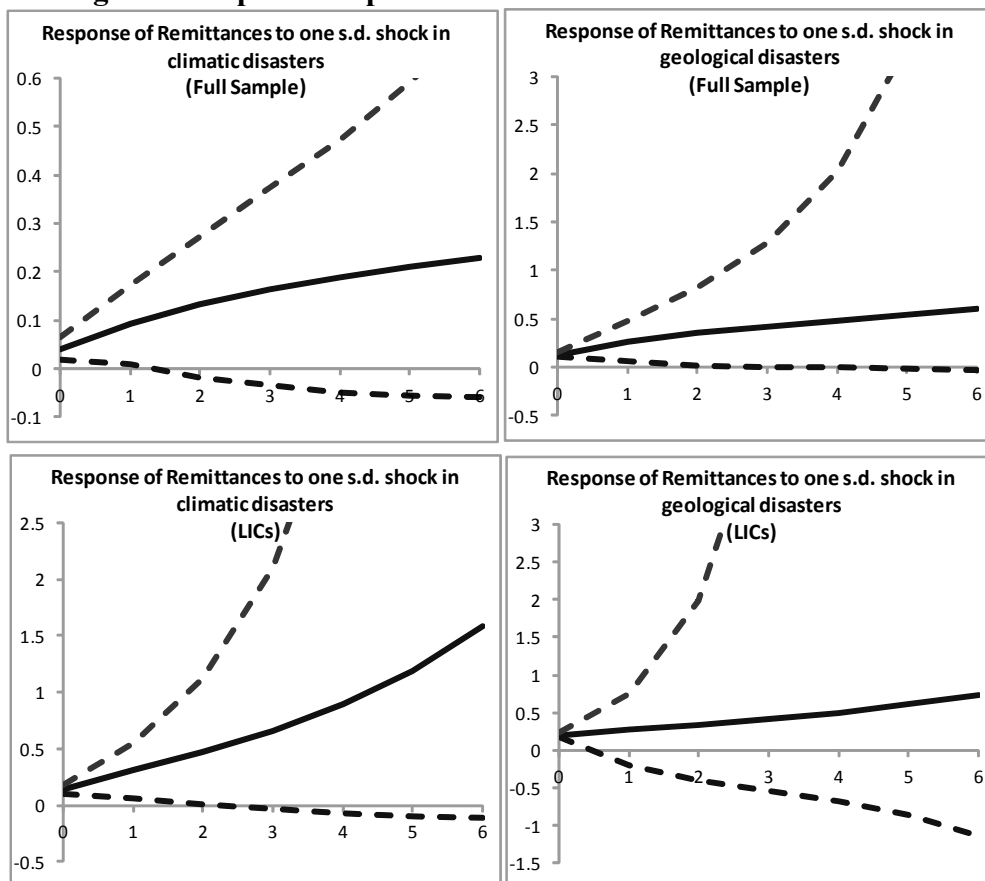
The solid line is the impulse response function to a one standard deviation shock to the natural disaster variable. 95 percent level error bands (dashed lines) were calculated using Monte Carlo simulations (1,000 repetitions). One lag VAR models were estimated for all panels, except for the model including geological disasters in Low-Income countries only, for which a two lag VAR was estimated.

The results for the PVAR models including international aid are presented in Figure 2. The models including the full sample of developing countries indicate that there is no statistically significant response of international aid to climatic shocks. The response of aid to geological shocks is negative, but barely statistically significant and the error bands for this model are very wide. When only large disasters are considered, the response of foreign aid to geological shocks is not statistically significant, while the response to large climatic shocks is significant on impact, but the FEVD reveals that climatic shocks account for merely one percent of the variance in aid flows. These results are not surprising given that the sample includes a very diverse set of countries that present vastly different levels of reliance on external assistance to finance their needs.

