# How do monthly remittances respond to natural disasters in migrants' home countries?

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**Abstract**

The literature on the impact of natural disasters on remittances has provided mixed evidence so far, with identification remaining a key challenge. This paper studies the insurance role of remittances by investigating their dynamic response in the aftermath of a disaster. We use a novel and rich panel dataset of monthly remittance flows from Italy to 81 developing countries for the period 2005 to 2015. We find that monthly remittance flows on average increase by 2% due to natural disasters in migrants' home countries. The response gets significant a few months after the event and tends to disappear within a year from the disaster occurrence. The intensity and timing of remittances' responsiveness are heterogeneous according to the nature of the disaster, the receiving country's characteristics, and migrants' socio-economic conditions in the host country.

JEL codes: migrants' remittances, international migration, natural disasters

Keywords: F24, F22, Q54

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# 1 Introduction

The Earth's global warming, the severe changes in the climate system, and the increasing environmental degradation of urban, peri-urban, and rural areas have determined a sharp increase in the frequency, intensity, and destructive force of natural disasters in the last decades (Van Aalst, 2006; Coronese et al., 2019).

The impact of natural disasters on GDP growth rates and other macroeconomic variables of affected countries in the medium-long run is ambiguous, this being the result of both negative abandonment effects and positive reconstruction effects (Cavallo and Noy, 2011; Osberghaus, 2019). Be that as it may, human and material losses, as well as the ability to cope with and recover from disasters are strongly affected by the countries' level of economic development as well as their institutional setting (Kahn, 2005; Noy, 2009; Fomby et al., 2013; Felbermayr and Gröschl, 2014; Berlemann and Wenzel, 2018; Dzator and Dzator, 2021). It is therefore not surprising that fostering economic and social resilience to extreme natural events is a major issue on the agenda of governments of low- and middle-income countries, development agencies and international institutions (World Bank, 2014; Marto et al., 2018; GFDRR, 2020).

Despite the structural efforts to prevent and cope with extreme natural events, the response of international financial flows in the aftermath of a disaster remains a key factor to mitigate its adverse impact on the local population (David, 2011; Becerra et al., 2014; Heger and Neumayer, 2019). In particular, to the extent that migrant remittances proved to be a less volatile source of financial flows than foreign aid or foreign direct investments and a valuable source of risk sharing for many developing countries (Yang, 2011; Combes et al., 2014; Balli and Rana, 2015; Bettin et al., 2017), their contribution to the recovery and reconstruction process following a natural disaster is considered of utmost importance. Moreover, intra-family transfers, remittances can bear an immediate and direct relieving effect on the livelihoods of receiving households (Skidmore and Toya, 2002).

However, the growing empirical evidence on remittances and natural disasters is far from being conclusive. Some studies find that remittance flows increase in the aftermath of natural disasters and significantly contribute to disaster preparation (David, 2011; Mohapatra et al., 2012; Bettin and Zazzaro, 2018), while others find that migrant transfers do not significantly respond to disasters in the country of origin (Lueth and Ruiz-Arranz, 2008; Bettin et al., 2017). Different methodologies and sample composition, as well as different types of natural disasters considered in the analysis, may all contribute to explaining such mixed results. However, although natural disasters can be viewed as predominantly exogenous and hardly predictable events, identification remains the key issue to uncover the response of migrants' remittances to disasters in the home country and measure it unambiguously.

Existing cross-country studies use annual data on global or bilateral flows of incoming remittances and disaster indicators that aggregate the adverse natural events that occurred over the same time horizon (David, 2011; Mohapatra et al., 2012; Naudé and Bezuidenhout, 2014). Obviously, it is difficult to appraise the response of remittances to natural disasters from yearly data. A rapid increase in sending money home is often vital to mitigate the impact of disasters on the affected communities, and migrants abroad are likely to concentrate their financial support to relatives at home in the months immediately following a disaster. As a result, the effect of disasters on the annual amount of remittance inflows can be confounded by several additional events and factors that may not be easy to control for.

In particular, there could be a redistribution of remittances within the year. If migrants' financial capacity in host countries is largely fixed, they may decide, in response to a disaster, to front-load their transfers and reduce them in subsequent months, while keeping their annual remittances roughly unchanged. This pattern is consistent with case study evidence reported in Le De et al. (2015) and Bragg et al. (2018). The former conducted interviews and participatory activities in five Samoan coastal areas hit by the tsunami in September 2009. Overall, they found that remittances increased immediately after the tsunami and came back to the standard level after six months, but also that "tsunami-impacted households received fewer remittances in December 2009 [because] most remitters put all their efforts in supporting their relatives immediately after the disaster, thus limiting their ability to afford the usual Christmas remittances" (Le De et al., 2015, p. 661). Similarly, in the eighteen case studies analyzed by Bragg et al. (2018), remittances usually showed an increase in the quarter in which the disaster occurred, which was rarely followed by a significant annual increase.

In addition, adverse natural events (for example, tornadoes, hurricanes, floods, or droughts) are not randomly distributed throughout the year but often follow a seasonal pattern, which differs from country to country. The seasonality of disasters introduces an issue of appropriate temporal specification of the econometric model that makes the identification of the remittance-disaster nexus on the basis of annual observations even more problematic, especially where disasters are concentrated in the first or last months of the year.

Finally, the use of annual data for remittances requires disaster data to be aggregated on a yearly basis as well. This makes it hard to estimate the average effect of one natural disaster, as well as to test for the non-linearity of remittances response to damage caused by extreme events or other forms of heterogeneity in the link between disasters and remittances.

The above concerns highlight the potential gains from using high-frequency data on remittance inflows for proper identification of the impact that the occurrence of a natural disaster has on migrant transfers to the country of origin, the time profile of the remittances response to disasters, and the role that possible moderator factors have in explaining remittance flows. To this end, we exploit a unique dataset on monthly bilateral remittance flows from Italy towards a panel of 81 low-middle income countries for the period 2005-2015, which we merge with disaster data for the same countries at the same monthly frequency.

Observing remittances on a monthly basis, we can adopt a non-parametric event study approach, which allows us to flexibly characterize the dynamic response of remittances to natural disasters in migrants' home countries over a 12-month horizon. We use three alternative specifications, which differ from each other in the way our key disaster variables are constructed and in the underlying assumptions regarding the effect of disaster events outside the estimation window. First, we focus on disasters that occurred between 2006 and 2014 and make the assumption that the response of remittances to disasters diminishes to zero outside a 12-month window. To the extent that natural disasters occur randomly, such an assumption does not bias our results once we control for time and country-fixed effects. However, for robustness, following recent advances in the literature on multiple event studies (Schmidheiny and Siegloch, 2020; Sun and Abraham, 2020), we also estimate two further model specifications in which we redefine our disaster variables to control for both past and future disasters and assume that the effect of disasters does not vanish outside the chosen 12-month window, but remains constant.

By way of preview, our results show that international remittances can play a significant role in mitigating the effects of natural disasters in migrants' countries of origin. On average, monthly bilateral remittance flows from Italy increase by about 2% in response to a natural disaster in the receiving country. Results are robust to controlling for the economic vulnerability of the home country and for economic conditions in Italy as well as for past and future disasters and possible long-lasting effects of disasters. In addition, the positive response of remittance to natural disasters at home is confirmed when we take into consideration the frequency and intensity of the disasters that occur in a given month: in particular, we find that the increase in remittances in the aftermath of the largest disasters is significantly greater, exceeding 3% on average.

The positive nexus between disasters and remittances is mainly driven by the response to disasters occurring in upper-middle-income countries and in countries with a larger stock of migrants in Italy. Moreover, we find that the response of remittances is stronger for events occurring before the global financial crises, and for climatic and meteorological events compared to other geophysical disasters.

Moving on to the timing of remittances response to natural disasters, our results indicate that it is heterogeneous according to the nature of the disaster. When distinguishing between sudden-occurring (e.g., earthquakes or storms) and slow-occurring disasters (e.g., droughts or extreme temperatures), we find a swifter response to sudden-occurring disasters mostly within the first three months after their occurrence, whereas, in the case of slow-occurring disasters, remittances respond with a lag of about three months. However, the increase in remittances induced by slow-occurring disasters is relatively larger and lasts for a longer period compared to that following sudden disasters.

Finally, we find that the condition of immigrants in the host country matters for the response of remittances to disasters. First, immigrant communities that are spatially more concentrated in Italy display a smaller and less significant increase in remittances in the aftermath of extreme events in the country of origin. Second, the increase of remittances after a disaster appears to be restricted to the pre-crisis period (2005-2008), thus suggesting that the economic conditions of migrants in the host country limit their ability and willingness to send additional financial resources at home.

The paper proceeds as follows: section 2 provides a brief review of the literature, section 3 explains the empirical framework and section 4 describes the data on disasters and remittances. Sections 5 and 6 present respectively the main results and additional estimates or robustness checks. Section 7 concludes.

## 2 Related literature

An increasing number of empirical studies have analyzed the relationship between migrant remittances and natural disasters in the home countries. Whereas case studies for countries in Central and Latin America or South Asia consistently document a positive response of remittances to different types of natural disasters (Halliday, 2006; Fagen, 2006; Yang and Choi, 2007; Attzs, 2008; Le De et al., 2015; Shivakoti, 2019; Su and Le Dé, 2021), results from cross-country studies are more nuanced.

David (2011) document a positive association between remittance inflows and the occurrence of natural disasters. By considering a panel of 78 developing for the period 1970-2005, they provide evidence of a statistically significant increase in contemporaneous remittance flows due to the number of climatic and geological disasters in a given year and show that this increase is statistically significant even one year later. Similarly, Naudé and Bezuidenhout (2014), focusing on 23 sub-Saharan African countries, show that remittances respond positively, although slowly, to natural disasters in the region and that such response is greater than that resulting from other types of shock such as armed conflicts or financial crises.

Other studies find that the response of remittances to natural disasters is less clear-cut and moderated by some country characteristics. By extending the study of David (2011) to a larger sample of 129 developing countries, Mohapatra et al. (2012) confirm that the flow of remittances in a given year increases with the share of the home country population affected by natural disasters in the same year and the year before, but this effect is statistically significant only if the stock of migrants abroad is sufficiently large (more than 15% of home country population). Yang (2008) looks at the impact of hurricanes on international financial flows to developing countries. Unlike foreign aid, which reacts positively to hurricane exposure wherever it occurs, remittance inflows increase only in very poor countries. Interestingly, Amuedo-Dorantes et al. (2010) document that there may also be some crowding out effects between different types of capital inflows: they show that, although remittances and foreign aid both increase in the aftermath of natural disasters in Small Island Developing States, migrants abroad may strategically choose to remit less when foreign countries step in with official assistance. Bettin and Zazzaro (2018) find that remittance inflows respond positively to the occurrence of natural disasters and also increase with the number of natural disasters that have already occurred in the past thus suggesting that remittances contribute to increasing ex-ante preparedness for probable adverse natural events. However, this insurance role of remittances is shown to be statistically significant only for countries with low-developed financial systems, in line with the evidence provided by Arezki and Brückner (2012).

