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Responding to natural disasters: What do monthly remittance data tell us?☆

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ABSTRACT

Identifying the insurance role of remittances against natural disasters through aggregate annual data is challenging due to the dynamics of remittances and disasters throughout the year and possible intertemporal substitution effects. In an event-study setting based on monthly remittance flows from Italy to 81 developing countries for 2005–2015, we investigate their dynamics in the aftermath of disasters. We find that monthly remittances positively respond to natural disasters in migrants' home countries. The response is immediate and significant up to 3–4 months after the event. Later on remittances return to pre-disaster levels but there is no evidence of intertemporal substitution. We observe some anticipation effects, which could be related to the recurrent nature of some types of disasters. The intensity and timing of remittances' responsiveness are heterogeneous according to the nature of disasters, to the receiving country's characteristics, and to migrants' socio-economic conditions in the host country.

1. Introduction

The Earth's global warming, significant changes in the climate system, and increasing environmental degradation have led to a sharp rise in the frequency, intensity, and destructive force of natural disasters over the past few 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, along with the ability of countries to cope with and recover from disasters, are strongly influenced by their level of economic development and institutional settings (Kahn, 2005; Noy, 2009; Fomby et al., 2013; Felbermayr and Gröschl, 2014; Berlemann and Wenzel, 2018; Dzator and Dzator, 2021). As a result, enhancing economic and social resilience to extreme natural events has become a major focus for governments in low- and middle-income countries, as well as development agencies and international institutions (World Bank, 2014; Marto et al., 2018; FDRR, 2020).

Despite efforts to prevent and manage extreme natural events, the response of international financial flows to disasters is a key factor in mitigating their adverse impact on local populations (David, 2011; Becerra et al., 2014; Heger and Neumayer, 2019; Horn et al., 2021). Migrant remittances have been shown to be less volatile than foreign aid or foreign direct investments and serve as a valuable source of risk sharing for many developing countries (Yang, 2011; Combes et al., 2014; Balli and Rana, 2015; Bettin et al., 2017). Therefore, their role in recovery and reconstruction following natural disasters is crucial (Mohapatra et al., 2012). Moreover, intra-family transfers can provide immediate relief to the livelihoods of receiving households (Skidmore and Toya, 2002; Gröger and Zylberberg, 2016).

The growing body of empirical evidence about aggregate remittances and natural disasters is far from being conclusive. Some studies indicate that remittance flows increase in the aftermath of natural disasters and significantly contribute to disaster preparedness (David, 2011; Mohapatra et al., 2012; Bettin and Zazzaro, 2018). Other research finds that remittance increases are typically observed only in poorer countries affected by disasters, or that migrants' financial transfers do

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not significantly respond to disasters in their home countries (Lueth and Ruiz-Arranz, 2008; Yang, 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 considered predominantly exogenous and unpredictable events, identification remains the key issue to uncover their impact on migrants' remittances and measure it unambiguously.

Existing cross-country studies rely on annual data for global or bilateral remittance flows and disaster indicators that aggregate adverse natural events over the same time horizon. However, assessing the immediate response of remittances to natural disasters using yearly data poses challenges. A rapid increase in financial support from abroad is often crucial in mitigating the effects of disasters on affected communities. Consequently, migrants are likely to concentrate their financial support to relatives at home in the months immediately following a disaster. Furthermore, 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.

First, there could be a redistribution of remittances within the year. If migrants' financial capacity in host countries is largely fixed, they may decide to front-load their transfers in response to a disaster and reduce them in later months, while keeping their annual remittances roughly unchanged. This pattern is supported by 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 affected by the tsunami in September 2009. Despite issues of under-reporting and recall bias, they found that remittances spiked immediately after the tsunami but returned to standard levels after six months. Indeed, Le De et al. (2015, p. 661) noted, "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". Similarly, in the eighteen case studies analyzed by Bragg et al. (2018), remittances typically increased in the quarter during which the disaster occurred, although this effect rarely translated into a significant annual increase.

Second, adverse natural events - such as tornadoes, hurricanes, floods, and droughts - are not randomly distributed throughout the year; they often exhibit a seasonal pattern that varies by country. The seasonal nature of disasters complicates the appropriate temporal specification of econometric models, making it challenging to identify the relationship between remittances and disasters when relying solely on annual observations based on the standard calendar year. This issue is particularly pronounced if disasters cluster in the first or last months of the year. Utilizing annual data for remittances necessitates aggregating disaster data on a yearly basis as well, which hinders the estimation of the average effect of a single natural disaster and obstructs the analysis of nonlinear responses in remittances to damages inflicted by extreme events or other forms of heterogeneity in the disaster-remittance connection.

The above concerns highlight the potential advantage of employing high-frequency data on remittance inflows to accurately assess the impact of natural disasters on migrant transfers to their home countries, as well as the temporal dynamics of remittance response and the influence of possible moderators. To this end, we exploit a unique dataset on monthly bilateral remittance flows from Italy to a panel of 81 low- and middle-income countries during the period 2005–2015, which we merge with disaster data at the same monthly frequency.

We adopt a non-parametric event study approach, which allows us to characterize the dynamic response of remittances flexibly over a t-month horizon. Following recent advancements in the literature on multiple event studies, we define our effect window as an open interval with binned endpoints (Schmidheiny and Siegloch, 2023). This allows us to assume that the effect of disasters does not vanish but remains constant outside the chosen t-month window and to control for both past and future disasters.

Our findings indicate that migrants promptly increase remittances in response to natural disasters in their country of origin, although this effect wears off during the first six months after the event. During this period, aggregate remittance flows from Italy to affected countries rise by approximately 1% per month compared to pre-disaster levels. By the seventh month, these flows return to their pre-disaster level without exhibiting any significant negative rebound. The positive response of remittance to natural disasters at home is confirmed when we take into consideration the intensity and the number of disasters that occur in a given month. In particular, we find that the increase in remittances in the aftermath of large-scale disasters is greater, with a cumulative effect of 10%–20% over a 12-month horizon, depending on the different specifications and set of countries analyzed.

The dynamics of remittance response is heterogeneous according to the nature of the disaster. We find a swift response to sudden-onset disasters (e.g., earthquakes and storms) within the first three months, whereas remittances respond with a delay of about three months to slow-onset disasters (e.g., droughts or extreme temperature events). However, the increase in remittances following slow-onset disasters tends to be larger and more prolonged than that following sudden disasters. Furthermore, the response of remittances is notably stronger for climatic events compared to meteorological and geophysical disasters.