When we focus on a more homogenous set of low-income countries (bottom two panels of Figure 2), the models suggest that aid increases on impact following a geological disaster shock. Nevertheless, the response of aid to climatic shocks in low-income countries is not statistically significant. The forecast error variance decomposition presented in Table 6, suggests that geological events account for 11 percent of the variance of aid flows to low income countries.

The lack of response of aid to climatic shocks is in line with our preliminary estimations presented in Section IV and with the results reported by Raddatz (2009) and Raddatz (2007), but the statistically significant response of aid flows to geological shocks in low-income countries suggests a more nuanced role for aid than indicated by the preliminary analysis. The impulse responses show that foreign aid plays a role in attenuating the negative impact of geological disasters in the poorest group of countries.

Figure 2: Impulse Response Functions for Development Aid Flows

The solid line is the impulse response function to a one standard deviation shock to the natural disaster variable. 95 percent level error bands (dashed lines) were calculated using Monte Carlo simulations (1,000 repetitions). Two lags VAR models were estimated for all models, except for models with large natural disasters, for which one lag VAR models were estimated.

Table 6: Forecast Error Decomposition for Remittance Inflows and ODA Flows

Forecast Error Variance Decomposition for Remittance Inflows (at t=10)

Variance of remittance inflows explained by shock in each variable				
	Full Sample	**Full Sample**	**LICs Only**	**LICs Only**
Climatic Events	0.16	n.a.	0.53	n.a.
Income Differential	0.03	0.14	0.06	0.09
Real Exchange Rate	0.00	0.00	0.00	0.00
Interest Differential	0.00	0.00	0.00	0.00
Remittances	0.82	0.52	0.41	0.55
Geological Events	n.a.	0.34	n.a.	0.35

One lag Panel VAR models for two samples: all developing countries (full) and low income contries only (LICs). A two lag VAR was estimated for the model with geological disasters for LICs.

Forecast Error Variance Decomposition for ODA flows (at t=10)

| Variance of ODA flows explained by shock in each variable				
	Full Sample	**Full Sample**	**LICs Only**	**LICs Only**
Climatic Events	0.89	n.a.	0.12	n.a.
Income Differential	0.09	0.15	0.04	0.06
Real Exchange Rate	0.00	0.01	0.09	0.06
Interest Differential	0.01	0.00	0.03	0.02
ODA	0.01	0.39	0.72	0.75
Geological Events	n.a.	0.44	n.a.	0.11

Two lag Panel VAR models for two samples: all developing countries (full) and low income contries only (LICs).

Figure 3 presents results for PVAR models including net bank lending flows. These models exclude three large emerging markets: Brazil, India and China, because the responses of bank flows to disasters in these countries are very likely to be atypical when compared to the rest of the sample and also because the models tended to perform better when these countries were excluded, with impulse responses presenting narrower error bands.

The impulse response functions show that bank flows present a negative and significant response to climatic and geological disasters on impact that becomes statistically not significantly different from zero in subsequent periods. This negative response corroborates the conclusions obtained by Yang (2008) regarding the reaction of private financial flows to hurricanes and our preliminary results presented in previous sections

that also pointed to the lack of persistence in the response of bank flows. Nevertheless, the forecast error variance decomposition analysis presented in Table 7 suggests that while geological shocks account for 23 percent of the variation in bank flows at the 10 period forecast horizon, climatic shocks account for only 2 percent of the variation. When only large climatic disasters are considered, the response of bank flows is not statistically significant and while the response to large geological disasters is significant and positive on impact, the FEVD shows that large geological disasters account for less than one percent of the variance in bank lending flows.