Finally, using data on annual bilateral remittance flows to 11 developing (home) countries from (on average) 16 sending countries for the period 1980-2004, Lueth and Ruiz-Arranz (2008) do not find a statistically significant response of remittances to earthquakes, floods or wind storms in the home country. This negative result is confirmed by Bettin et al. (2017) that use the data on bilateral remittance flows from Italy to developing countries compiled by the Bank of Italy, as we do in the present study. However, it is important to note that Bettin et al. (2017), as well as all the other studies reviewed in this Section, consider remittance flows at a yearly frequency, thus suffering from the identification problems that we have discussed in the introduction.

# 3 Empirical strategy

## 3.1 Baseline model

To estimate the dynamic response of monthly remittance flows to the occurrence of disasters in the home country, we exploit the exogenous nature of such catastrophic events and conduct an event study analysis. We use a non-parametric event study specification similar to Dobkin et al. (2018). One of the main advantages of this approach is that it allows one to flexibly observe and describe the pattern of remittance flows relative to the time when a disaster occurs.

Unlike the standard setting for event studies with one event per unit of observation, in our context, many countries experience multiple disaster events during the period of analysis. To deal with multiple events, we follow the *Multiple Dummies On* (MDO) approach suggested by Sandler and Sandler (2014), in which multiple event-time dummies are taken on at once, such that remittance inflows to a given country in a given period can respond to multiple disasters with overlapping effect windows. As Sandler and Sandler (2014) shows, the MDO approach allows to yield unbiased estimates of the event-time dummies without creating spurious trends in outcome variables before and after the event, as it happens, instead, with the alternative approach of using country-event-time units and duplicating observations for overlapping disasters (the *Duplicating Observations* approach).

Let $i = \{1, ...N\}$ be the receiving country, $t \in T_s = [\underline{t}_s,\ \bar{t}_s]$ the calendar time within the remittance sample period $T_s$, $D_i^{T_e}$ the number of months in which a disaster event occurred in country $i$ during the event window $T_e = [\underline{t}_e,\ \bar{t}_e]$ – i.e., in our main analysis, the number of months country $i$ has been affected by at least one natural disaster – and $e_{d_i} \in T_e$ the calendar time when country $i$ experienced the $d$-th disaster event. By restricting the effect window to the time interval $[-\underline{m}, \bar{m}]$ that considers $[\bar{m}]$ months after the disaster event and $\underline{m}$ months before it, the MDO specification for our multiple event study is:

$$Y_{it} = \lambda_i + \tau_t + \sum_{d_i=1}^{D_i^{T_s}} \sum_{m=-\underline{m}}^{\bar{m}} \beta_m \mathbb{D}_{it}^m + \sum_{z \in Z} \delta_z X_{zit} + \varepsilon_{it} \tag{1}$$

where $Y_{it}$ is the log of real remittances per-capita from Italy to country $i$ in month $t$, $\mathbb{D}_{i,t}^m = \mathbb{1}\,(t = e_{d_i} + m)$ is an indicator variable that takes the value 1 if $m$ months away from $t$ – with $m \in [-\underline{m},\ \bar{m}]$ – the country experienced a disaster event, and 0 otherwise, $X_z$ denotes a set of $Z$ additional factors $X$ that may affect remittance flows, and $\lambda_i$ and $\tau_t$ denote country and calendar time fixed effects, respectively.

Our key dependent variables $\sum_{d_i} \mathbb{D}_{i,t}^m$ are a set of dummies that document the dynamics of remittance flows in response to a disaster during the effect window. The main identifying assumption is that, once we condition on observables $\{X_1, ...X_Z\}$, country and time fixed effects, the occurrence of each disaster is uncorrelated with other unobserved shocks (Schmidheiny and Siegloch, 2020). The estimated $\beta_m$ coefficient is interpreted as the semi-elasticity of remittance inflows $Y_{it}$ at time $t$ with respect to the disaster event occurred $m$ months away, at time $e_{d_i}$. Insignificant coefficients of our parameter estimates in the pre-event period can be viewed as evidence in favor of considering disasters as exogenous events.

The estimation of the event study model (1) with a finite effect window and multiple events requires making assumptions about (i) the effect of disasters on remittance inflows outside the selected effect window, and (ii) the effect of disaster events that occur outside the sample period $T_s$ – between $[\underline{t}_s - \bar{m},\ \underline{t}_s]$ and between $[\bar{t}_s,\ \bar{t}_s + \underline{m}]$ – on remittances within our sample period. In the baseline specification, we assume that the effect of any disaster event on remittances diminishes to zero outside our effect window and that no disasters occur before and after our sample period. The baseline model, as well as all the other model specifications presented below are estimated with standard errors clustered at the country level (Bertrand et al., 2004).

## 3.2 Controlling for past and future disasters

In the context of multiple disaster events, additional adverse natural events occurring outside the sample period can have effects on in-sample remittances thus biasing our results. To address this concern, we extend the event window to disasters that occurred within the $\bar{m}$ periods before the first calendar time of the sample period and within the $\underline{m}$ periods after the last calendar time of the sample period. In other words, we estimate a specification where the event window $T_e = [\underline{t}_s - \bar{m},\ \bar{t}_s + \underline{m}]$ is larger than the sample period:

$$Y_{it} = \lambda_i + \tau_t + \sum_{d_i=1}^{D_i^{Te}} \sum_{m=-\underline{m}}^{\bar{m}} \beta_m \mathbb{D}_{it}^m + \sum_{z \in Z} \delta_z X_{zit} + \varepsilon_{it} \tag{2}$$

## 3.3 Remittances response to disasters outside the effect window

In models (1) and (2) we assume that the effect of disasters on remittances diminishes to zero outside the effect window. This amounts to ignore possible country specific trends that are correlated with the disaster-time indicators and once again could bias our baseline estimates.

Alternatively, following Schmidheiny and Siegloch (2020), we estimate a specification where the effect of disasters is assumed to stay constant outside the effect window by *binning* the disaster indicator at the endpoints of the window:

$$Y_{it} = \lambda_i + \tau_t + \sum_{d_i=1}^{D_i^{Te}} \sum_{\substack{m=-\underline{m} \\ m \neq m^*}}^{\bar{m}} \beta_m \mathbb{B}_{it}^m + \sum_{z \in Z} \delta_z X_{Z_{it}} + \varepsilon_{it} \tag{3}$$

where $\mathbb{B}_{it}^m$ is the disaster indicator binned at the endpoints, such that:

$$\mathbb{B}_{it}^{m} = \begin{cases} \sum_{k=t-\underline{m}}^{\bar{t}_s} \mathbb{D}_{ik}^{m} & if\ m = \underline{m} \\ \mathbb{D}_{it}^{m} & if\ \underline{m} < m < \overline{m} \\ \sum_{k=\underline{t}_s}^{t-\bar{m}} \mathbb{D}_{ik}^{m} & if\ m = \overline{m} \end{cases} \tag{4}$$

Model (3) allows for the response of remittances to disasters to extend outside the chosen effect window by assuming that in any $t$, $\mathbb{B}_{it}^{m}$ takes a value that reflects the sum of all the disaster events occurred in the sample period until the period $t$, and $\mathbb{B}_{it}^{\bar{m}}$ takes a value equal to the sum of all the disaster indicators before the period $t$.[1] It is worth noting that in this case the disaster indicators $\mathbb{B}_{it}^{m}$ sum up to zero or one over the effect window according to whether the country has ever experienced a disaster event during the sample period or has undergone at least one. Therefore, due to the inclusion of country-fixed effects, the parameters $\beta_m$ are identified only up to a constant. To ensure identification, we normalize our parameter estimates by expressing the parameters $\beta_m$ relative to a reference period $m^*$, and drop the disaster indicator $\mathbb{B}_{it}^{m^*}$ (Schmidheiny and Siegloch, 2020). The estimated parameters must therefore be interpreted as the differential response of remittances in the $m$-th month before or after a disaster event compared to the response of remittances in the month $m*$ from the disaster occurrence.

# 4 Data and descriptive statistics

In this section, we present our dependent and independent variables, the sources of data and some descriptive statistics (see Table 1). The estimation sample includes 81 countries for which data on the full set of variables are available. The list of countries included in our regression analysis and the average monthly remittances they receive are reported in Table 2.

[1] As Schmidheiny and Siegloch (2020) show, this assumption is equivalent to assume that the effect window is infinitely large and that $\beta_m = \beta_{\underline{m}}$ for any $m < \underline{m}$ and $\beta_m = \beta_{\bar{m}}$ for any $m > \bar{m}$.

[Table 1 around here]

[Table 2 around here]

### 4.1 Migrant remittances

This study relies on a rich dataset on nominal remittances in euros from Italy to over 150 developing countries released by the Bank of Italy for the period 2005 to 2015 on a monthly basis.[2] Nominal remittances are deflated by the CPI index. Then, monthly real remittance data are seasonally adjusted by using the standard X-12 tools in Stata (Wang and Wu, 2012). Our dependent variable, *RemitPC*, is defined as the log of real remittances per-capita, i.e., real remittances sent to country $i$ at time $t$ divided by the stock of immigrant population from country $i$ residing in Italy in $t-1$ to take into account the significant size heterogeneity across migrant communities in Italy. The average aggregate monthly real remittances sent from Italy are equal to about 350,000 euros, ranging from zero to 7.6 million euros depending on the receiving country (Table 1). This great variability mirrors the significant heterogeneity across migrant communities residing in Italy, whose size goes from 44 individuals to more than 1 million persons, but also very different remitting attitudes and patterns that lead remittances per-capita to vary between 22,025 and 19 euros per month.

Figure 1(a) displays the monthly flow of real remittances sent from Italy to the rest of the world in the sample period 2005-2015. In the first part of the period, remittances from Italy have been steadily increasing even if at diminishing growth rates, with a slight decline in 2010 before reaching their peak in 2011 at about 7 billion euros. Between 2011 and 2013, a steep decline in remittance outflows is observed, with the growth rate dropping from 10% to -20%, before stabilizing in the last two years of our sample period.[3] This sharp drop in remittances is due both to a slowdown in migration flows to Italy and to the worsening of

[2] Data are publicly available at https://www.bancaditalia.it/statistiche/tematiche/rapporti-estero/rimesse-immigrati/index.html?com.dotmarketing.htmlpage.language=1. Monthly outflows were published up to 2015; from 2016 onward data were released only on a quarterly basis.

[3] On average, Romania received the largest amounts, followed by the Philippines, Bangladesh, Morocco, Peru, Brazil, Ecuador and Albania (see table 2).

migrants' economic conditions which followed the severe recession Italy was facing at the time. Indeed, the growth in the number of migrants in Italy had a sudden stop, with the overall stock of foreign residents decreasing by more than 11% (from 4,5 millions in 2010 to 4 millions in 2011), but became positive again in the next years, reaching 5 million immigrants in 2015 (see figure 1(b)).[4] At the same time, employment statistics reveal a sharp increase in the unemployment rate for the foreign population, from about 11.6% in 2010 to a peak of 17.2% in 2013, which slowly decreased to 16.2% by 2015.