As one would expect, results are predominantly influenced by disasters occurring in countries where Italy is among the top destinations for the diaspora. Additionally, the geographical distribution of migrants within Italy plays a crucial role: migrant communities that are more spatially dispersed demonstrate a greater and more significant increase in remittances in response to extreme events in their home countries, compared to communities that are more spatially concentrated.

Finally, socio-economic conditions in the host and home country significantly affect the response of remittances to disasters. The ability and willingness of migrants to send additional financial resources at home in response to a natural disaster were notably constrained during the double financial and sovereign debt crisis, and this trend persisted in subsequent years. Moreover, our analysis indicates that the overall response of remittances is primarily driven by the diaspora from low-income countries, as previously noted by Yang (2008), while also being influenced by migrants from upper-middle-income countries.

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

2. Related literature

An increasing number of empirical studies have analyzed the relationship between migrant remittances and natural disasters in the home countries. While 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) documents a positive association between remittance inflows and the occurrence of natural disasters. By considering a panel of 78 developing countries for the period 1970–2005, he provides evidence of a statistically significant increase in contemporaneous and one-year-ahead remittance flows due to the number of climatic and geological disasters in a given year. 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. Moreover, they document that the remittance response to natural disasters is greater than that resulting from other types of shocks 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. However, they find that this effect is statistically significant only if the stock of migrants abroad is sufficiently large (more than 15% of the 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) remittance flows towards 98 low- and middle-income countries over the period 1990–2010. They find that remittance inflows respond positively to natural disasters and increase with the number of disasters that have already occurred in the past thus suggesting that remittances contribute to increase ex-ante preparedness for recurrent 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 insignificant result is confirmed by Bettin et al. (2017) who 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 highlighted in the introduction.

3. Data and descriptive statistics

The estimation sample includes 81 countries for which data on the full set of variables are available. Table 1 reports the list of countries included in our regression analysis and the average monthly remittances they receive from their migrants in Italy. Despite being among the top recipient countries, China has been excluded from the estimation sample due to the dubious nature of outflows from Italy officially labeled as remittances. Transfers to China are strongly correlated to the significant presence of Chinese firms in some Italian provinces (e.g., Prato). This suggests that the Money Transfer Operators (MTOs) channel was not used exclusively to remit money home, but also "misused" by Chinese entrepreneurs to make other payments or to repatriate business profits (Oddo et al., 2016; Ferriani and Oddo, 2019; Ciarlone, 2023). This issue was quite evident up to 2011, when transfers to China peaked at 2,5 billion euros, whereas from the subsequent year stricter supervisory controls on MTOs translated into a significant decrease in official remittance outflows to China. Given that our analysis covers the 2005–2015 period, we exclude China in order to reduce the risk of biased estimates, and add it to our sample only in a robustness check discussed in Section 5.2.2. In Table 2, we report the description of our dependent and independent variables, the data sources and some descriptive statistics.

3.1. 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.[1]

The data on outward (and inward) remittances are estimated by the Bank of Italy for the compilation of the current account of the balance of payments and reported under the item "secondary income". They include cross-border transactions between natural persons carried out through authorized financial intermediaries – banks, post offices and MTOs – with reporting obligations to the Bank of Italy, and recorded by receiving country and province of residence of the foreign remitter in Italy.

The definition of remittances used by the Bank of Italy is narrower than the one used by the World Bank to compile the "Annual Remittances Data" (ARD). This also includes "earnings from work" paid to non-resident foreigners – cross-border workers, seasonal workers and workers abroad for periods of less than one year –, or to foreign residents working for a non-resident employer. The same broad definition of remittances is used in the World Bank's "Bilateral Remittance Matrix" (BRM): this is computed by imputing the inward remittances reported in the current account of each receiving country to the countries of destination of its migrant population in proportion to the stock of migrants in each of these countries and to the per capita income in the receiving and destination countries, both expressed in purchasing power parities (Ratha and Shaw, 2007). This imputation method of bilateral remittances has the merit to partially take into account informal transfers. However, it introduces other distortions due to specific assumptions and approximations that the direct collection of information from commercial banks and MTOs conducted by the Bank of Italy does not introduce.[2] These discrepancies in the definition of remittances and in the bilateral flow estimation method may explain the differences between the amount of inward remittances reported by the Bank of Italy, that we use in this paper, and the data reported in the World Bank ARD and BRM.[3]

Of course, the official macro data provided by the Bank of Italy represent a partial measure of remittances from Italy. First, the information flow of the Bank of Italy does not cover all money transfer operators, as demonstrated by the sharp increase in outgoing remittances recorded in Italy in 2018 (outside our period of analysis) when the Bank of Italy extended the reporting obligation to additional MTOs previously excluded from data collection. Second, official data do not include remittances sent home using informal brokerage services or direct cash transfers, which are estimated to be a substantial proportion of total remittances to developing countries (Page and Plaza, 2006; Freund and Spatafora, 2008; Clemens and McKenzie, 2018). As regards Italy, recent estimates by Oddo et al. (2016) and Ferriani and Oddo (2019) document that remittances through informal channels are on average between 3% and 18% of formal remittances, depending on the estimation method and the geographical area considered, with

[1] 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 from 2005 up to 2015; from 2016 onward data were released only on a quarterly basis.

[2] In a recent study, De Arcangelis et al. (2023) document the importance of relying on administrative data directly collected by banks and MTOs in order to have reliable measures for remittances, as they are usually not affected by the common sources of measurement error which may affect survey data, such as recall bias and social desirability bias.

[3] According to the figures reported by Croce and Oddo (2020), in the period 2010–2015 aggregate remittance outflows calculated with the Bank of Italy's methodology were on average equal to approximately 6.1 billion euros per year, which is about 67% of the value reported in the World Bank ARD series (9.1 billion euros) and 57% of that reported in the World Bank BRM series estimated with the Ratha and Shaw (2007) methodology.

Table 1
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 2
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
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
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
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
Unemployment rate (%)	Monthly unemployment rate in Italy. Source: Istat.	9.00	2.40	5.30	14.30
Interest rate (%)	Monthly Treasury Bill rate in Italy. Source: IMF-IFS	1.93	1.41	−.07	6.4

peaks up to 35% in foreign countries geographically closer to Italy. Therefore, given the incidence of informal channels, our estimates are likely a lower bound of the actual response to natural disasters in migrants' home countries. However, given the strong role of distance in predicting informal remittances, for robustness we repeat our analysis by excluding four recipient countries (Albania, Morocco, Romania and Tunisia) that, according to Oddo et al. (2016), account for nearly 75% of total annual informal transfers from Italy.