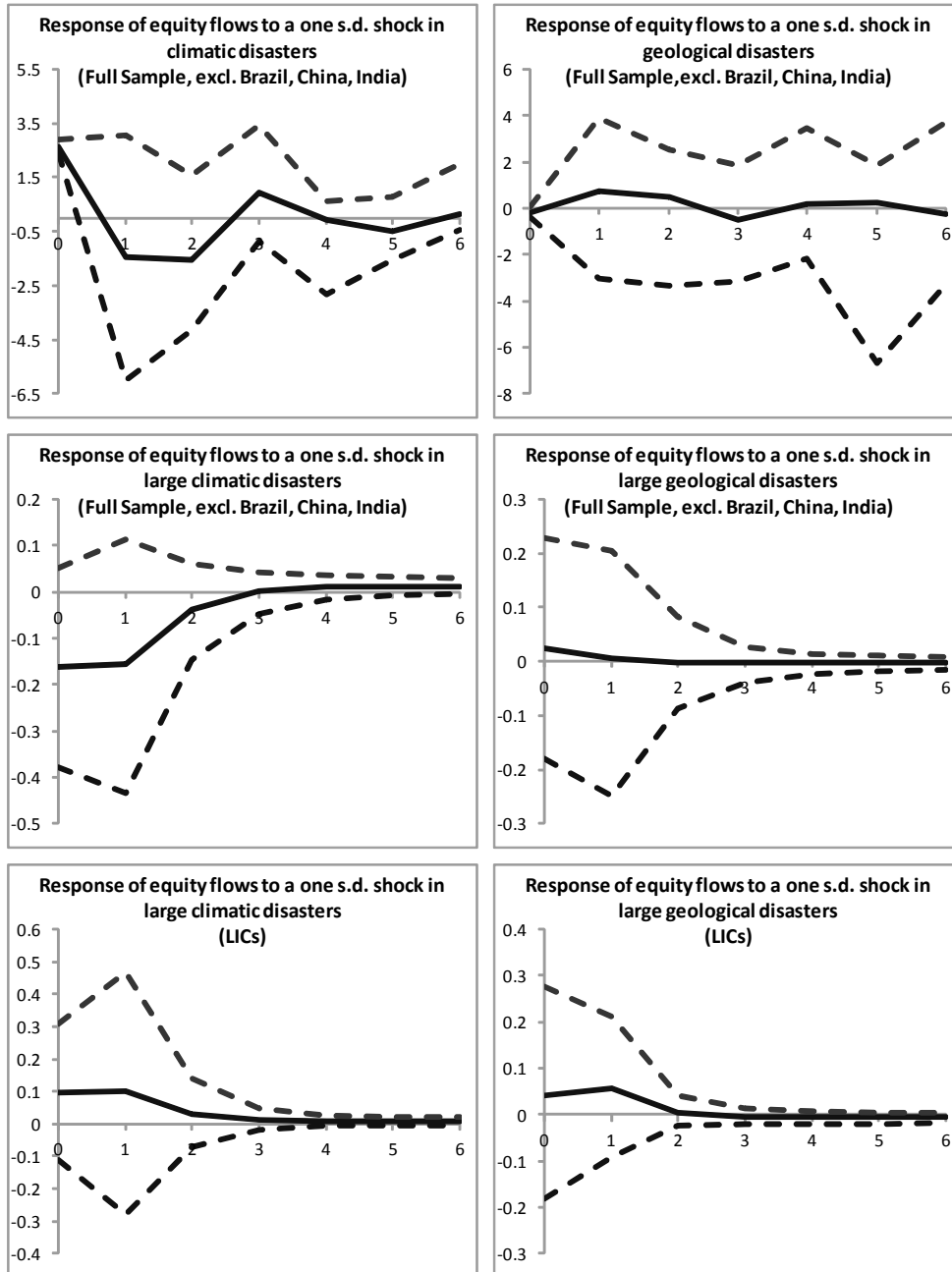## Figure 3: Impulse Response Functions for Net Bank flows
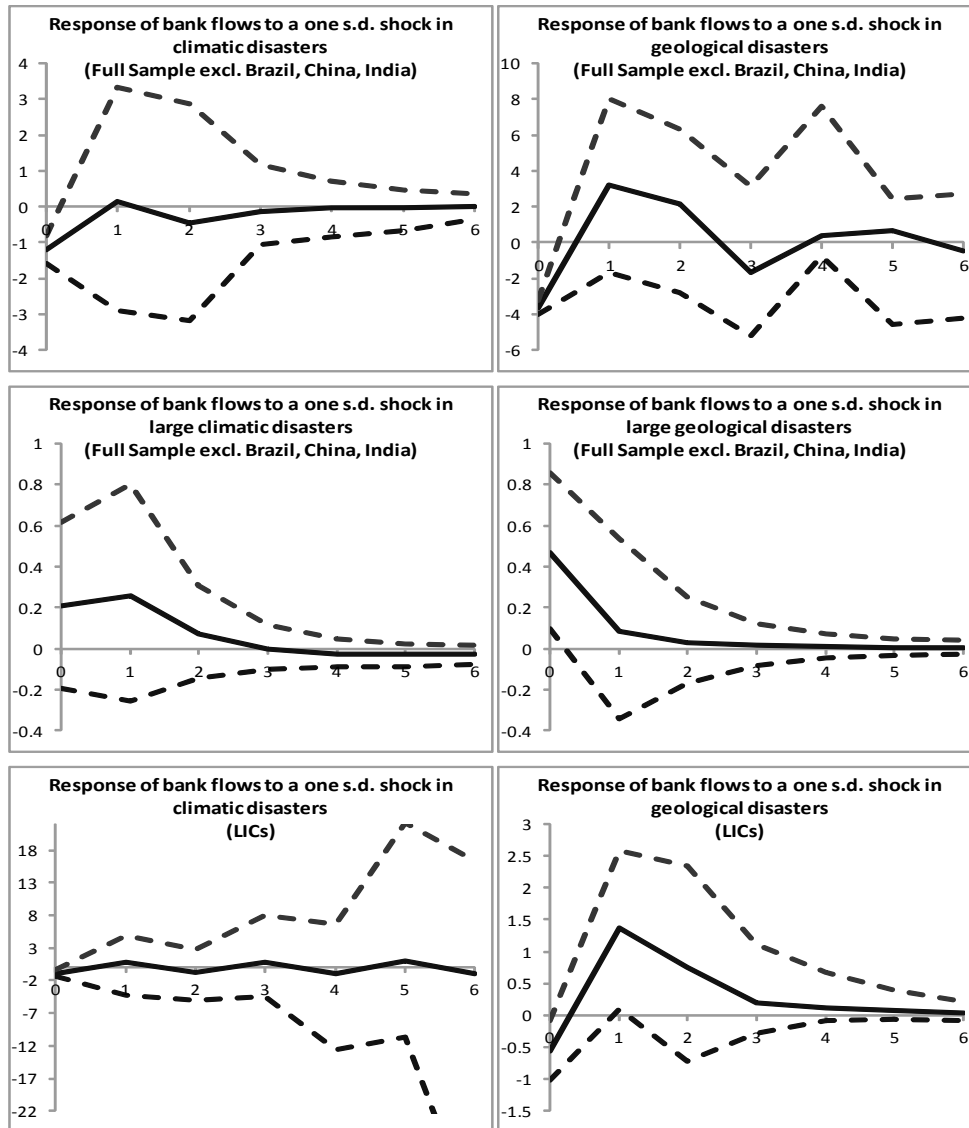
The solid line is the impulse response function to a one standard deviation shock to the natural disaster variable. 95 percent level error bands (dashed lines) were calculated using Monte Carlo simulations (1,000 repetitions). Two lag VAR models were estimated for the models including climatic and geological shocks in the full sample and for the model including geological shocks in the LIC sample. One lag VAR models were estimated for the models presented in all other panels.