[Figure 1 around here]

## 4.2 Disasters

Disaster data are taken from the EM-DAT database compiled by the Centre for Research on the Epidemiology of Disasters (CRED) at the University Catholique de Louvain. The database provides information on the date of occurrence of a large set of climatic, hydrological, geophysical and meteorological disasters – e.g. flooding, droughts, extreme temperature, wildfire, landslides, storms, earthquakes, volcanic activity, mass movements of the land (dry) – and their effects on people and properties as far back as 1900.[5] We aggregate all the previously mentioned types of disasters at a monthly frequency to build a country-level indicator, *Disaster*, that takes the value of 1 if country $i$ experienced at least one disaster in month $t$, and 0 otherwise. By restricting the effect window to the time interval $[-\underline{m}, \bar{m}]$, as explained above in section 3.1, we include the event indicator variables equal to 1 up to $\underline{m}$ months before the disaster and $[\bar{m}]$ months after the disaster.

[4] Data from the Italian National Institute of Statistics only provide information on migrants based on citizenship. Therefore, the official figures do not account for migrants that already got Italian citizenship, whereas they include second generations born in Italy from foreign parents which have not been yet recognized as Italian citizens.

[5] The inclusion of a natural event as disaster in EM-DAT depends on whether the event meets at least one out of the following alternative criteria: (i) the number of people killed is at least 10; (ii) 100 or more people are displaced, injured or homeless as a result of the disaster; (iii) significant property damage amounting to 0.5 percent of GDP occurred; (iv) a state of emergency has been declared or an international appeal for assistance has been made. In the documentation provided by the CRED, it is noted that recent data is more reliable due to better data recordings. For additional information, see https://www.emdat.be/.

In order to perform some heterogeneity analysis, we investigate whether the timing and the magnitude of remittances' response changes according to the different type and nature of natural disasters. The classification of disasters by type that we use closely mimics the one provided in the EM-DAT database and distinguishes three groups of events: (i) *climatic disasters*, which include events related to weather conditions such as floods, droughts, wildfire and landslides; (ii) *geophysical disasters*, which are defined as those brought by tectonic activity below the earths surface and include earthquakes, volcanic activity and mass movements (dry); (iii) *meteorological disasters*, which are related to the earth's atmosphere and include extreme temperatures and storms.[6]

Alternatively, we classify events by nature, according to the length of time needed before the full scale of the disaster is realized. Following the Sendai Framework for Disaster Risk Reduction 2015-2030, adopted by UN Member States in 2015,[7], we distinguish between *sudden-onset disasters*, which include earthquakes, volcanic activity, mass movements (dry), storm, landslides and flooding, and *slow-onset disasters*, which include extreme temperatures, wildfire and droughts. Sudden-onset disasters are hazardous events that happen quickly and largely unexpectedly, whereas slow occurring disasters are often related to environmental degradation processes that emerge gradually over time. If sudden-onset disasters generate an immediate and unanticipated need for resources for reconstruction, slow–onset disasters usually allow for an extended period of forewarning, which may translate into a potential proactive response (Staupe-Delgado, 2019), both at local and international level.

During the period under consideration we observe at least one natural disaster for about 14% of the country-month pairs in our sample, with the number of events ranging from 0 to 6 in a given month (Table 3). In terms of intensity, 1% of the total population is on average

[6]This classification is slightly different from the one employed in other studies. For instance, David (2011) distinguishes between climatic events (which include floods, droughts, extreme temperatures and hurricanes), geological events (which include earthquakes, landslides, volcano eruptions and tidal waves) and human disasters (which include famines and epidemics). We prefer to adopt a more conservative classification, which mostly reflects the original grouping provided by the data source. Furthermore, we choose to focus only on natural disasters by excluding epidemics and other biological disasters.

[7]The full document is available at https://www.preventionweb.net/publication/sendai-framework-disaster-risk-reduction-2015-2030.

affected by disasters as they happen, with maximum peaks that exceeds 51%. The average share of casualties is not different from zero, although it can raise up to 2.27% of the total population.

[Table 3 around here]

When looking at disasters by nature, the incidence of sudden-onset disasters is much higher compared to slow-onset events (13% versus 2%), as well as their average frequency (0.16 versus 0.02). On the other hand, the average share of population affected by slow-onset disasters is at least eight times larger (4.25% versus 0.52%). If we look at the type of disasters, climatic events are more frequent than geophysical and meteorological ones (0.12 compared to 0.01 and 0.05, respectively) and on average affect also a larger share of total population.

Table 4 shows the distribution of natural disasters across geographic regions. Events in our sample concentrate mostly in Sub -Saharan Africa (46%), Latin America and the Caribbean (20%) and Europe and Central Asia (15%), although the highest frequency of events in a single month (6) is registered in East Asia and the Pacific. This region experiences also the larger average share of population affected, which is equal to 0.36% of the country's total population. The maximum peak however has been in Sub-Saharan Africa, where the drought experienced by Niger in September 2009 affected over 7 million people, more than 51% of the country's population.

[Table 4 around here]

Latin America and the Caribbean has the highest number of casualties. The January 2010 earthquake in Haiti killed over 250,000 people, about 2.3% of the total population. This is by far the disaster with the largest human costs in our sample.

## 4.3 Control variables

We control for a number of factors that capture economic conditions in migrants' home countries which may potentially have an influence on remittance outflows from Italy. First we control for *Terms of trade*. Export price shocks have been identified as a major cause of instability for low- and middle-income countries, generating fluctuations in trade balance, reserve assets and domestic output (DiPace et al., 2020). We use the monthly commodity export price index, weighted by the ratio of individual commodity exports to total commodity exports, from the International Monetary Fund (IMF) database and express it in logs.[8] An additional source of vulnerability for many developing countries is related to agricultural production, which is heavily dependent on rainfall and temperature: a less than adequate or late amount of rainfall may affect crop yield and productivity, as well as an extraordinary amount of rain. To account for any potential rise in remittances fueled by significant although non-disastrous changes in weather conditions, we include two variables to control for *Abnormal rain* and *Abnormal temperature* at time $t$, which are defined as the square of the difference between the rainfall or temperature in month $t$ and the average rainfall or temperature in month $t$ over the past ten years.[9] Finally, we control for *Exchange rate* to take into account financial conditions in the home countries as the monthly real exchange rate between US dollar and domestic currency of country $i$, normalized with respect to its 2010 value for each country. Information on exchange rates are drawn from the IMF International Financial statistics database. Other home country characteristics such as GDP, population and migrant stocks, which we will ideally like to control for, are mostly available on an annual basis and are therefore excluded.

[8] IMF data on the terms of trade are dowloadable at https://data.imf.org/?sk=2CDDCCB8-0B59-43E9-B6A0-59210D5605D2. Precisely, the terms of trade are measured as the Commodity Export Price Index weighted by the ratio of individual commodities exports to total commodity export (Gruss and Kebhaj, 2019).

[9] Precisely, we use the loss function $\left(Rain_t - \frac{\sum_{n=1}^{10} Rain_{t-12n}}{10}\right)^2$ to compute this abnormal loss. We do the same with temperature. Monthly average temperature and rainfall data are drawn from the World Bank Climate Change Knowledge Portal, https://climateknowledgeportal.worldbank.org/download-data.

To capture economic and financial conditions in Italy (the host country) that may exert a direct effect on migrants' ability and willingness to remit, we control for the monthly unemployment rate and the monthly Tresaury Bill rates (*Unemployment rate* and *Interest rate*, respectively).

Finally, we include country fixed effects and month×year fixed effects in order to account for different seasonalities which may not be fully captured by the limited set of control variables available at monthly frequency.

# 5 Results

## 5.1 Baseline results

The results from estimating the baseline model in equation [1] are reported in Table 5. As stated earlier, this model is based on the assumption that the effect of disasters outside the chosen effect window diminishes to zero. Our preferred specification includes 3 leads and 12 lags for each disaster dummy (column 1). In order to test the sensitivity of baseline estimates to the number of leads and lags, we extend the number of leads to 6 (column 2) and the number of lags to 24 (column 3); then we augment the baseline specification by considering both 12 leads before and 24 lags after each event (column 4). Finally, we estimate our preferred specification by including the set of control variables available at a monthly frequency (column 5).

[Table 5 around here]

Results are broadly consistent across specifications. First, lead coefficients are never statistically significant, suggesting that migrants are unable to anticipate a disaster's occurrence, which can be considered an exogenous event. With regard to lags, remittances per-capita react almost immediately on impact when a natural disaster hits migrants' country of origin, as the response becomes significant at conventional significance levels from the second month onwards. Apart from the fifth lag, the effect persists over a 12-month horizon. Based on the estimates presented in column (1), the magnitude of the estimated response increases from about 1.8 percent on impact – although not statistically different from zero – to about 2.4 percent by the end of the fourth month after the disaster, and remains rather stable during the first year after the disaster. Remittances response is depicted in Figure 2(a). One year after the disaster, both the extent and the significance of the response of remittances show a decreasing pattern (see columns 3 and 4).

We test for the joint significance of leads and lags, respectively. Results, reported in the lower part of Table 5, show that leads are never significant, whereas lags are jointly significant at the 10 percent level in all specifications. This confirms that, despite a marginal drop in the magnitude of the estimated coefficients as the number of parameters to be estimated increases, our estimates of remittances' response are robust to different choices in terms of leads and lags.

The time dynamics that we observe in the response of remittances to disasters highlights the importance of using high frequency data. Most of the effects extend over two calendar years, and with a different intensity month by month that depends on the temporal distance from the disaster. As the distribution of disasters is unlikely to be uniform over time, estimates on annual data might be biased, especially when considering different types of disasters with their own seasonality.[10] By contrast, no long-term reallocation effect seems to be at work in remittance flows, which return to pre-disaster levels after twelve months and never become significantly lower.

After selecting the specification with 3 leads and 12 lags as our preferred specification, we further control for additional variables that are available at monthly frequency and may affect migrants' decisions to remit (column 5), such as the terms of trade, abnormal temperature, and rainfall, monthly interest rates and exchange rates in the country of origin, and

[10]In this view, the annual-frequency bias could explain why Bettin et al. (2017) using our same dataset fail to detect any significant impact of disasters in migrants' home countries on remittance flows from Italian provinces.

unemployment rate in the destination country. None of the additional controls is statistically significant, although they have the expected sign. But what matters most, we can confirm the positive response of remittances to disasters in terms of magnitude and significance of the estimated coefficients as well as with regard to the temporal pattern of remittance flows.

## 5.2 Robustness

### 5.2.1 Controlling for past and future disasters

As discussed in Section 3.2, results could be biased if additional disaster events occurring outside the event window have significant effects on in-sample remittances. This problem is mitigated by estimating Equation [2], where the event window $T_e = [\underline{t}_s - \bar{m},\ \bar{t}_s + \underline{m}]$ is larger than the sample period $[\underline{t}_s,\ \bar{t}_s]$. Indeed, data on disasters cover a longer period compared to remittance data. We can therefore control for disasters occurring during the twelve months before 2005 and after 2015 to allow us to capture the dynamics of remittances that otherwise can be wrongly attributed to disasters observed during the time window for remittances. The findings presented in Table [6], columns [1]-[2], are similar to our baseline results both in magnitude and significance. The estimated response of remittances is around 2 percent on impact – although not statistically different from zero – and becomes significant from the second month onwards. The largest increase is recorded in the fourth month (2.5 percent) and remains rather stable during the first year after the disaster.