Another possible concern for our estimates of the response of remittances to natural disasters is the donation of charity relief funds to disaster-affected areas. If immigrants collect additional resources through charity funds donated by local communities they live in and transfer them together with their own remittances, our estimates would overstate the role of remittance transfers (even if not the effort of immigrants in collecting resources to send home). On the other hand, immigrants themselves could choose to support the affected areas through indirect channels, such as participating in fundraising initiatives by NGOs or hometown associations active in Italy (Riccio and degli Uberti, 2013; Olowa, 2016). In this case, looking solely at the official personal remittances would underestimate migrants' true response to disasters. Unfortunately, since there are no publicly available data on the fundraising activity of charities, NGOs and hometown associations in Italy, we are unable to explore this issue further in our empirical analysis.

Monthly nominal remittances are deflated by the CPI index and seasonally adjusted by using the standard X-12-ARIMA method as implemented in Stata (Wang and Wu, 2012).[4] Seasonally adjusted data are

[4] The X-12 seasonal adjustment program was developed by the United States Census Bureau and it is widely used by national statistical offices around the world (Findley et al., 1998).

often used in empirical analyses with monthly frequency series which, as is the case with remittances, show significant seasonal variations that pose challenges for accurate estimates and inference. In our context, the adjustment allows us to take into account the different seasonal patterns of remittances in different countries which could interfere with the estimated response to natural disasters. The X-12 command in Stata employs a three-stage seasonal adjustment procedure.[5] First, it conducts prior adjustments for various effects (such as seasonal effects, moving holiday effects, and outliers) and estimates an ARIMA model. Second, it adjusts the original series using regression coefficients obtained from the first stage, employing a seasonal moving average for estimating seasonal factors. Third, the command provides diagnostics for modeling, model selection and adjustment stability, ensuring the mitigation of remaining seasonal variations. In our case, we allow the software to automatically select both the model and the moving average for estimating the seasonal factors that best fit the data.

Our dependent variable is defined as the log of real remittances sent to country i at time t.[6] 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 2). Fig. 1 displays the aggregate monthly flow of real remittances sent from Italy to the 81 countries in our sample in the period 2005–2015. On average, Romania received the largest amounts, followed by the Philippines, Bangladesh, Morocco, Peru, Brazil, Ecuador and Albania (see Table 1). Up to the beginning of 2008, transfers increased steadily, from less than 150 to almost 350 million euro per month. Afterwards, the pattern became more volatile, with significant drops at the beginning of 2010 and during 2012, which are related both to a slowdown in migration flows to Italy and to the worsening of 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% between 2010 and 2011, but became positive again in the following years, reaching 5 million immigrants in 2015.[7] 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.

3.2. 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. 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.[8] We aggregate all the 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 in Section 4, we include the event indicator variables equal to 1 up to $\underline{m}$ months before the disaster and $[\bar{m}]$ months after the disaster.

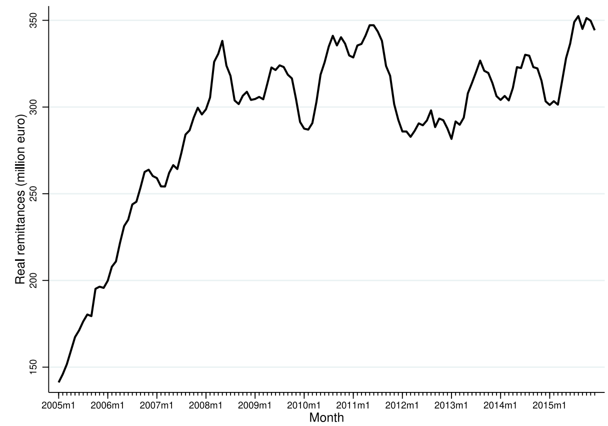

Fig. 1. Evolution of monthly remittance outflows from Italy.
Note: Real monthly remittance outflows from Italy are computed from data on nominal remittances in euros released by the Bank of Italy for the period 2005 to 2015 on a monthly basis. Nominal remittances are then deflated by the CPI index.

In order to perform heterogeneity analysis, we investigate whether the magnitude and temporal dynamics 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) *meteorological disasters*, which are related to the earth's atmosphere and include extreme temperatures and storms; (iii) *geophysical disasters*, which are defined as the adverse events brought by tectonic activity below the earth's surface and include earthquakes, volcanic activity and mass movements (dry).[9]

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,[10] we distinguish between sudden-onset disasters, which include earthquakes, volcanic activity,

[5] See Wang and Wu (2012).

[6] We also used real remittances per-capita as dependent variable, 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 $t-1$. The per-capita normalization allows us to take into account the significant size heterogeneity across migrant communities, but at the same time it could introduce a systematic measurement error due to the significant presence of irregular migration to Italy. Therefore, we prefer to assume a (broadly) constant migrant population over the event window, and use the logarithm of total remittances as dependent variable.

[7] Data from the Italian National Institute of Statistics (Istat) provide only annual 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 who have not yet been recognized as Italian citizens. Besides that, as stocks they do not account for inflow/outflow dynamics within the calendar year.

[8] 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/.

[9] 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.

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

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

	Disaster	Frequency		Total affected		Total deaths	
	Dummy	Mean	Max	Mean	Max	Mean	Max
Climatic disasters	0.11	0.12	5	359,692	36,000,000	30	2,665
Geophysical disasters	0.01	0.01	2	168,965	5,639,722	2,686	222,570
Meteorological disasters	0.04	0.05	5	293,109	16,106,870	202	55,736
Slow-onset disasters	0.02	0.02	2	946,074	27,000,000	245	55,736
Sudden-onset disasters	0.13	0.16	6	246,789	36,000,000	347	222,570
All disasters	0.14	0.18	6	353,638	36,000,000	340	222,570

Note: Descriptive statistics are disaggregated by nature and type of disasters. 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. Frequency is the average/maximum number of disasters by type or nature per month. Total affected people and total deaths (average/maximum) are computed only for those observations (country–month pairs) in which at least one disaster occurred.

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, both at local and international level (Staupe-Delgado, 2019).

During the period under consideration, 3131 disasters occurred in our sample of countries: 2215 were climatic, 601 were meteorological and 315 were geophysical disasters; 289 slow-onset and 2842 sudden-onset disasters. 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). The only country to experience no natural disasters throughout the whole period is Jordan, whereas the Philippines had the highest number of events (100). In terms of intensity, the average number of affected people is slightly larger than 350,000 people, with maximum peaks that exceed 36 million people (51% of total population). The average number of casualties is 340, although the January 2010 earthquake in Haiti killed over 220,000 people, about 2.3% of the country's total population. It was by far the disaster with the highest human costs in our sample.