When the analysis is restricted to the sample of low-income countries, the response of bank flows follows a similar pattern to the one observed for the full sample, except for the response to geological shocks that presents a marginally significant increase after one year. In addition, for the low-income countries, climatic disasters account for 13 percent of the forecast error variance of bank flows, whereas geological disasters account for only 5 percent. Overall, the results suggest that bank flows do not tend to attenuate the impact of natural disaster shocks and in fact, in most specifications they are likely to compound their negative economic impacts.

The impulse response functions for net equity flows are presented in Figure 4. For the full sample of developing countries, net equity flows increase on impact following a climatic disaster shock, but the response becomes statistically insignificant in subsequent periods. These dynamics suggest that equity flows respond relatively rapidly to disasters, but the effects of disasters on these types of financial flows tend to be short-lived. The impulse responses of equity flows to geological disaster shocks are not statistically significant. The FEVD presented in Table 7 also suggests climatic shocks account for about 29 percent of the forecast error in equity flows to the developing countries considered in the sample. When only large natural disasters are include in the models, the response of equity flows is not statistically significant as shown in Figure 4.

Figure 4: Impulse Response Functions for Net Equity Flows

The solid line is the impulse response function to a one standard deviation shock to the natural disaster variable. 95 percent level error bands (dashed lines) were calculated using Monte Carlo simulations (1,000 repetitions). One lag VAR models were estimated for all panels presented, except for the models with climatic and geological disasters for the full sample of countries (excluding emerging markets) for which a two lag VAR was estimated.

When the analysis is restricted to low-income countries, equity flows do not present statistically significant responses to either climatic or geological shocks. Results for models that include only large natural disasters are presented, because these models performed better, but the results do not change qualitatively when all disasters are included. The FEVD presented in Table 7 also suggests that natural disaster shocks account only for a negligible proportion of the variance of equity flows in these countries. In conclusion, whereas there is evidence that bank flows compound some of the negative macroeconomic effects of natural disasters, equity flows can play a role in mitigating the effects of climatic disasters at least in the middle-income countries that can access these markets. Nevertheless, the lack of deep equity markets in most developing countries, particularly low-income countries is likely to limit the role of these flows in the financing of reconstruction efforts.

Table 7: Forecast Error Variance Decomposition for Bank Flows and Equity Flows

Forecast Error Variance Decomposition for Bank flows (at t=10)

Variance of bank flows explained by shock in each variable				
	Full Sample	**Full Sample**	**LICs Only**	**LICs Only**
Climatic Events	0.02	n.a.	0.13	n.a.
Income Differential	0.02	0.03	0.01	0.01
Real Exchange Rate	0.00	0.00	0.00	0.00
Interest Differential	0.01	0.01	0.00	0.00
Bank	0.95	0.73	0.86	0.94
Geological Events	n.a.	0.23	n.a.	0.05

Two lag Panel VAR models for sample including all developing countries excluding Brazil, China and India (full). For sample of low income contries only (LICs) a one lag VAR was estimated for the model with climatic disasters and a two lag VAR for the model with geological disasters.

Forecast Error Variance Decomposition for Equity flows (at t=10)

Variance of equity flows explained by shock in each variable				
	Full Sample	**Full Sample**	**LICs Only**	**LICs Only**
Climatic Events	0.29	n.a.	0.00	n.a.
Income Differential	0.03	0.01	0.01	0.01
Real Exchange Rate	0.02	0.01	0.00	0.00
Interest Differential	0.00	0.00	0.00	0.00
Equity	0.66	0.93	0.99	0.99
Geological Events	n.a.	0.05	n.a.	0.00

Two lag Panel VAR models for sample including all developing countries excluding Brazil, China and India (full). For sample of low income contries only (LICs) one lag VAR models were estimated. Note that models for LICs include only large natural disasters (see Annex for definitions).

VI. CONCLUSIONS

This paper has used multivariate dynamic panel analysis to examine the response of international financial flows to natural disasters. In the analysis, natural disasters were considered to be a weakly exogenous real shock. The panel vector-autoregressive models estimated for a large sample of developing countries point to differentiated responses of specific types of financial flows to the shocks of interest. The results show that migrant remittance inflows to developing countries increase significantly in response to shocks to both climatic and geological disasters. Natural disasters can account for up to 53 percent of the forecast error variance of remittance inflows to low-income countries. The models estimated also suggest a nuanced role for foreign aid. International aid to low-income countries increases following geological disaster shock, but in more general circumstances, the responses of aid flows to natural disaster shocks are not statistically significant. Therefore, one can conclude that international aid typically only plays a limited role in attenuating the economic consequences of disasters, but its role is more significant in poorer countries.