[Table 6 around here]

### 5.2.2 Binning the end points

We then proceed by relaxing the assumption that the effect of disasters diminishes to zero outside the chosen effect window by estimating model [3]. Results are presented in Table [6], columns [3]-[4], and unlike baseline estimates, they are expressed relative to two months before the disaster occurred. Hence, the dummy $\beta_{k=-2}$ is set to zero and serves as the reference point[11].

Our findings reveal a clear increase in remittances at the time the disaster strikes and in the following months, as can be seen also in Figure 2(b). We estimate a statistically significant increase in remittances of about 1.2 percent on impact relative to two months before the disaster occurred. The peak in remittances' response (about 1.57 percent) corresponds to the fourth month after the disaster occurred, but all estimates are statistically significant at the 5 percent level in between. Beyond the fourth month the effect, though positive, is hardly significant.

The estimates on the binned coefficients are not statistically different from zero. This indicates that we cannot reject the hypothesis that the response of remittances diminishes to zero in the long run, beyond the one-year event window. Such a result is coherent with the low magnitude of the response observed towards the end of the 12-month window after the disaster. Indeed, if we look at the F-test of joint significance we can see that the first six lags are jointly significant at 5% (F-statistics = 4.81). When testing the significance of all 12 lags, instead, we fail to reject the null hypothesis that the coefficient estimates are jointly zero (F-statistics = 2.55).

As column [2] shows, estimates are robust to controlling for other shocks in the receiving country and for economic conditions in Italy. It is worth noting that the magnitude of the coefficients gets slightly larger compared to the specification without any control variable, especially in the third and fourth month after the disaster occurred (1.62 and 1.68 percent, respectively).

### 5.2.3 Disaster severity

We further test the robustness of our main results by employing alternative disaster measures. Indeed, one may expect that the response of remittances is not independent of either the frequency or the intensity of events that happen in a single month. Then, we start by

[11] Unreported results using $k = -1$ or $k = 0$ as reference point are practically identical.

replacing the disaster dummy with the number of disasters occurring in each country during a specific month. Results reported in column [1] of Table 7 are in line with our baseline findings: the estimates of the coefficients for the number of disasters remain statistically significant, although obviously slightly lower than those of the baseline.

[Table 7 around here]

Second, we restrict our attention to disasters of a relatively larger magnitude. We do this by considering disasters above the 25th percentile or, in alternative, above the 50th percentile of the distribution of the share of the total population affected by the event (Table 7, column [2] and [3]). The evidence provided above is confirmed, with the magnitude of the coefficients being much larger for disasters above the 50th percentile. As expected, the estimated response of remittances increases from the baseline. For the most serious disasters (column [3]) the reaction of remittances is concentrated in the first months immediately following the event, with an increase of about 2.5 percent in the first month following the event and more than 3 percent at the end of the fourth month, to become statistically indistinguishable from zero after 10 months.

#### 5.2.4 Collapsing pre- and post-disaster periods

To appreciate the importance of using monthly data to properly identify the remittance response to disasters, we estimate a specification of model (1) that combines the pre- and post-disaster parameters into six-month leads and lags:

$$Y_{it} = \lambda_i + \tau_t + \sum_{d_i=1}^{D_i^{Ts}} \sum_{\mu=-1}^{2} \beta_\mu \mathbb{D}_{it}^{\mu} + \sum_{z \in Z} \delta_z X_{zit} + \varepsilon_{it} \tag{5}$$

where $\mu$ refers to a lead or lag of six months and $\mathbb{D}_{i,t}^{\mu} = \mathbb{1}\,(t = e_{d_i} + m)$, with $m \in [1, 6]$, is an indicator variable that for any $t$ takes the value 1 if within six months away from $t$ the country was hit by at least one natural disaster. Essentially, $\beta_{\mu,s}$ coefficients capture the average monthly response of remittances over the six-month periods before and after the disaster. For symmetry, the month of the disaster event is combined neither into the leads nor the lags indicator. The estimated response of remittances to disasters, though positive, is statistically insignificant for all the three lead and lags indicators in Table 8. This is consistent with the idea that considering the average impact of disasters on remittances over a long time horizon can return imprecise estimates, hiding the different patterns of remittance response to disasters over shorter time periods.

[Table 8 around here]

## 5.3 Heterogeneity

### 5.3.1 Migrant community size and home country level of development

In Table 9, we provide estimates obtained by restricting the sample according to specific characteristics of migrants' home countries. Column [1] refers to the subsample of countries with average monthly remittance inflows larger than 100,000 euros whereas column [2] refers to the subset of countries with a migrant community in Italy larger than 1,000 persons per year. Both restrictions are then considered together in column [3]. Compared to our baseline estimates for the whole sample, disaster lag coefficients are larger: on impact, remittances increase by about 2.7/3.1 percent and such effect is statistically significant. Once again, the estimated response peaks after four months, with the largest increase of 3.5 percent estimated in column [3]. Both the results are consistent with the evidence on the important role that the size of the diaspora plays for the magnitude of remittance flows (Bettin et al., 2017; Mohapatra et al., 2012)[12].

[Table 9 around here]

In columns [4]-[6], we split our sample according to the level of development of the home country, distinguishing between low-income (LIC), lower-middle-income (LMIC) and upper-middle-income (UMIC) countries. Although the drastic drop in the number of observations

[12]Unfortunately, we are not able to control for the stock of migrants in our model because this information is available only at yearly frequency.

reduces the precision and the power of our estimates, it is interesting to note that the response of remittances to natural disasters in the home country is especially strong for migrants from UMICs: the estimated increase of remittances on impact is about 2.9 percent and peaks at about 3.8 percent eight months after the disaster. By contrast, migrants from LICs seem to transfer less in the aftermath of disasters. Such heterogeneity suggests complementarity between migrants' response to natural disasters via remittances and the probability of reconstruction in the home country. Richer countries, where the post-disaster reconstruction process is likely to be easier and faster, can count on a larger and more rapid response of remittance flows from their migrant community abroad.

#### 5.3.2 Type and nature of disasters

In this section, we explore the heterogeneity of remittance response based on the type and the nature of disaster events. As discussed in Section 4.2, we classify disasters into three main categories: climatic, geophysical, and meteorological. Results are reported in Table 10, columns [1]-[3].

[Table 10 around here]

Post-disaster coefficients are all positive and mostly significant for climatic disasters in column [1]. The magnitude is in line with our baseline estimates, and the peak of the response is registered four months after the disaster took place. The response of remittances is weaker in the face of meteorological disasters and becomes statistically significant between 9 and 12 months following the occurrence of the event. No statistically significant effect on remittances is associated with geophysical disasters. Indeed, the impact of earthquakes and tsunamis are likely to be localized, with often severe consequences on existing infrastructures, and information and telecommunication facilities, thereby disrupting channels through which remittances are usually sent. Despite differences in the classification of disasters and in the empirical methodology, our results are consistent with earlier findings by David (2011), who found a significant response of remittances to climatic disasters only.

Second, we distinguish disasters between sudden-onset and slow-onset disasters based on the length of time needed before the full scale of the event is realized. Subsample estimates by disaster nature reported in Table 10, columns [4]-[5], show that remittances react to sudden-onset disasters, although the response is not immediate and becomes significant only from the fourth month after the event. The estimated increase relative to two months before the disaster occurred is about 2.2 percent and remains pretty stable up to 12 months after the disaster. On the other hand, the response of remittances to slow-onset disasters is apparently too weak to detect any statistical significance either in terms of single lag coefficients or when considering them jointly.

#### 5.3.3 Immigrants spatial concentration and economic conditions in the host country

A well established literature has documented that the spatial density of an immigrant ethnic population in the host country matters for economic and social integration of its members, (Chiswick and Miller, 1996; Edin et al., 2003; Damm, 2009; Danzer and Yaman, 2013), and that in turn this may have an influence on the ability and willingness to remit (Marcelli and Lowell, 2005; Bettin et al., 2012; Carling and Hoelscher, 2013). In this section, we explore whether spatial concentration of a same-country migrant community in Italy affects how the flow of remittance to that country respond to natural disasters at home.

We measure the spatial concentration of immigrants from a country $c$ in Italy by the average annual Hirschman-Herfindahl index (HHI) on the share of immigrants from country $c$ residing in the 20 Italian NUTS2 regions $r$ in year $t$ as percentage of country $c$'s total immigrant population in Italy in the same year $t$:

$$HHI_c = \frac{\sum_{t=2005}^{2015} HHI_{ct}}{11} = \frac{1}{11} \sum_{t=2005}^{2015} \sum_{r=1}^{20} \left( \frac{Immigrant_{irt}}{Immigrant_{ct}} \right)^2 \quad (6)$$

In columns [1] and [2] of table 11 we report regression results for sub-samples of immigrant groups with a high or low spatial concentration of immigrants in Italy, respectively. We find that remittances originating from immigrant groups with an HHI index above the median value do not show a statistically significant increase in the aftermath of natural disasters in the country of origin. By contrast, the response of remittances to natural disasters of immigrant groups more sparsely distributed across Italian regions (with an HHI index less than or equal to the median value) is statistically significant and economically stronger.

[Table 11 around here]

Finally, we split our sample period in three sub-periods: the pre-crisis period 2005-2008, the crisis period 2009-2012 and the post-crisis period 2013-2015. Regression results reported in Table 11, columns [3]-[5] show that the ability of immigrants to increase their remittances in response to a natural disaster in the home country is limited to the years before the great financial crisis. During this period, remittances increase on disaster's impact by about 2 percent, exceeding 5 percent eight and twelve months after the disaster. This estimates are statistically significant up to 10 months after the disaster. In the two other sub-periods, the effect of disasters on remittance flows is statistically not different form zero.

# 6 Conclusions

The present empirical analysis highlights the importance of using high-frequency data in event study settings to identify the response of international remittances to natural disasters in migrants' countries of origin. Inconclusive evidence provided by cross-country studies may indeed be explained by the fact that annual data fail to account for the actual response in migrants' transfer, which according to our estimates is rather quick, reaching its maximum 4 months after the disaster occurred, and tend to disappear in 12 months at most.

On average, migrants increase their transfers by 2% in response to a natural disaster in their home country. This effect is driven by the diaspora of upper-middle-income countries and by larger migrant communities. At the same time, when such communities are more concentrated geographically in the host country, migrants are less responsive to the occurrence of disasters back home. Bad socio-economic conditions of migrants abroad also act as a hindering factor that decreases their remitting capacity, so that we fail to observe any significant increase in international transfers in the aftermath of natural disasters. It is also worth highlighting the heterogeneity in the response of remittances according to the nature of disaster events. International transfers react more rapidly to sudden-occurring events, whereas the response to slow-occurring events is apparently delayed, although more intense and more persistent over time.

Understanding the exact timing of remittances' response to natural disasters, and the factors driving their dynamics over time, is of utmost importance for developing countries that have a large diaspora abroad and are increasingly exposed to natural disasters. Indeed, migrant remittances may act as immediate and direct aid to households affected by disasters, often substituting for the delayed arrival of official aid, if any. The nature of these cash transfers may also provide affected households with greater flexibility compared to in-kind official assistance.