When looking at disasters by nature, the incidence of sudden-onset disasters on the country–month pairs in our sample is much higher compared to slow-onset events (13% versus 2%), as well as their average number per month (0.16 versus 0.02). On the other hand, the average number of people affected by slow-onset disasters is almost four times larger. If we look at the type of disasters, climatic events are more frequent than geophysical and meteorological ones (0.12 per month compared to 0.01 and 0.05, respectively) and on average affect also a larger number of people.

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 and South Asia experiences the largest average number of people affected. Latin America and the Caribbean has the highest number of casualties, due to the 2010 earthquake in Haiti already mentioned above.

3.3. Disasters-remittances nexus

Fig. 2 provides an intuitive illustration of how relevant it could be to consider the monthly dynamics of remittances to identify migrants' response to disasters at home. Here we plot the monthly variability of remittances to Bangladesh overlaid with bars for the timing of disasters in the country and with a broken line for the average yearly amount that Bangladeshi migrants in Italy transfer home, zooming in on the period 2010–2015.[11]

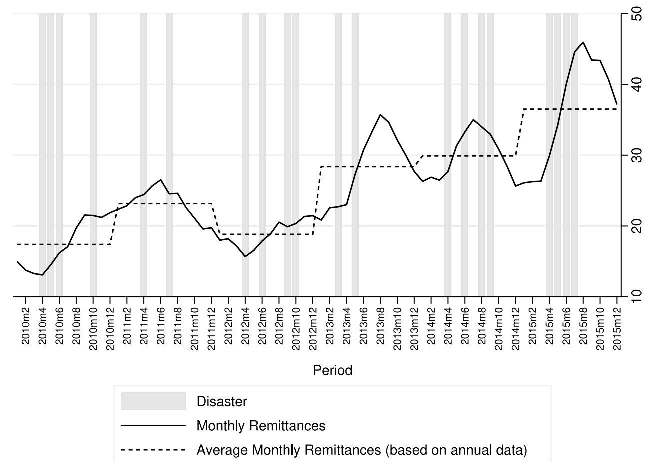

Fig. 2. Remittances and disasters in Bangladesh,2010–2015.
Note: Monthly remittances are computed from monthly data on nominal remittances in euros from Italy to Bangladesh released by the Bank of Italy. Nominal remittances are then deflated by the CPI index. Average monthly remittances are computed as one twelfth of the annual total amount sent to Bangladesh. Gray vertical bars correspond to months in which Bangladesh experienced natural disasters.

From the graph, it is possible to easily detect seasonality patterns both in the occurrence of disasters during the year and the dynamics of remittances, which must be appropriately accounted for in the estimation setting. At the same time, we observe that the annual average of remittance inflows fails to capture their monthly variability, which is rather pronounced and seems to be positively correlated with the occurrence of natural disasters. From this descriptive evidence it is in any case impossible to detect both the significance of remittances' response following a disaster event and the time pattern of such response, whether it is immediate or lagged by one or more months. Moreover, we cannot rule out the existence of anticipation effects, especially in the case of recurrent seasonal disasters. In Bangladesh, for example, disasters concentrate in the second and third quarters, when remittances usually have their annual peak. However, in years such as 2010 and 2012, where the country experienced disasters also later on during the year (October), we do not observe the significant drop that monthly remittance inflows display in all the other years. An event study setting based on monthly data is therefore needed to further explore the suggestive evidence displayed in Fig. 2 and provide reliable evidence on the response of remittances to natural disasters.

[11] Bangladesh is the third top recipient country of remittances from Italy (see Table 1) and has been plagued by a series of disasters in our sample period.

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

	Disaster	Frequency		Total affected		Total deaths	
	Dummy	Mean	Max	Mean	Max	Mean	Max
East Asia & Pacific	0.09	0.05	6	203,154	16,106,870	207	165,708
Europe & Central Asia	0.15	0.01	2	2,917	20,000,000	29	55,736
Latin America & Caribbean	0.20	0.05	5	39,387	27,000,000	97	222,570
Middle East & North Africa	0.07	0.00	2	2,493	10,00,000	2	628
South Asia	0.04	0.01	4	233,242	36,000,000	126	35,405
Sub-Saharan Africa	0.46	0.05	5	33,739	15,000,000	2	871

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. Frequency is the average/maximum number of disasters by type or nature per month. Total affected people and total deaths (average/maximum) are computed only for those observations (country–month pairs) in which at least one disaster occurred.

4. Empirical strategy

To estimate the dynamic response of monthly remittance flows to 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 to flexibly observe and describe the pattern of remittance flows relative to the precise time when a disaster occurs.

Unlike the standard setting with one event per unit of observation, in our context many countries (i.e., the cross-sectional unit of observation) 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, so that remittance inflows to a given country in a given period can respond to multiple disasters with overlapping effect windows. Therefore, in this setting the event variables are not mutually exclusive, since, for example, a country in a certain period t could be three periods after a catastrophic event that occurred in $t-3$ and 1 period before another disaster occurs at $t+1$, with both -3 and $+1$ within the considered effect window. As Sandler and Sandler (2014) show, the MDO approach allows to yield unbiased estimates of the event-time dummies without creating spurious trends in the 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 $i = \{1, \dots, N\}$ be the receiving country, t the calendar time within the remittance sample period $T = [\underline{t}_s, \bar{t}_s]$, $t_{e,i}$ the calendar time within the event period $T_e = [\underline{t}_e, \bar{t}_e]$ in which country i experiences a disaster event. Restricting the effect window to the time interval $M = [\underline{m}, \bar{m}]$ that considers $\bar{m} > 0$ months after the disaster event and $\underline{m} < 0$ months before it, the MDO specification for our multiple event study is:

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

where Y_{it} is the (log of) amount of outward remittances from Italy to country i in month t, $\mathbb{D}_{i,t}^m$ is an indicator variable that takes the value 1 if m months away from t country i experienced a disaster event, X_z denotes a set of Z additional factors X that may affect remittance flows (see Section 4.1), and λ_i and τ_t denote country and calendar time fixed effects, respectively. Standard errors are clustered at country level.