Furthermore, we sought to investigate whether private capital flows amplify or mitigate the negative economic consequences of natural disasters. Both our preliminary results and the PVAR models indicate that bank lending flows in general do not attenuate the effects of disasters and in some specifications, net bank lending outflows typically occur after the onset of disasters, therefore amplifying the negative economic effects of these events. Equity flows are not an important source of finance for disaster recovery in low-income countries. Nevertheless, they respond positively to climatic disasters for the larger sample of developing countries, but not to geological disaster shocks. In addition, this effect is short-lived. Overall, the results presented in the paper are robust to model specifications for which only large natural disasters were included.

Our analysis is subject to several caveats that should be addressed in future research. In particular, there is substantial scope for refining the natural disaster measures considered in the models such that additional variation in the magnitude of the economic impact of these events is introduced. Moreover, there is also scope to further differentiate between types of financial flows. For example, foreign aid in the form of budget support is likely to respond differently to disasters than project-related international assistance. The GMM estimator used for the PVAR models also presents shortcomings; most significantly, it assumes that all the countries included in the sample follow the same dynamics. Coefficient estimates will be biased if this is not the case. Subsequent work could test whether the results obtained still hold when alternative estimators that are not subject to this problem (such as mean-group estimators) are used.

The findings of the paper entail several possible policy implications. Given the compensatory nature of remittances, developing countries that are vulnerable to natural disasters would benefit from fostering these flows by, for example, pursuing policies to reduce transaction costs associated with them. In addition, policy makers in disaster stricken countries typically should not rely on substantial increases in foreign assistance to finance reconstruction or consumption smoothing needs, except for specific circumstances. Furthermore, the international community should continue its efforts to

strengthen the capacity to scale-up foreign aid following natural disaster events, given that in the past, recorded financial assistance only provided a mitigated response to such events, particularly in what concerns climatic disasters. Nevertheless, it is also important to take into account the absorptive capacity of the specific country to increased aid flows. In fact, the lack of response of aid to natural disasters might in part be related to concerns by donors regarding the lack of absorptive capacity for additional flows. Hence, it is important to have a clear perspective of the incentives governing international assistance when interpreting the results obtained in this paper.

The conclusions of the paper also have implications for capital/financial account management policies. In particular, countries should carefully take into account their vulnerability to natural disasters and the impact of disasters on capital flows when considering the benefits and costs of capital account liberalization. The potential benefits of liberalization in terms of facilitating additional financing for disaster recovery and consumption smoothing typically do not appear to have materialized for a large number of developing countries, but there is evidence of considerable risks of private capital outflows following natural disaster events.

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Annex Table 1: Variables Definitions and Sources

Variable	Description/Notes	Source
Remittance Flows	Log of net remittance inflows (denominated in US dollars and deflated by the US CPI).	Global Development Finance Dataset.
Aid Flows	Log of net overseas development assistance inflows (denominated in US dollars and deflated by the US CPI). Used the log of the absolute value multiplied by (-1) when the number is negative.	Global Development Finance Dataset.
Portfolio Equity Flows	Log of net equity inflows (denominated in US dollars and deflated by the US CPI). Used the log of the absolute value multiplied by (-1) when the number is negative.	Global Development Finance Dataset.
Bank Loan Flows	Log of net bank loan inflows (denominated in US dollars and deflated by the US CPI). Used the log of the absolute value multiplied by (-1) when the number is negative.	Global Development Finance Dataset.
Interest Rate Differential	$\ln(1+i) - \ln(1+i^*)$, where i is the domestic real reference rate and i^* is the real 3-month US Treasury Bill rate. Real rates are calculated ex-post, as the nominal rate minus the observed inflation rate.	IMF/IFS.
Real Effective Exchange Rate	Log of the real effective (trade weighted) exchange rate index for country i.	IMF/WEO Dataset and World Bank DEC-PG data.
Output Differential	Log of the ratio of output in country i and US output. Variables are measured in PPP terms.	Penn World Tables.
Climatic Disasters	Number of Droughts, Floods, Windstorms (including hurricanes) and extreme temperature events in a given year.	EM-DAT Dataset.
Geological Disasters	Number of earthquakes, landslides, volcano eruptions and tidal wave events in a given year.	EM-DAT Dataset.
Human Disasters	Number of famines and epidemics in a given year.	EM-DAT Dataset.
Large Disaster Events	Number of climatic, geological or human disaster events in a given year that classify as a large disaster according to the following criteria: the event affects at least half a percent of a country's population, or causes damages of at least half a percent of national GDP, or results in more than one fatality every 10,000 people	Calculated by Raddatz (2007) based on EM-DAT data.