However, remittance effectiveness after a disaster crucially depends on two aspects. On the one hand, people lacking access to any remittance-receiving technology would remain extremely vulnerable in case of natural disasters, given that the diaspora abroad could hardly play any mitigating role. On the other hand, the still high transaction costs may limit migrants' altruistic responsiveness in the aftermath of a disaster. Even though remitting capacity strongly depends on migrants' economic conditions in host countries, a substantial reduction in the costs of international transfers would free up additional resources that may prove critical in the case of a humanitarian emergency. Achieving the Sustainable Development Goal of reducing remittance costs to less than 3% by 2030 could then represent a useful instrument not only to contribute to poor countries' social and economic development but also to increase their resilience to extreme natural events.

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# Tables

Table 1: Variables and summary statistics

| Variables | Description and sources | Mean | St. dev. | Min | Max |
|---|---|---|---|---|---|
| Remittances (100,000 euros) | Monthly flow of real remittances from Italy to country $i$ deflated by CPI Sources: Bank of Italy and Istat. | 3.59 | 9.55 | 0 | 76.07 |
| Stock of immigrants (thousands) | Annual stock of immigrants in Italy from country $i$. Source: ISTAT | 39,01 | 117.99 | 0.044 | 1,151.4 |
| Remittance per capita (log) | Monthly flow of real remittances to country $i$ at time $t$ over the stock of immigrant from country $i$ at $t-1$. | 6.33 | 1.53 | 2.97 | 10.04 |
| Population (millions) | Population of country $i$. Source: IMF. | 31.96 | 45.46 | 0.46 | 258.38 |
| Disasters | Dummy variable that takes the value 1 if the country $i$ experiences at least one disaster in the month and 0 otherwise. Source: EM-DAT. | 0.14 | 0.35 | 0 | 1 |
| Number of disasters | Number of natural disasters occurring in country $i$ at month $t$. Source: EM-DAT. | 0.18 | 0.5 | 0 | 6 |
| Population affected | Population affected by disasters occurring in country $i$ at month $t$. Source: EM-DAT. | 0.05 | 0.52 | 0 | 27 |
| Share of population affected (%) | Share population affected by disasters occurring in country $i$ at month $t$. Source: EM-DAT. | 0.148 | 1.48 | 0 | 51.33 |
| Disaster deaths | Number deaths caused by natural disasters occurring in country $i$ at month $t$. Source: EM-DAT. | 33.8 | 2,223.22 | 0 | 222,570 |
| Disaster damages (Millions USD) | Cost of material damages caused by natural disasters occurring in country $t$ at month $t$. Source: EM-DAT. | 17.99 | 441.37 | 0 | 40,000 |
| Rainfall (mm) | Monthly rainfall in country $i$. Source: World Bank-CCKP. | 102.42 | 98.16 | 4.2e-5 | 600.96 |
| Abnormal rainfall | $\left(Rain_t - \frac{\sum_{n=1}^{10} Rain_{t-12n}}{10}\right)^2.$ | 4.63 | 3.77 | -21.04 | 13.54 |
| Temperature (Celsius) | Average monthly temperature in country $i$. Source: World Bank-CCKP. | 21.12 | 8.84 | -26.29 | 34.17 |
| Abnormal temperature | $\left(Temperature_t - \frac{\sum_{n=1}^{10} Temperature_{t-12n}}{10}\right)^2.$ | -2.08 | 2.47 | -23.22 | 4.52 |
| Terms of trade (log) | Monthly Commodity Export Price Index (weighted by the ratio of individual commodities exports to total commodity export). Source: IMF-IFS. | 4.52 | 0.23 | 3.7 | 5.28 |
| Unemployment rate (%) | Monthly unemployment rate in Italy. Source: Istat. | 9.00 | 2.40 | 5.30 | 14.30 |
| Exchange rate | Monthly real exchange rate between US dollar and domestic currency of country $i$. Source: IMF-IFS. | 102.95 | 27.94 | 42.42 | 547.84 |
| Interest rate (%) | Monthly Treasury Bill rate in Italy. Source: IMF-IFS | 1.93 | 1.41 | -.07 | 6.4 |
| Observations | 10,692 | | | | |

Table 2: List of receiving countries and average monthly remittances from Italy (million euros)

| Country | Remittances | Country | Remittances | Country | Remittances |
|---|---|---|---|---|---|
| Albania | 10.173 | Egypt | 1.375 | Mongolia | 0.013 |
| Algeria | 0.144 | El Salvador | 1.352 | Morocco | 21.668 |
| Angola | 0.041 | Ethiopia | 0.251 | Mozambique | 0.035 |
| Argentina | 1.727 | Gabon | 0.040 | Nepal | 0.140 |
| Armenia | 0.053 | Georgia | 3.873 | Nicaragua | 0.180 |
| Azerbaijan | 0.020 | Ghana | 1.979 | Niger | 0.083 |
| Bangladesh | 18.547 | Guinea | 0.137 | Nigeria | 3.935 |
| Belarus | 0.308 | Guinea-Bissau | 0.076 | Paraguay | 0.473 |
| Benin | 0.478 | Guatemala | 0.183 | Peru | 12.999 |
| Bolivia | 2.362 | Haiti | 0.047 | Philippines | 41.765 |
| Bosnia and Herz. | 0.280 | Honduras | 0.588 | Romania | 63.888 |
| Brazil | 10.859 | Indonesia | 0.465 | Russian Fed. | 2.674 |
| Bulgaria | 3.891 | Jamaica | 0.096 | Rwanda | 0.044 |
| Burkina Faso | 1.057 | Jordan | 0.126 | Senegal | 18.166 |
| Burundi | 0.040 | Kazakhstan | 0.131 | Sierra Leone | 0.070 |
| Cabo Verde | 0.314 | Kenya | 0.621 | Sri Lanka | 7.160 |
| Cambodia | 0.037 | Kyrgyz Republic | 0.257 | South Africa | 0.118 |
| Cameroon | 1.104 | Lebanon | 0.164 | Tanzania | 0.352 |
| Central African Rep. | 0.020 | Liberia | 0.032 | Thailand | 0.837 |
| Chad | 0.045 | Madagascar | 0.225 | Togo | 0.530 |
| Colombia | 7.343 | Malaysia | 0.090 | Tunisia | 5.359 |
| Congo, Dem. Rep. | 0.534 | Malawi | 0.011 | Turkey | 1.472 |
| Congo, Rep. | 0.121 | Mali | 0.631 | Uganda | 0.166 |
| Costa Rica | 0.186 | Mauritania | 0.046 | Ukraine | 9.932 |
| Cote d'Ivoire | 1.931 | Mauritius | 0.215 | Vietnam | 0.132 |
| Dominican Rep. | 7.694 | Mexico | 0.445 | South Africa | 0.118 |
| Ecuador | 10.464 | Moldova | 5.423 | Zambia | 0.035 |

Table 3: Incidence, frequency and magnitude of disasters by type and nature

| | **Disaster** | **Frequency** | | | **Share affected population** | | | **Share death tolls** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Dummy | Mean | Min | max | Mean | Min | max | Mean | Min | max |
| Climatic disasters | 0.11 | 0.12 | 0 | 5 | 1.19 | 0 | 51.33 | 0.00 | 0 | 0.00 |
| Geophysical disasters | 0.01 | 0.01 | 0 | 2 | 0.89 | 0 | 37.76 | 0.02 | 0 | 2.27 |
| Meteorological disasters | 0.04 | 0.05 | 0 | 5 | 0.70 | 0 | 32.34 | 0.00 | 0 | 0.04 |
| Slow-onset disasters | 0.02 | 0.02 | 0 | 2 | 4.25 | 0 | 51.33 | 0.00 | 0 | 0.04 |
| Sudden-onset disasters | 0.13 | 0.16 | 0 | 6 | 0.52 | 0 | 37.76 | 0.00 | 0 | 2.27 |
| All disasters | 0.14 | 0.18 | 0 | 6 | 1.01 | 0 | 51.33 | 0.00 | 0 | 2.27 |

*Note*. Descriptive statistics are disaggregated by disasters' nature and type. Average figures for all disasters are also reported. The Disaster dummy column refers to the share of observations (country-month pairs) affected by at least one disaster. The mean frequency is computed as the number of disaster events by type or nature divided by the total number of observations (country-month pairs). The share of affected population and dead over total population are computed only for those observations in which at least one disaster occurred.

Table 4: Incidence, frequency and magnitude of disasters by region

| | Disaster | Frequency | | | Share affected population | | | Share death tolls | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Dummy | Mean | Min | max | Mean | Min | max | Mean | Min | max |
| East Asia & Pacific | 0.09 | 0.05 | 0 | 6 | 0.36 | 0 | 32.34 | 0.00 | 0 | 0.00 |
| Europe & Central Asia | 0.15 | 0.01 | 0 | 2 | 0.08 | 0 | 37.5 | 0.00 | 0 | 0.00 |
| Latin America & Caribbean | 0.20 | 0.05 | 0 | 5 | 0.15 | 0 | 37.76 | 0.00 | 0 | 2.27 |
| Middle East & North Africa | 0.07 | 0.00 | 0 | 2 | 0.02 | 0 | 15.97 | 0.00 | 0 | 0.00 |
| South Asia | 0.04 | 0.01 | 0 | 4 | 0.27 | 0 | 20.95 | 0.00 | 0 | 0.03 |
| Sub-Saharan Africa | 0.46 | 0.05 | 0 | 5 | 0.14 | 0 | 51.33 | 0.00 | 0 | 0.04 |

*Note*. Descriptive statistics for all disasters reported in the last row of Table 3 are disaggregated by region according to the UN regional classifications. The Disaster dummy column refers to the share of observations (country-month pairs) affected by at least one disaster. The mean frequency is computed as the number of disaster events by type or nature divided by the total number of observations (country-month pairs). The share of affected and dead over total population are computed only for those observations in which at least one disaster occurred.