Our key variables $\mathbb{D}_{i,t}^m$ document the dynamics of remittance flows in response to disasters during the effect window. The main identifying assumption is that, once we condition on observables $\{X_1, \dots, X_Z\}$, country and time fixed effects, the occurrence of each disaster is uncorrelated with other unobserved shocks (Schmidheiny and Siegloch, 2023). The estimated β_m coefficient on lags (i.e., on the event dummies for $0 \geq m \geq \bar{m}$) is interpreted as the semi-elasticity of remittance inflows Y_{it} at time t with respect to the disaster event which occurred m months away, at time e_{d_i}. Estimated coefficients on leads (i.e., on $\mathbb{D}_{i,t}^m$ for $\underline{m} \geq m < 0$) can be used to assess the absence of pre-treatment trends and the credibility of the identification strategy. However, in our context we cannot rule out that immigrants anticipate the occurrence of (possibly recurrent) disasters. In other words, pre-disaster dummies close to the event date could capture potential anticipation effects of natural disasters on remittances, while the coefficients of pre-disaster dummies further away from the event date should be statistically not different from zero. Despite the potential anticipation of recurrent disasters, however, their intensity is unlikely to be predictable.

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 on remittances observed within our sample period, that is, the effect of the natural disasters experienced between the periods $[\underline{t}_s - \bar{m}, \underline{t}_s]$ and between the periods $[\bar{t}_s, \bar{t}_s - \underline{m}]$ on remittances made during the sample period $T_s = [\underline{t}_s, \bar{t}_s]$.

A first simple approach is to 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 the sample period. However, the assumption that the effect of disasters on remittances suddenly diminishes to zero outside the effect window is rather implausible in our context where many countries are plagued by multiple and recurrent natural disasters; moreover, it amounts to ignoring possible country-specific trends that are correlated with the disaster-time indicators and once again could bias our baseline estimates. Similarly, the assumption that no adverse natural events occur outside the sample period or that they have no effects on transfers made during the sample period introduces an obvious potential bias in the estimated coefficients on disaster dummies.

To address these concerns, we follow the end-point binning approach proposed by Schmidheiny and Siegloch (2023). In this case, the effect of disasters is assumed to stay constant outside the effect window by *binning* the disaster indicator at the endpoints of the window. Moreover, we extend the event window to disasters that occurred within the $\bar{m}-1$ periods before the first calendar time of the sample period and within the $\underline{m}-1$ periods after the last calendar time of the sample period, i.e., we estimate a specification where the event window $T_e = [\underline{t}_s - \bar{m} + 1, \bar{t}_s + \underline{m} - 1]$ for which we observe disaster events is larger than the sample period T_s for which we observe remittances:[12]

$$Y_{it} = \lambda_i + \tau_t + \sum_{m=\underline{m}}^{\bar{m}} \beta_m \mathbb{B}_{it}^m + \sum_{z \in Z} \delta_z X_{Z_{it}} + \varepsilon_{it} \tag{2}$$

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

$$\mathbb{B}_{it}^m = \begin{cases} \sum_{k=t+\underline{m}}^{\bar{t}_s+\underline{m}-1} \mathbb{D}_{ik}^m & if \quad m = \underline{m} \\ \mathbb{D}_{it}^m & if \quad \underline{m} < m < \overline{m} \\ \sum_{k=\underline{t}_s-\bar{m}+1}^{t-\bar{m}} \mathbb{D}_{ik}^m & if \quad m = \overline{m} \end{cases} \tag{3}$$

[12] A detailed description of the structure of the dataset in the case of binned endpoints is reported in the online Appendix.

Model (2) allows for the response of remittances to disasters to extend outside the chosen effect window by assuming that in any t, $\mathbb{B}_{it}^{\underline{m}}$ takes a value that reflects all disaster events that occurred in the event period starting from $t+\underline{m}$ onwards and $\mathbb{B}_{it}^{\bar{m}}$ takes a value equal to the sum of all disaster indicators in the event window until $t-\underline{m}$.[13]

Recently, a growing number of studies have adopted event study designs with binned endpoints to analyze dynamic treatment effects (Casi et al., 2020; Brülhart et al., 2022; Lähdemäki, 2024).

In a context closely related to our study, Coury (2023) examines the dynamic effect of wildfire exposures on voter preferences in the U.S. counties. Coury's setting parallels ours as treated groups (i.e., counties) experience multiple treatments at different points in time, thus necessitating the adoption of a staggered treatment event study design. Coury (2023) relies on the binning approach for proper identification of pre-trends. However, since the availability of data on wildfires is limited to the last year for which information on the dependent variable is also available, he shortens the observation window for the dependent variable in order to bin the post-treatment endpoints.

4.1. 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., 2024). We use the monthly commodity export price index,[14] weighted by the ratio of individual commodity exports to total commodity exports, from the International Monetary Fund (IMF) database and express it in logs.[15] 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 would ideally like to control for, are mostly available on an annual basis and are therefore excluded.

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

Finally we include a set of fixed effects. First, we control for country fixed effects to account for all country-specific factors that may be correlated with remittances and/or natural disasters and are not fully captured by the limited set of control variables available at monthly frequency. Second, we add a set of month×year fixed effects to adjust for time-specific confounders and account for possible common time patterns between remittances and disasters that may generate a spurious correlation which is mistakenly interpreted as a causal effect. The inclusion of month×year fixed effects, together with the use of seasonally adjusted remittances as dependent variable, should mitigate significantly such risk in our framework of analysis. Third, we add region×year fixed effects to take into account possible common climate risk trends at the regional[16] level.[17]

5. Results

5.1. Baseline results

In this Section we discuss regression results of the baseline model in Eq. (2). As stated earlier, the effect of disasters is assumed to stay constant outside the effect window by *binning* the disaster indicator at its endpoints. Results are expressed relative to two months before the disaster occurred, in order to highlight possible anticipation effects immediately preceding recurrent adverse natural events that could be predictable in their occurrence even if not in their intensity. Hence, the dummy β_{-2} is set to zero and serves as the reference point. For reasons of clarity, we display results through the event-study graphs in Fig. 3, which provide an immediate visual representation of the dynamics of the response of remittances to natural disasters in the country of origin. Point estimates, standard errors and diagnostics are reported in Table 6. Our preferred specification includes 3 leads and 12 lags for each disaster event. In the robustness Section, we consider different event windows.

Results are broadly consistent in our baseline specification with and without controls revealing an increase in remittances at the time the disaster strikes and in the following months. Lag coefficients show that remittances react immediately on impact, as the response becomes significant at conventional significance levels from $m = 0$. The effect increases over a 2-month horizon. From the third month onwards, the positive response of remittances start to slightly decline even if it remains statistically significant at 8%–15% level up to six months after the disaster. In the following months, the estimated coefficients undergo a strong reduction, bringing remittances back, on average, to levels that are not statistically different from those realized before the disaster (at time −2). The estimates on the binned coefficients are not statistically significant. This indicates that we cannot reject the hypothesis that the response of remittances diminishes to zero in the long run, beyond the end of our 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.