Annex Table 2: Descriptive Statistics for Selected Variables

		Entire Sample of Countries						Low Income Country Sample				
Variable		Mean	Std. Dev.	Min	Max	Observations		Mean	Std. Dev.	Min	Max	Observations
Geological Disasters	overall	0.30	0.96	0.00	14	N = 2808	overall	0.10	0.39	0.00	4.00	N = 1116
	between		0.66	0.00	3.69	n = 78	between		0.22	0.00	0.86	n = 31
	within		0.70	-3.39	10.61	T = 36	within		0.33	-0.76	3.30	T = 36
Climatic Disasters	overall	1.06	2.10	0.00	23	N = 2808	overall	0.76	1.36	0.00	11.00	N = 1116
	between		1.63	0.00	8.89	n = 78	between		0.96	0.08	5.44	n = 31
	within		1.34	-7.83	15.17	T = 36	within		0.97	-4.68	6.32	T = 36
Human Disasters	overall	0.26	0.71	0.00	8	N = 2808	overall	0.42	0.89	0.00	8.00	N = 1116
	between		0.30	0.00	1.64	n = 78	between		0.26	0.11	1.25	n = 31
	within		0.65	-1.38	7.01	T = 36	within		0.85	-0.83	7.17	T = 36
Income Differential	overall	2.28	0.88	-0.84	4.48	N = 2886	overall	1.51	0.55	-0.84	2.93	N = 1147
	between		0.82	0.81	4.21	n = 78	between		0.41	0.81	2.35	n = 31
	within		0.31	0.42	4.29	T = 37	within		0.38	-0.34	2.95	T = 37
Real Exchange Rate	overall	-0.02	0.31	-11.66	2.20	N = 1942	overall	-0.03	0.18	-1.88	1.00	N = 762
	between		0.03	-0.24	0.04	n = 76	between		0.02	-0.10	0.02	n = 30
	within		0.31	-11.45	2.41	T-bar = 25.5	within		0.18	-1.83	1.04	T-bar = 25.4
Interest Differential	overall	-0.03	0.24	-4.58	1.67	N = 2604	overall	-0.05	0.26	-4.58	0.52	N = 1054
	between		0.12	-0.78	0.18	n = 78	between		0.15	-0.78	0.08	n = 31
	within		0.22	-3.94	1.63	T-bar = 33.4	within		0.22	-3.86	0.78	T-bar = 34
Remittances	overall	3.18	2.94	-0.16	9.99	N = 2886	overall	2.17	2.41	-0.16	8.53	N = 1147
	between		2.23	0.00	8.38	n = 78	between		1.90	0.00	6.58	n = 31
	within		1.93	-3.94	8.46	T = 37	within		1.52	-4.42	7.45	T = 37
Foreign Aid	overall	11.80	3.22	-13.69	16.09	N = 2866	overall	12.63	1.06	3.66	16.09	N = 1144
	between		2.24	0.00	14.69	n = 78	between		0.80	10.99	14.27	n = 31
	within		2.33	-13.01	20.17	T-bar = 36.7	within		0.72	5.16	16.42	T-bar = 36.9
Bank Flows	overall	1.12	9.57	-16.45	17.07	N = 2886	overall	-0.40	7.63	-14.43	15.26	N = 1147
	between		3.26	-5.26	10.41	n = 78	between		1.87	-5.26	3.62	n = 31
	within		9.00	-25.07	21.64	T = 37	within		7.41	-16.58	20.12	T = 37
Equity Flows	overall	1.32	4.93	-16.23	17.42	N = 2886	overall	1.03	3.38	-11.76	14.19	N = 1147
	between		1.92	-1.48	9.34	n = 78	between		1.48	0.00	5.62	n = 31
	within		4.54	-21.04	15.97	T = 37	within		3.05	-15.30	11.92	T = 37