Table 5: Event study regressions. Baseline

| | (1)<br>Remittance PC | (2)<br>Remittance PC | (3)<br>Remittance PC | (4)<br>Remittance PC | (5)<br>Remittance PC |
|---|---|---|---|---|---|
| 12 months before Disaster | | | | .0066 | |
| | | | | (.0117) | |
| 11 months before Disaster | | | | .0049 | |
| | | | | (.0110) | |
| 10 months before Disaster | | | | .0083 | |
| | | | | (.0103) | |
| 9 months before Disaster | | | | .0132 | |
| | | | | (.0095) | |
| 8 months before Disaster | | | | .0121 | |
| | | | | (.0094) | |
| 7 months before Disaster | | | | .0115 | |
| | | | | (.0096) | |
| 6 months before Disaster | | .0110 | | .0111 | |
| | | (.0105) | | (.0099) | |
| 5 months before Disaster | | .0095 | | .0105 | |
| | | (.0100) | | (.0101) | |
| 4 months before Disaster | | .0090 | | .0101 | |
| | | (.0099) | | (.0103) | |
| 3 months before Disaster | .0117 | .0111 | .0126 | .0129 | .0111 |
| | (.0105) | (.0096) | (.0105) | (.0104) | (.0105) |
| 2 months before Disaster | .0138 | .0135 | .0146 | .0154 | .0128 |
| | (.0098) | (.0094) | (.0100) | (.0102) | (.0098) |
| 1 months before Disaster | .0127 | .0128 | .0130 | .0136 | .0115 |
| | (.0095) | (.0095) | (.0098) | (.0097) | (.0094) |
| Month of Disaster | .0154 | .0160 | .0147 | .0150 | .0143 |
| | (.0108) | (.0112) | (.0108) | (.0103) | (.0106) |
| 1 month after Disaster | .0180* | .0191* | .0161* | .0158* | .0172* |
| | (.0103) | (.0111) | (.0095) | (.0090) | (.0101) |
| 2 month after Disaster | .0206* | .0216* | .0178* | .0168* | .0202* |
| | (.0108) | (.0117) | (.0095) | (.0089) | (.0106) |
| 3 month after Disaster | .0242** | .0250** | .0215** | .0200** | .0236** |
| | (.0109) | (.0115) | (.0093) | (.0086) | (.0106) |
| 4 month after Disaster | .0270** | .0271** | .0248** | .0227** | .0267** |
| | (.0116) | (.0118) | (.0101) | (.0091) | (.0114) |
| 5 month after Disaster | .0215* | .0207* | .0199** | .0178* | .0213* |
| | (.0115) | (.0110) | (.0100) | (.0090) | (.0112) |
| 6 month after Disaster | .0210* | .0192* | .0203** | .0184** | .0214* |
| | (.0111) | (.0100) | (.0099) | (.0089) | (.0108) |
| 7 month after Disaster | .0201* | .0180* | .0200* | .0187** | .0203* |
| | (.0108) | (.0096) | (.0101) | (.0092) | (.0106) |
| 8 month after Disaster | .0183* | .0167* | .0184* | .0179* | .0182* |
| | (.0107) | (.0099) | (.0102) | (.0099) | (.0107) |
| 9 month after Disaster | .0173* | .0169* | .0174* | .0179* | .0178* |
| | (.0098) | (.0095) | (.0092) | (.0093) | (.0099) |
| 10 month after Disaster | .0184* | .0188* | .0179* | .0189* | .0184* |
| | (.0104) | (.0106) | (.0096) | (.0099) | (.0104) |
| 11 month after Disaster | .0175 | .0182 | .0166 | .0176* | .0171 |
| | (.0110) | (.0113) | (.0102) | (.0105) | (.0111) |
| 12 month after Disaster | .0189* | .0195* | .0176* | .0183* | .0192* |
| | (.0114) | (.0116) | (.0104) | (.0106) | (.0114) |
| 13 month after Disaster | | | .0153 | .0155 | |
| | | | (.0101) | (.0103) | |
| 14 month after Disaster | | | .0133 | .0132 | |
| | | | (.0109) | (.0110) | |
| 15 month after Disaster | | | .0113 | .0109 | |
| | | | (.0099) | (.0100) | |
| 16 month after Disaster | | | .0120 | .0112 | |

Continued on next page

Table 5: Event study regressions. Baseline – continued from previous page

| | (1) Remittance PC | (2) Remittance PC | (3) Remittance PC | (4) Remittance PC | (5) Remittance PC |
|---|---|---|---|---|---|
| | | | (.0099) | (.0098) | |
| 17 month after Disaster | | | .0062 | .0057 | |
| | | | (.0091) | (.0088) | |
| 18 month after Disaster | | | .0072 | .0067 | |
| | | | (.0092) | (.0088) | |
| 19 month after Disaster | | | .0063 | .0063 | |
| | | | (.0083) | (.0080) | |
| 20 month after Disaster | | | .0041 | .0048 | |
| | | | (.0083) | (.0081) | |
| 21 month after Disaster | | | .0035 | .0048 | |
| | | | (.0080) | (.0080) | |
| 22 month after Disaster | | | .0038 | .0054 | |
| | | | (.0084) | (.0083) | |
| 23 month after Disaster | | | .0046 | .0061 | |
| | | | (.0079) | (.0078) | |
| 24 month after Disaster | | | .0043 | .0057 | |
| | | | (.0081) | (.0077) | |
| log Terms of trade | | | | | -.1885 |
| | | | | | (.1325) |
| Abnormal Temperature | | | | | .0007 |
| | | | | | (.0010) |
| Abnormal Rainfall | | | | | .0008 |
| | | | | | (.0008) |
| Exchange rate | | | | | .0001 |
| | | | | | (.0007) |
| Interest rate | | | | | -.1114 |
| | | | | | (.1582) |
| Unemployment rate | | | | | -.0152 |
| | | | | | (.0274) |
| Constant | 6.2053*** | 6.2052*** | 6.1942*** | 6.1936*** | 7.1559*** |
| | (.0316) | (.0316) | (.0325) | (.0326) | (.3167) |
| Month×Year FE | Yes | Yes | Yes | Yes | yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10692 | 10692 | 10692 | 10692 | 10641 |
| No. of countries | 81 | 81 | 81 | 81 | 81 |
| Joint significance F-test of leads | 0.32 | 0.42 | 0.44 | 0.45 | 0.31 |
| Joint significance F-test of lags | 3.82* | 3.73* | 3.12* | 3.09* | 4.04* |

*Note.* The table shows the fixed effects estimation results of Equation (1) using remittance data for the period 2005 to 2015 and disaster data from 2006 to 2014. Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p - value < 0.10$, ** $p - value < 0.05$, *** $p - value < 0.01$. The dependent variable is the log of real remittances per-capita. The dummy variables take value 1 in the $m$-th month before (leads) and after (lags) the month in which a country experienced at least one natural disaster. Column (1) presents our baseline estimates with 3 leads and 12 lags. Column (2) extends the number of leads to 12 whereas column (3) extends the number of lags to 24. In column (4) we include both 12 leads and 24 lags. In column (5) the basic specification with 3 leads and 12 lags includes also control variables.

Table 6: Event study regressions. Past and future disasters, and binned endpoints

| | (1) Remittance PC Past+Future disasters | (2) Remittance PC Past+Future disasters with controls | (3) Remittance PC Binned endpoints | (4) Remittance PC Binned endpoints with controls |
|---|---|---|---|---|
| Binned leads beyond 3 months | | | -.0082 | -.0079 |
| | | | (.0114) | (.0112) |
| 3 months before Disaster | .0050 | .0053 | | |
| | (.0123) | (.0122) | | |
| 2 months before Disaster | .0070 | .0067 | | |
| | (.0124) | (.0122) | | |
| 1 months before Disaster | .0083 | .0078 | .0019 | .0017 |
| | (.0116) | (.0114) | (.0026) | (.0026) |
| Month of Disaster | .0182 | .0183 | .0120** | .0123** |
| | (.0124) | (.0123) | (.0057) | (.0058) |
| 1 month after Disaster | .0179 | .0180 | .0113** | .0117** |
| | (.0120) | (.0119) | (.0053) | (.0053) |
| 2 month after Disaster | .0208* | .0210* | .0130** | .0135** |
| | (.0119) | (.0118) | (.0057) | (.0059) |
| 3 month after Disaster | .0238* | .0243** | .0154** | .0162** |
| | (.0124) | (.0122) | (.0062) | (.0063) |
| 4 month after Disaster | .0243* | .0252** | .0157** | .0168** |
| | (.0123) | (.0121) | (.0072) | (.0074) |
| 5 month after Disaster | .0202 | .0210* | .0111 | .0122 |
| | (.0124) | (.0121) | (.0078) | (.0081) |
| 6 month after Disaster | .0232* | .0243** | .0144* | .0158* |
| | (.0119) | (.0117) | (.0084) | (.0087) |
| 7 month after Disaster | .0215* | .0225* | .0130 | .0142* |
| | (.0115) | (.0114) | (.0082) | (.0084) |
| 8 month after Disaster | .0219* | .0225* | .0139 | .0148 |
| | (.0113) | (.0114) | (.0094) | (.0095) |
| 9 month after Disaster | .0216** | .0222** | .0140 | .0149 |
| | (.0103) | (.0103) | (.0094) | (.0095) |
| 10 month after Disaster | .0215** | .0215** | .0137 | .0140 |
| | (.0106) | (.0106) | (.0107) | (.0106) |
| 11 month after Disaster | .0195* | .0192* | .0120 | .0118 |
| | (.0111) | (.0112) | (.0114) | (.0113) |
| Binned lags beyond 12 months | | | -.0073 | -.0070 |
| | | | (.0126) | (.0124) |
| log Terms of trade | | -.1954 | | -.1939 |
| | | (.1334) | | (.1317) |
| Abnormal Temperature | | .0007 | | .0006 |
| | | (.0010) | | (.0010) |
| Abnormal Rainfall | | .0008 | | .0009 |
| | | (.0008) | | (.0008) |
| Exchange rate | | .0001 | | .0001 |
| | | (.0007) | | (.0007) |
| Unemployment rate | | -.0090 | | -.0073 |
| | | (.0299) | | (.0293) |
| Interest rate | | -.0761 | | -.0744 |
| | | (.1728) | | (.1706) |
| Constant | 6.1711*** | 7.0762*** | 6.3079*** | 7.1797*** |
| | (.0344) | (.3074) | (.2190) | (.4118) |
| Month×Year FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Observations | 10692 | 10641 | 10692 | 10641 |
| No. of countries | 81.0000 | 81.0000 | 81.0000 | 81.0000 |
| Joint significance of leads F-test | 0.32 | 0.31 | 0.25 | 0.26 |
| Joint significance of lags (1 to 6) F-test | 3.25 | 3.53* | 4.81** | 5.17* |

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Table 6: Event study regressions. Past+future disasters and binned endpoints – continued from previous page

| | (1) Remittance PC Past+Future disasters | (2) Remittance PC Past+Future disasters with controls | (3) Remittance PC Binned endpoints | (4) Remittance PC Binned endpoints with controls |
|---|---|---|---|---|
| Joint significance of lags F-test | 3.82* | 4.04** | 2.55 | 2.80* |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Note.* The table shows the fixed effects estimation results of Equation 2 (columns 1-2) and 3 (columns 3-4) using remittance data from 2005 to 2015 and disaster data for the same period. Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p - value < 0.10$, ** $p - value < 0.05$, *** $p - value < 0.01$. The dependent variable is the log of real remittances per-capita. In columns 3-4, two additional coefficients are added for the binned leads and the binned lags, respectively. The dummy $\beta_{k=-2}$ is set to zero and serves as the reference point.