The temporal dynamics that we observe in the response of immigrants' remittances to disasters highlights the importance of using high-frequency data. Most of the effects extend over a short time span, and with a different intensity month by month that depends on the temporal distance from the disaster event. However, no intertemporal

[13] As Schmidheiny and Siegloch (2023) show, this assumption is equivalent to assuming 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 $m > \bar{m}$.

[14] 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 included two further variables to control for *Abnormal rain* and *Abnormal temperature* at time t, which were 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. Monthly average temperature and rainfall data were drawn from the World Bank Climate Change Knowledge Portal, https://climateknowledgeportal.worldbank.org/download-data. Due to the high correlation with disasters, however, we prefer not to include these two additional variables in our standard set of controls, although results were very similar and are available from the authors upon request.

[15] 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).

[16] Following the World Bank classification, we consider 6 regions: East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, South Asia and Sub-Saharan Africa. North America is excluded because none of its countries is included in our estimation sample.

[17] Alternatively, we saturate the model with a set of country–year fixed effects to control for unobserved annually varying country-level confounders. However, since the within-country–year model restricts the estimated monthly dynamics of remittances within the calendar year and since it makes the analysis of the heterogeneity of the disaster-remittance nexus on small subsamples less statistically powerful, we adopt this specification as a robustness check.

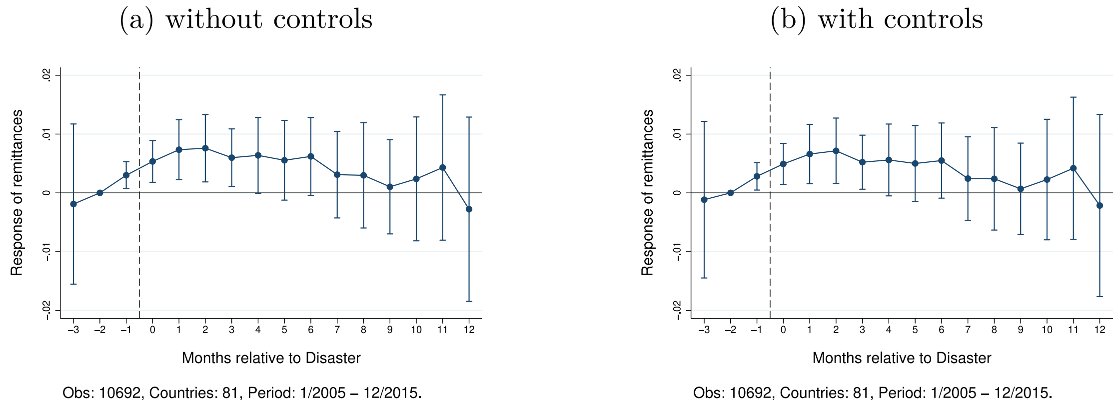

Fig. 3. Remittances response to disasters in the baseline binned-end estimates.
Note: Panel (a) is based on our baseline estimates of Eq. (1) with 3 leads and 12 lags, with Fixed Effects only. Panel (b) is based on the estimates of Eq. (1) with 3 leads and 12 lags including the following control variables: terms of trade, exchange rate, unemployment rate and interest rate (for further details, see Section 4.1). Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

substitution effect seems to be at work in remittance flows which tend to return to the pre-disaster level approximately nine months after the disaster, but never become significantly lower.[18] 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 = 3.74, p-value: 0.0567). When testing the joint significance of lag coefficients 7–12, instead, we fail to reject the null hypothesis that the coefficient estimates are jointly zero (F-statistics = 0.09, p-value: 0.7607). Interestingly, this result is confirmed when we test the significance of all 12 lags (F-statistic = 1.07, p-value: 0.3042), thus suggesting that analysis on annual data would likely hide the impact of disasters on remittances from abroad. Moreover, since the distribution of different types of disasters is unlikely to be uniform over a standard calendar year, annual estimates may be biased. Consistently with these concerns, when we estimate a model by collapsing monthly remittances at the standard annual level we do not detect any significant effect of disasters both on impact, and in the following year (see Table 5).[19] Even when considering intermediate levels of aggregation, such as semi-annual and quarterly data, the response of remittances – despite being positive – is never statistically different from zero.[20]

As far as the leads are considered, one would expect estimated coefficients to be never statistically significant, suggesting that pre-treatment trends are absent and that migrants are unable to anticipate a disaster's occurrence. However, our estimates point to some anticipation effect, which could be related to the recurrent nature of some types of natural disasters, as the first lead is positive and statistically significant, thus denoting an increase in remittances compared to our reference period $m = -2$. When testing for the joint significance of all the leads coefficients, however, they are not significantly different from zero (F-statistics = 0.04, p-value: 0.8438). This result is reassuring about the fact that pre-disaster dummies further away from the event date are not statistically different from zero and that natural disasters can be considered an exogenous event.

Table 5
Baseline Event study regressions with annual, semi-annual and quarterly data.

	(1) Annual	(2) Semi-annual	(3) Quarterly
Period 1 before Disaster	.0126	−.0063	−.0092
	(.2514)	(.0774)	(.02946)
Period of Disaster	.1072	−.0258	−.0037
	(.2517)	(.0810)	(.0342)
Period 1 after Disaster	−.4641	.0117	.0025
	(.2445)	(.0555)	(.0356)
Period 2 after Disaster			.0176
			(.0313)
Period 3 after Disaster			.0086
			(.0276)
Country FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Period * Region FE	Yes	Yes	Yes
Observations	891	1782	3564
N countries	81	81	81

Note: Standard errors in parentheses. Annual, semi-annual and quarterly data are obtained by collapsing our original monthly dataset respectively at annual, semi-annual and quarter level following the standard calendar year. Column (1) is estimated by including three dummies for the year of disaster, the year after and the year before the event. Column (2) is estimated by including four dummies for the semester of disaster, the semester before and two semesters after the event. Column (3) is estimated by including six dummies for the quarter of disaster, the quarter before and four quarters after the event. All columns include country FE, period FE and period*region FE.