Annex Table 3: List of Countries Included in the Regressions and their Income Classification

Country	Code	Income Group	Country	Code	Income Group	Country	Code	Income Group
Argentina	ARG	UMC	Honduras	HND	LMC	Chad	TCD	LIC
Burundi	BDI	LIC	Hungary	HUN	HIC	Togo	TGO	LIC
Benin	BEN	LIC	Indonesia	IDN	LMC	Thailand	THA	LMC
Burkina Faso	BFA	LIC	India	IND	LMC	Trinidad and Tobago	TTO	HIC
Bangladesh	BGD	LIC	Jamaica	JAM	UMC	Tunisia	TUN	LMC
Bolivia	BOL	LMC	Jordan	JOR	LMC	Turkey	TUR	UMC
Brazil	BRA	UMC	Kenya	KEN	LIC	Tanzania	TZA	LIC
Barbados	BRB	HIC	Lebanon	LBN	UMC	Uganda	UGA	LIC
Bhutan	BTN	LMC	Liberia	LBR	LIC	Uruguay	URY	UMC
Botswana	BWA	UMC	Sri Lanka	LKA	LMC	Venezuela, RB	VEN	UMC
Central African Republic	CAF	LIC	Lesotho	LSO	LMC	South Africa	ZAF	UMC
Chile	CHL	UMC	Morocco	MAR	LMC	Congo, Dem. Rep.	ZAR	LIC
China	CHN	LMC	Madagascar	MDG	LIC	Zambia	ZMB	LIC
Cote d'Ivoire	CIV	LIC	Mexico	MEX	UMC	Zimbabwe	ZWE	LIC
Cameroon	CMR	LMC	Mali	MLI	LIC			
Congo, Rep.	COG	LMC	Malawi	MWI	LIC			
Colombia	COL	LMC	Malaysia	MYS	UMC			
Cape Verde	CPV	LMC	Niger	NER	LIC			
Costa Rica	CRI	UMC	Nigeria	NGA	LIC			
Algeria	DZA	LMC	Nicaragua	NIC	LMC			
Ecuador	ECU	LMC	Nepal	NPL	LIC			
Egypt, Arab Rep.	EGY	LMC	Pakistan	PAK	LIC			
Ethiopia	ETH	LIC	Peru	PER	LMC			
Fiji	FJI	UMC	Philippines	PHL	LMC			
Gabon	GAB	UMC	Papua New Guinea	PNG	LIC			
Ghana	GHA	LIC	Paraguay	PRY	LMC			
Guinea	GIN	LIC	Rwanda	RWA	LIC			
Gambia, The	GMB	LIC	Senegal	SEN	LIC			
Guinea-Bissau	GNB	LIC	Sierra Leone	SLE	LIC			
Equatorial Guinea	GNQ	HIC	Swaziland	SWZ	LMC			
Guatemala	GTM	LMC	Seychelles	SYC	UMC			
Guyana	GUY	LMC	Syrian Arab Republic	SYR	LMC			

Note: LIC=Low-income country; LMC= Lower Middle-income country; UMC= Upper Middle Income country, HIC High Income Country. Income group classification based on latest World Bank definition.