Table 7: Event study regressions. Alternative disaster measures

| | (1) Remittance PC Disaster frequency | (2) Remittance PC Disaster severity above $Q_1$ | (3) Remittance PC Disaster severity above $Q_2$ |
|---|---|---|---|
| 3 months before Disaster | .0069 | .0060 | .0088 |
| | (.0107) | (.0123) | (.0131) |
| 2 months before Disaster | .0063 | .0076 | .0122 |
| | (.0104) | (.0124) | (.0123) |
| 1 month before Disaster | .0068 | .0089 | .0146 |
| | (.0093) | (.0121) | (.0126) |
| Month of Disaster | .0112 | .0127 | .0119 |
| | (.0090) | (.0130) | (.0138) |
| 1 month after Disaster | .0110 | .0186 | .0252* |
| | (.0080) | (.0131) | (.0138) |
| 2 month after Disaster | .0135* | .0202 | .0245* |
| | (.0077) | (.0131) | (.0146) |
| 3 month after Disaster | .0163** | .0246* | .0285** |
| | (.0079) | (.0133) | (.0142) |
| 4 month after Disaster | .0166** | .0254* | .0307** |
| | (.0075) | (.0131) | (.0152) |
| 5 month after Disaster | .0124* | .0200 | .0253 |
| | (.0073) | (.0133) | (.0156) |
| 6 month after Disaster | .0144** | .0223* | .0257* |
| | (.0069) | (.0130) | (.0148) |
| 7 month after Disaster | .0133** | .0198 | .0250* |
| | (.0064) | (.0121) | (.0141) |
| 8 month after Disaster | .0124** | .0178 | .0215 |
| | (.0060) | (.0116) | (.0138) |
| 9 month after Disaster | .0117** | .0207* | .0236* |
| | (.0053) | (.0112) | (.0136) |
| 10 month after Disaster | .0124** | .0201* | .0204 |
| | (.0057) | (.0109) | (.0128) |
| 11 month after Disaster | .0108* | .0200* | .0186 |
| | (.0063) | (.0115) | (.0134) |
| 12 month after Disaster | .0122* | .0227* | .0217 |
| | (.0063) | (.0119) | (.0131) |
| Month×Year FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Observations | 10692 | 10692 | 10692 |
| No. of countries | 81 | 81 | 81 |

Continued on next page

Table 7: Event study regressions. Alternative disaster measure – continued from previous page

| | (1) | (2) | (3) |
|---|---|---|---|
| | Remittance PC | Remittance PC | Remittance PC |
| | Disaster frequency | Disaster severity above $Q_1$ | Disaster severity above $Q_2$ |
| Joint significance of leads F-test | 0.44 | 0.38 | 0.89 |
| Joint significance of lags F-test | 4.75** | 3.18* | 3.22* |

*Note.* The table shows the fixed effects estimation of our baseline model with 3 leads and 12 lags (Equation 1). Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$. The dependent variable is the log of real remittances per-capita. In Column (1) the disaster dummy is replaced the number of disasters occurring in each country during a specific month whereas in Column (2) and (3) the dummy variables take value 1 in the $m$-th month before (leads) and after (lags) the month in which a country experienced at least one natural disaster above the 25th/50th percentile of the distribution of the share of total population affected by an event.

Table 8: Event study regressions. Half-yearly leads and lags

| | (1) Remittance PC | (2) Remittance PC with controls |
|---|---|---|
| 1 to 6 months before disaster | .0075 | .0062 |
| | (.0142) | (.0139) |
| Disaster | .0181 | .0178 |
| | (.0128) | (.0127) |
| 1 to 6 months after disaster | .0276 | .0283 |
| | (.0189) | (.0187) |
| 7 to 12 months after disaster | .0259 | .0269 |
| | (.0179) | (.0179) |
| log Terms of trade | -.1939 | -.1935 |
| | (.1317) | (.1327) |
| Abnormal Temperature | .0006 | .0006 |
| | (.0010) | (.0010) |
| Abnormal Rainfall | .0009 | .0008 |
| | (.0008) | (.0008) |
| Exchange rate | .0001 | .0001 |
| | (.0007) | (.0007) |
| Interest rate | -.0744 | -.0393 |
| | (.1706) | (.1734) |
| Unemployment rate | -.0073 | -.0052 |
| | (.0293) | (.0293) |
| Month×Year FE | Yes | Yes |
| Country FE | Yes | Yes |
| Observations | 10692 | 10641 |
| No. of countries | 81 | 81 |
| Joint significance of leads F-test | 0.28 | 0.20 |
| Joint significance of lags (1 to 6) F-test | 2.13 | 2.30 |
| Joint significance of lags F-test | 2.17 | 2.34 |

*Note.* The table shows the fixed effects estimation results of Equation 3 (columns 1-2) and 5 (columns 3-4). Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$. The dependent variable is the log of real remittances per-capita. In columns 1-2, two additional coefficient are added for the binned leads and the binned lags, respectively. The dummy $\beta_{k=-2}$ is set to zero and serves as reference point. In columns 3-4, the 6 month leads are collapsed into a single dummy whereas and the 12 month lags into two different dummies (1-6 months and 7-12 months after the disaster).

Table 9: Event study regressions. Migrant community size and home country's development

| | (1) Remittance PC Rem. flows ≥ €100,000 | (2) Remittance PC Migrants ≥ 1,000 | (3) Remittance PC Rem. flows ≥ €100,000 Migrants ≥ 1,000 | (4) Remittance PC Low income countries | (5) Remittance PC Lower-middle income countries | (6) Remittance PC Upper-middle income countries |
|---|---|---|---|---|---|---|
| 3 months before Disaster | .0102 | .0122 | .0132 | -.0131 | .0086 | .0110 |
| | (.0146) | (.0161) | (.0165) | (.0110) | (.0298) | (.0163) |
| 2 months before Disaster | .0123 | .0139 | .0149 | -.0121 | .0077 | .0148 |
| | (.0146) | (.0162) | (.0165) | (.0099) | (.0304) | (.0162) |
| 1 months before Disaster | .0133 | .0159 | .0170 | -.0148 | .0103 | .0165 |
| | (.0135) | (.0149) | (.0152) | (.0102) | (.0275) | (.0160) |
| Month of Disaster | .0278* | .0272* | .0316* | -.0114 | .0233 | .0295* |
| | (.0143) | (.0159) | (.0160) | (.0125) | (.0304) | (.0171) |
| 1 month after Disaster | .0237* | .0279* | .0289* | -.0152 | .0190 | .0311 |
| | (.0138) | (.0150) | (.0152) | (.0116) | (.0228) | (.0198) |
| 2 month after Disaster | .0266* | .0295* | .0300* | -.0110 | .0201 | .0316 |
| | (.0137) | (.0148) | (.0151) | (.0135) | (.0232) | (.0189) |
| 3 month after Disaster | .0293** | .0327** | .0328** | -.0111 | .0248 | .0331 |
| | (.0141) | (.0151) | (.0154) | (.0154) | (.0216) | (.0197) |
| 4 month after Disaster | .0311** | .0343** | .0351** | -.0136 | .0290 | .0340 |
| | (.0142) | (.0149) | (.0152) | (.0164) | (.0189) | (.0203) |
| 5 month after Disaster | .0261* | .0283* | .0298* | -.0187 | .0220 | .0313 |
| | (.0143) | (.0151) | (.0154) | (.0159) | (.0192) | (.0209) |
| 6 month after Disaster | .0285** | .0327** | .0329** | -.0164 | .0245 | .0325 |
| | (.0136) | (.0143) | (.0145) | (.0161) | (.0177) | (.0196) |
| 7 month after Disaster | .0266** | .0305** | .0306** | -.0129 | .0174 | .0354* |
| | (.0132) | (.0141) | (.0144) | (.0153) | (.0153) | (.0202) |
| 8 month after Disaster | .0278** | .0315** | .0325** | -.0113 | .0158 | .0384* |
| | (.0129) | (.0138) | (.0141) | (.0125) | (.0139) | (.0215) |
| 9 month after Disaster | .0260** | .0299** | .0298** | -.0110 | .0184 | .0352* |
| | (.0117) | (.0126) | (.0129) | (.0113) | (.0152) | (.0185) |
| 10 month after Disaster | .0252** | .0291** | .0287** | -.0079 | .0124 | .0383* |
| | (.0121) | (.0129) | (.0132) | (.0117) | (.0140) | (.0205) |
| 11 month after Disaster | .0226* | .0246* | .0245* | -.0046 | .0094 | .0344 |
| | (.0129) | (.0139) | (.0143) | (.0114) | (.0153) | (.0223) |
| 12 month after Disaster | .0253* | .0288** | .0297** | -.0064 | .0172 | .0347 |
| | (.0132) | (.0140) | (.0145) | (.0105) | (.0160) | (.0224) |
| Month×Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7920 | 7392 | 6864 | 2904 | 3564 | 4224 |
| No. of countries | 60 | 56 | 52 | 22 | 27 | 32 |
| Joint significance of leads F-test | 0.71 | 0.80 | 0.88 | 1.72 | 0.09 | 0.77 |

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Table 9: Event study regressions. Migrant community size and home country's development – continued from previous page

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Remittance PC | Remittance PC | Remittance PC | Remittance PC | Remittance PC | Remittance PC |
| | Rem. flows $\geq$ €100,000 | Migrants $\geq$ 1,000 | Rem. flows $\geq$ €100,000<br>Migrants $\geq$ 1000 | Low income<br>countries | Lower-middle<br>income countries | Upper-middle<br>income countries |
| Joint significance of lags F-test | 4.43* | 5.01* | 4.93* | 0.78 | 1.72 | 2.96* |

*Note*. The table shows the fixed effects estimation of our baseline model with 3 leads and 12 lags (Equation 1). Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p - value < 0.10$, ** $p - value < 0.05$, *** $p - value < 0.01$. The dependent variable is the log of real remittances per-capita. The dummy variables take value 1 in the $m$-th month before (leads) and after (lags) the month in which a country experienced at least one natural disaster. In column 1, we consider only the sample of countries with average monthly remittances larger than 100 Euro whereas in column 2 we consider only countries with a diaspora abroad larger than 1,000 migrants. Both restrictions are considered together in column 3. In columns 4-6, the sample is splitted according to the country's level of development: lower income (LIC), lower middle income (LMIC) and upper middle income (UMIC) countries.