Since our analysis is based on aggregate remittances sent home by a migrant community residing in a single destination country (Italy), it is arduous to obtain a precise sense of the economic impact of disasters on remittances from the estimated coefficients. National migrant communities in Italy typically represent a small fraction of the overall population that emigrated from the country. Furthermore, diaspora strategies often follow network patterns such that the migrant population from the same region of origin tends to locate in the same area of destination (Beine et al., 2011; Giulietti et al., 2018; Mahajan and Yang, 2020; Gröger, 2021; Stuart and Taylor, 2021). When natural disasters strike places in the country of origin that are distant from the birth town of migrants in Italy, it is likely that transfers home will increase less and that any aid will take the form of contributions to operating associations or charities in Italy rather than direct increases in remittances sent to relatives and friends. In this sense, our estimates

[18] With the data at our disposal, we do not capture opposite flows and we are not able to control for any possible repayment obligation attached to remittances sent home from migrants in Italy. We therefore assume that there is zero repayment obligation for remittance recipients in the home country, or, to put it differently, that remitting behavior is fully driven by altruistic motivations.

[19] The annual-frequency bias could explain why (Bettin et al., 2017) found no significant response of yearly remittance flows from Italian provinces to disasters in migrants' home countries.

[20] Therefore, our results suggest that the change introduced by the Bank of Italy in the frequency (from monthly to quarterly) of the reported amount of bilateral remittances from Italy entails the loss of important information which is apparently necessary to detect the response of remittance to shocks in the home country.

Table 6
Baseline event study regressions (Fig. 2).

	(1)	(2)
Binned lead beyond 3 months	−.0019	−.0019
	(.0083)	(.0075)
1 months before Disaster	.0030**	.0022
	(.0014)	(.0015)
Month of Disaster	.0053**	.0055**
	(.0022)	(.0024)
1 month after Disaster	.0073**	.0058*
	(.0031)	(.0032)
2 month after Disaster	.0076**	.0064*
	(.0035)	(.0033)
3 month after Disaster	.0060**	.0047*
	(.0030)	(.0027)
4 month after Disaster	.0064	.0049
	(.0039)	(.0036)
5 month after Disaster	.0055	.0033
	(.0041)	(.0038)
6 month after Disaster	.0062	.0046
	(.0040)	(.0040)
7 month after Disaster	.0031	.0015
	(.0045)	(.0044)
8 month after Disaster	.0030	.0008
	(.0054)	(.0054)
9 month after Disaster	.0010	−.0005
	(.0049)	(.0048)
10 month after Disaster	.0024	.0001
	(.0064)	(.0064)
11 month after Disaster	.0043	.0012
	(.0075)	(.0074)
Binned lead beyond 12 months	−.0028	−.0030
	(.0095)	(.0089)
Exchange rate		−.0009**
		(.0004)
Unemployment rate		−.0582***
		(.0173)
Interest rate		−.3067***
		(.0956)
log Terms of trade		.0824
		(.0739)
Country FE	Yes	Yes
Month x Year FE	Yes	Yes
Region x Year FE	Yes	Yes
Observations	10 692	10 641
N countries	81	81
Joint significance of leads F-test	0.02	0.04
Joint significance of lags (0 to 6) F-test	4.22	3.74
Joint significance of lags (7 to 12) F-test	0.11	0.09
Joint significance of lags (1 to 12) F-test	1.26	1.07

Note: Standard errors in parentheses. Column 1) shows baseline estimates of Eq. (1) with 3 leads and 12 lags. Column 2) shows estimates of Eq. (1) with 3 leads and 12 lags including the following control variables: terms of trade, abnormal rain and abnormal temperature, exchange rate, unemployment rate and interest rate, stock of migrants (for further details, see Section 4.1). The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

are a lower bound of the response of remittances to natural disasters in migrants' countries of origin.[21]

That said, based on the estimates presented in Fig. 3(b), the magnitude of the response of aggregate remittances is equal to approximately 0.5% on impact and reaches a cumulative value of 4% in the first six months after the disaster (5.2% in twelve months).

By considering the monthly real remittances outflows at their in-sample average equal to 359,000 euros, this translates approximately into a cumulated flow of 16,000 (18,600) euros of additional remittances at constant prices over the 6 (12) months following a disaster. If we consider the average monthly official development aids sent from Italy as emergency response towards the same sample of countries, that is roughly equal to 22,516 USD, the response of remittance outflows toward the average country in our sample is not negligible. Obviously, the average impact of disasters on remittances conceals the strong variability between countries regarding both the presence of migrants in Italy and the usual size of remittance flows. For example, in the cases of the Philippines, which experiences frequent and often severe disasters, and Romania, which is by far the top remittance recipient in our sample, the cumulative increase over the 6-month period following the disaster is approximately equal to 167,000 and 255,000 euros, respectively.

As Fig. 3(b) shows, estimates are robust when controlling for shocks to export prices and exchange rate with the US dollar in the receiving country and for economic conditions in Italy, which may affect both migrants' decision and their concrete possibility to remit. From the regression results reported in Table 6, we find that both unemployment and interest rates in Italy as well as the country of origin's exchange rate are associated to lower remittances. No significant correlation with remittances is detected for terms of trade. What matters most is that we confirm the positive response of remittances to disasters in terms of magnitude, significance and dynamics. The robustness checks and the heterogeneity analysis in the next Sections will be performed on the baseline specification with control variables.

5.2. *Additional results*

In this Section, we test the sensitivity and the relevance of the baseline results to several choices related on the one hand to the definition of remittances and disaster variables and the sample of countries considered in our estimates, on the other hand to the model specification and possible anticipation effects and treatment effects heterogeneity across countries. Results are displayed in the ten event-study graphs in Figs. 4 and 5 by using the specification with control variables.[22]

5.2.1. *Measuring remittances and disasters*

A first robustness check concerns the measurement of our key variables. As regards the dependent variable, in Fig. 4(a) we replicate the estimates using the series of unadjusted remittances (i.e., using the logarithm of real remittances as the dependent variable). Results are almost identical to the baseline in terms of temporal dynamics, but point estimates are slightly larger and less precisely estimated, thus reassuring us of the validity of using the seasonally adjusted remittance series.

Then, we examine whether and how the response of remittances changes if we consider either the severity or the number of natural disasters that happen in a single month. In Fig. 4(b), we restrict the analysis to disasters of a large magnitude. In this case, the disaster dummies are equal to one for natural disasters above the 50th percentile of the distribution of the total number of people affected by the event.[23] The temporal dynamics of remittance outflows is similar to that of the baseline model. As expected, however, the magnitude and significance of the coefficients increase with respect to the baseline. For the most serious disasters the response of remittances peaks in the first month immediately following the event, with an increase of about 1.15 percent

[21] Consistent with this conjecture, we find that when we repeat our event study analysis on the subsample of "small countries" (i.e., countries with a population below the median in our sample) the cumulative increase of remittances in response to a natural disaster is, on average, 6.2% up to six months and 12.2% up to 12 months after the event.