Table 10: Event study regressions. Type and nature of disasters

| | (1) Remittance PC Climatic disasters | (2) Remittance PC Geophysical disasters | (3) Remittance PC Meteorological disasters | (4) Remittance PC Slow-onset disasters | (5) Remittance PC Sudden-onset disasters |
|---|---|---|---|---|---|
| 3 months before Disaster | .0107 | .0059 | -.0105 | -.0067 | .0023 |
| | (.0126) | (.0228) | (.0280) | (.0202) | (.0129) |
| 2 months before Disaster | .0151 | .0084 | -.0208 | -.0082 | .0045 |
| | (.0116) | (.0216) | (.0316) | (.0200) | (.0129) |
| 1 months before Disaster | .0145 | .0137 | -.0157 | -.0008 | .0058 |
| | (.0114) | (.0211) | (.0256) | (.0171) | (.0119) |
| Month of Disaster | .0206 | .0034 | -.0014 | -.0077 | .0169 |
| | (.0127) | (.0192) | (.0213) | (.0177) | (.0125) |
| 1 month after Disaster | .0205* | .0053 | -.0017 | .0010 | .0151 |
| | (.0119) | (.0185) | (.0188) | (.0174) | (.0120) |
| 2 month after Disaster | .0215* | .0049 | .0110 | .0170 | .0177 |
| | (.0120) | (.0186) | (.0175) | (.0186) | (.0119) |
| 3 month after Disaster | .0244* | .0076 | .0114 | .0249 | .0198 |
| | (.0124) | (.0185) | (.0168) | (.0187) | (.0123) |
| 4 month after Disaster | .0256** | -.0044 | .0133 | .0238 | .0216* |
| | (.0118) | (.0179) | (.0157) | (.0183) | (.0123) |
| 5 month after Disaster | .0196 | -.0105 | .0156 | .0154 | .0174 |
| | (.0120) | (.0177) | (.0148) | (.0192) | (.0124) |
| 6 month after Disaster | .0218* | -.0124 | .0186 | .0187 | .0203* |
| | (.0117) | (.0162) | (.0141) | (.0199) | (.0119) |
| 7 month after Disaster | .0206* | -.0117 | .0085 | .0163 | .0185 |
| | (.0114) | (.0161) | (.0115) | (.0193) | (.0115) |
| 8 month after Disaster | .0207* | -.0101 | .0114 | .0300 | .0172 |
| | (.0113) | (.0152) | (.0098) | (.0201) | (.0109) |
| 9 month after Disaster | .0160 | .0056 | .0210* | .0260 | .0191* |
| | (.0097) | (.0263) | (.0109) | (.0252) | (.0099) |
| 10 month after Disaster | .0186* | -.0104 | .0213* | .0299 | .0190* |
| | (.0102) | (.0151) | (.0122) | (.0242) | (.0102) |
| 11 month after Disaster | .0161 | -.0153 | .0267* | .0270 | .0178* |
| | (.0108) | (.0140) | (.0142) | (.0255) | (.0106) |
| 12 month after Disaster | .0171 | -.0158 | .0270* | .0160 | .0203* |
| | (.0105) | (.0144) | (.0160) | (.0195) | (.0111) |
| Month×Year FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10692 | 10692 | 10692 | 10692 | 10692 |
| No. of countries | 81 | 81 | 81 | 81 | 81 |
| Joint significance of leads F–test | 1.31 | 0.19 | 0.31 | 0.08 | 0.11 |
| Joint significance of lags F–test | 3.58* | 0.15 | 1.83 | 1.20 | 3.00* |

*Note.* The table shows the fixed effects estimation of our baseline model with 3 leads and 12 lags (Equation 1). Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$. The dependent variable is the log of real remittances per-capita. The dummy variables take value 1 in the $m$-th month before (leads) and after (lags) the month in which a country experienced at least one natural disaster. Column (1)-(3) refer to climatic, geophysical and meteorological disasters, respectively. Column (4)-(5) refer to slow-onset and sudden-onset disasters.

Table 11: Event study regressions. Spatial location of immigrants and economic conditions in the host country

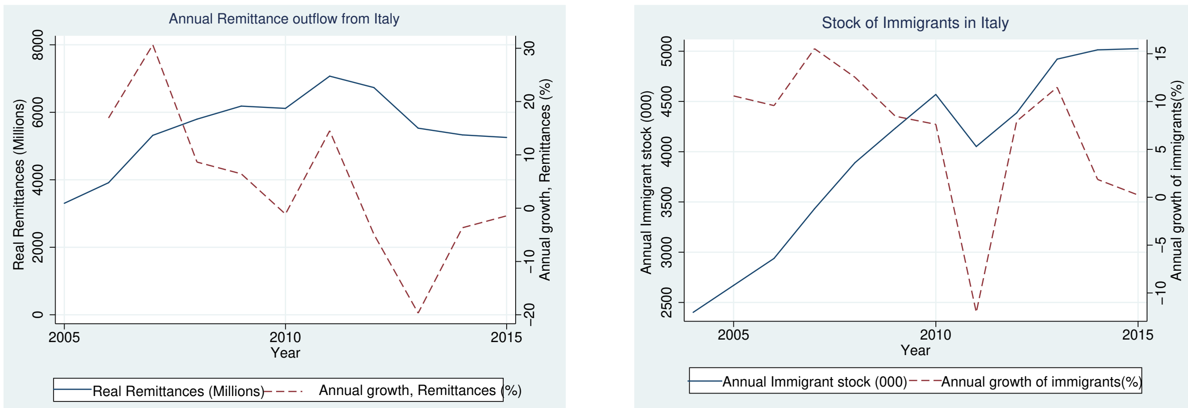
| | (1) Remittance PC $HHI_c > \text{Me}(HHI)$ | (2) Remittance PC $HHI_c \leq \text{Me}(HHI)$ | (3) Remittance PC 2005-2008 | (4) Remittance PC 2009-2012 | (5) Remittance PC 2013-2015 |
|---|---|---|---|---|---|
| 3 months before Disaster | -.0198 | .0292* | .0027 | -.0024 | -.0046 |
| | (.0185) | (.0152) | (.0154) | (.0062) | (.0060) |
| 2 months before Disaster | -.0172 | .0299** | .0048 | .0011 | -.0046 |
| | (.0196) | (.0143) | (.0163) | (.0072) | (.0049) |
| 1 months before Disaster | -.0158 | .0316** | .0110 | -.0030 | .0001 |
| | (.0168) | (.0141) | (.0158) | (.0066) | (.0056) |
| Month of Disaster | -.0027 | .0372** | .0042 | -.0042 | .0373*** |
| | (.0160) | (.0173) | (.0171) | (.0095) | (.0129) |
| 1 month after Disaster | -.0029 | .0359** | .0260 | .0005 | .0027 |
| | (.0144) | (.0168) | (.0160) | (.0073) | (.0059) |
| 2 month after Disaster | .0058 | .0337* | .0310* | .0051 | .0021 |
| | (.0130) | (.0180) | (.0158) | (.0083) | (.0050) |
| 3 month after Disaster | .0081 | .0380** | .0352** | .0017 | .0094 |
| | (.0136) | (.0183) | (.0171) | (.0096) | (.0065) |
| 4 month after Disaster | .0118 | .0367** | .0394** | .0038 | .0095 |
| | (.0148) | (.0178) | (.0171) | (.0095) | (.0063) |
| 5 month after Disaster | .0105 | .0309* | .0359** | -.0021 | .0030 |
| | (.0148) | (.0182) | (.0167) | (.0093) | (.0073) |
| 6 month after Disaster | .0156 | .0312* | .0456** | .0007 | .0070 |
| | (.0149) | (.0174) | (.0178) | (.0095) | (.0068) |
| 7 month after Disaster | .0160 | .0274 | .0443** | -.0050 | .0102 |
| | (.0148) | (.0165) | (.0169) | (.0086) | (.0062) |
| 8 month after Disaster | .0216 | .0220 | .0513*** | -.0055 | .0025 |
| | (.0163) | (.0148) | (.0178) | (.0083) | (.0057) |
| 9 month after Disaster | .0186 | .0215 | .0427** | -.0048 | .0128 |
| | (.0139) | (.0139) | (.0164) | (.0082) | (.0087) |
| 10 month after Disaster | .0241 | .0140 | .0473*** | -.0075 | .0102 |
| | (.0159) | (.0130) | (.0177) | (.0080) | (.0064) |
| 11 month after Disaster | .0227 | .0116 | .0441** | -.0049 | .0078 |
| | (.0167) | (.0135) | (.0181) | (.0064) | (.0061) |
| 12 month after Disaster | .0175 | .0200 | .0513*** | -.0044 | .0059 |
| | (.0158) | (.0147) | (.0193) | (.0061) | (.0076) |
| Constant | 5.9802*** | 6.3580*** | 6.3679*** | 6.4181*** | 6.1921*** |
| | (.0548) | (.0388) | (.0222) | (.0168) | (.0138) |
| Month×Year | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 5279 | 5411 | 3889 | 2913 | 3888 |
| No. of countries | 40 | 41 | 81 | 81 | 81 |
| Overall-$R^2$ | .0078 | .0043 | .0000 | .0019 | .0007 |
| $R^2$ | .2451 | .2108 | .1000 | .3521 | .1968 |
| F-test | . | . | . | 25.5367 | 82.6055 |
| log(likelihood) | -85.4127 | 986.3813 | 1431.8637 | 2706.9487 | 3499.2226 |

*Note.* The table shows the fixed effects estimation of our baseline model with 3 leads and 12 lags (Equation 1). Standard errors clustered at the country level are reported in parentheses. Significance levels: * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$. The dependent variable is the log of real remittances per capita. The dummy variables take value 1 in the $m$-th month before (leads) and after (lags) the month in which a country experienced at least one natural disaster. Column (1) restricts the sample to the countries for which the spatial concentration of immigrants in Italy, computed at the regional level, is above the median value of spatial concentration of immigrant communities in our sample: $HHI_c > \text{Me}(HHI)$. Column (2) restricts the sample to the countries for which the spatial concentration of immigrants in Italy, computed at the regional level, is lower than or equal to the median of spatial concentration of immigrant communities in our sample: $HHI_c \leq \text{Me}(HHI)$.Column (3) restricts the sample to the period between 2005 and 2008. Column (4) restricts the sample to to the period between 2009 and 2012. Column (5) restricts the sample to the period between 2013 and 2015.

# Figures

Figure 1: Evolution of remittances and stock of migrants in Italy

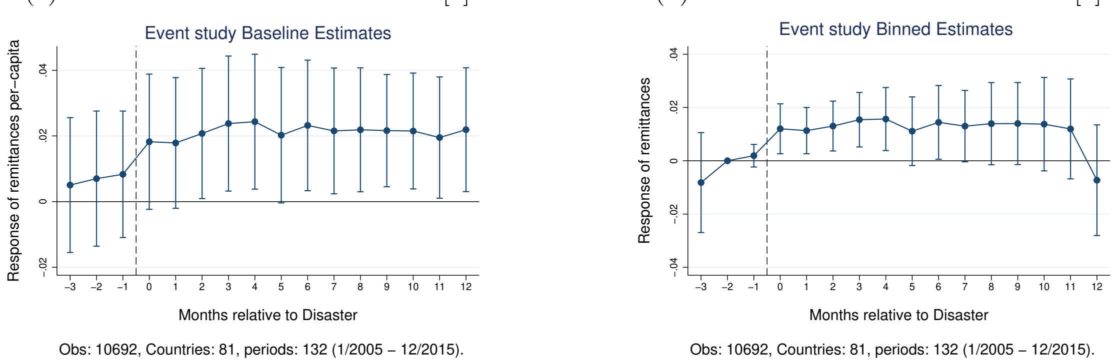
(a) Real annual remittance outflows from Italy (b) Stock of migrants in Italy




Note: Real annual remittance outflows from Italy are computed from data on nominal remittances in euros released by the Bank of Italy for the period 2005 to 2015 on a monthly basis. Nominal remittances are then deflated by the CPI index. Data on the stock of migrants in Italy come from the Italian National Institute of Statistics, which provide information on migrants based on citizenship.

Figure 2: Remittances response to disasters in baseline and binned end estimates

(a) Results from column 1 in Table [5] (b) Results from column 1 in Table [6]




Note: Panel a) is based on our baseline estimates of Equation 1 with 3 leads and 12 lags. Panel b) is based on the estimates of Equation 2 where we control for disasters occurring during the twelve months before 2005 and after 2015.