[22] Regression results for specifications without control variables are qualitatively and quantitatively pretty similar and are available from the authors upon request.

[23] Alternatively, in order to take into account the size of the country, we define the cutoff on the basis of the distribution of the share of the total population affected by the event. Results are largely confirmed.

compared to two months before the disaster, and remains significant up to the end of the sixth month. The magnitude of the cumulative increase of aggregate remittances in the first six-month period after the disaster is equal to 6%, almost two percentage points higher compared to our baseline estimates. Over a 12-month horizon, it rises up to 8.4% (3.2 percentage points higher than in the baseline). Moreover, it is interesting to note that the coefficient on the first lead is lower and loses significance. This is consistent with the hypothesis that migrants on average may anticipate the occurrence of natural disasters that are somewhat recurring, but are not able to anticipate their severity.

Alternatively, we replace the disaster dummies with the number of disasters which occur in each country during a specific month. Results reported in Fig. 4(c) are also in line with our baseline findings. The estimates of the lag coefficients for the number of disasters remain significantly greater than zero during the first three months after the disaster and point estimates confirm the expected stronger response of remittances when the home country is affected by multiple disasters.[24]

5.2.2. Country sample

Two additional concerns about the robustness of our baseline analysis may be related to the fact that (i) results may be driven by a few countries in the list of top remittance receivers from Italy that are also prone to several (often severe) natural disasters per year; (ii) results may underestimate or overestimate the response of migrants as official data on remittances do not include monetary transfers sent home through informal channels (money transfer organizations not subject to the obligation to report to the Bank of Italy information on transactions, direct money transfers, or indirect transfers through friends and relatives, when visiting the country of origin). For this reason, we rerun our event-study regressions by excluding, alternatively, (i) the top ten recipients of remittances from Italy (Romania, the Philippines, Morocco, Senegal, Bangladesh, Perù, Brazil, Ecuador, Albania and Ukraine); (ii) the four countries that, according to recent estimates by researchers at the Bank of Italy (Oddo et al., 2016), are the largest receivers of unofficial remittances, amounting to 75% of total money transfers leaving Italy through informal channels (Albania, Morocco, Romania and Tunisia).

Fig. 4(d) and (e) reassure us that baseline results are not driven by these countries. The response of remittances is positive and significant up to three/four months after the disaster. However, when excluding top recipient countries (panel (d)), the effect of disaster on remittances, though hardly significant, remains rather stable in magnitude for the entire effect window.

Finally, our results are broadly robust to the inclusion of remittances to China, despite the dubious nature of such outflows at least up to 2011. Baseline results are reinforced in terms of both magnitude and persistence, with point estimates steadily around 1% and significant at 10% level up to 6 months after the disaster (Fig. 4(f)).[25]

5.2.3. Effect window

An important robustness check of our results on the temporal dynamics of migrants' remittances to natural disasters in the country of origin concerns the size of the effect window and how to define the effect window endpoints.

First, we extend the number of leads and lags to 12 and 24 periods, respectively (thus, considering disaster events from February 2004 to November 2017). This exercise helps to assess whether the anticipation effect detected in our baseline specification with respect to the first lead is confirmed, and whether other lead coefficients are also statistically different from zero thus casting doubts on the disaster exogeneity hypothesis. At the same time, the inclusion of 24 lags allows us to test for intertemporal substitution effects in the response of remittances over a longer time frame following the disaster. Fig. 5(a) broadly confirms the temporal pattern of remittances irrespective of the length of the effect window. The anticipation effect is always limited to the month before the disaster, and the test of joint significance of lead coefficients confirms that pre-disaster dummies further away from the event date are not statistically different from zero. When focusing on lags, the initial positive response of remittances is followed by a slight contraction between 13–24 months after the disaster, although estimates become much less precise.

Second, we compare our baseline results with those obtained from Eq. (1) by assuming that the effect of any disaster event on remittances diminishes to zero outside the effect window [−3,+ 12] and that no disasters occur before and after the sample period. The presence of a country, Jordan, which was not affected by natural disasters during our entire event period (i.e., the presence of a never-treated unit) allows the model to be estimated for all leads and lags; however, to properly identify the secular time trend of remittances and the dynamic effects of disasters, the untreated country should have experienced no natural disasters outside the sample period too (Schmidheiny and Siegloch, 2023), an assumption which does not hold in our case as Jordan was hit by disaster events in years prior to the period considered in the analysis (precisely, 9 disasters between 1990 and 2002).

The restrictive assumption on the impact of disasters at the effect window endpoints generates results that are quite different from our preferred specification (Fig. 5(b)). In line with the baseline estimates with the binning of endpoints, remittances start to increase one month before the disaster strikes. However, throughout the twelve months following the disaster, remittance outflows to affected countries are on average higher by more than 1% compared to those sent to the countries that are not affected by disasters in the same months, without any tendency to reduce over the course of the year. Furthermore, this positive effect on remittances only becomes statistically significant eight months after the disaster, in contrast not only with our baseline results but also with previous evidence provided in the literature (Le De et al., 2015; Bragg et al., 2018).

5.2.4. Country–year fixed effects

In order to account for any (annual) potential confounder at the country level, we check the robustness of our results to the inclusion of a set of country–year fixed effects.[26] However, adopting a within-country–year approach limits the monthly dynamics of remittances to a calendar year. Thus, we expect the estimated average response in post-disaster periods (i.e., estimated lag coefficients) to be flatter as the weight of the months immediately following disasters increases.

The results reported in Fig. 5(c) largely confirm the positive response of remittances in the months following disasters that we find in the baseline model. However, as expected, the point estimates of the lag coefficients tend to remain rather stable over the entire effect window even if their statistical significance decreases.

[24] If we consider a country affected by two disasters in a month, the 6-month and 12-month cumulative response of remittances is 8% and 10.4%, respectively.

[25] When including China in our estimation sample, we only control for destination country's characteristics, as China's terms of trade and exchange rate may be strongly correlated with other private capital flows that up to 2011 had a prominent role in total transfers from Italy, as discussed in Section 3.

[26] To avoid excessive saturation of the model, in addition to country–year fixed effects we include a set of monthly fixed effects instead of monthly–year fixed effects. Results for the specification with both country–year and monthly–year fixed effects are qualitatively identical but coefficients are slightly less precisely estimated (results are available upon request from the authors).

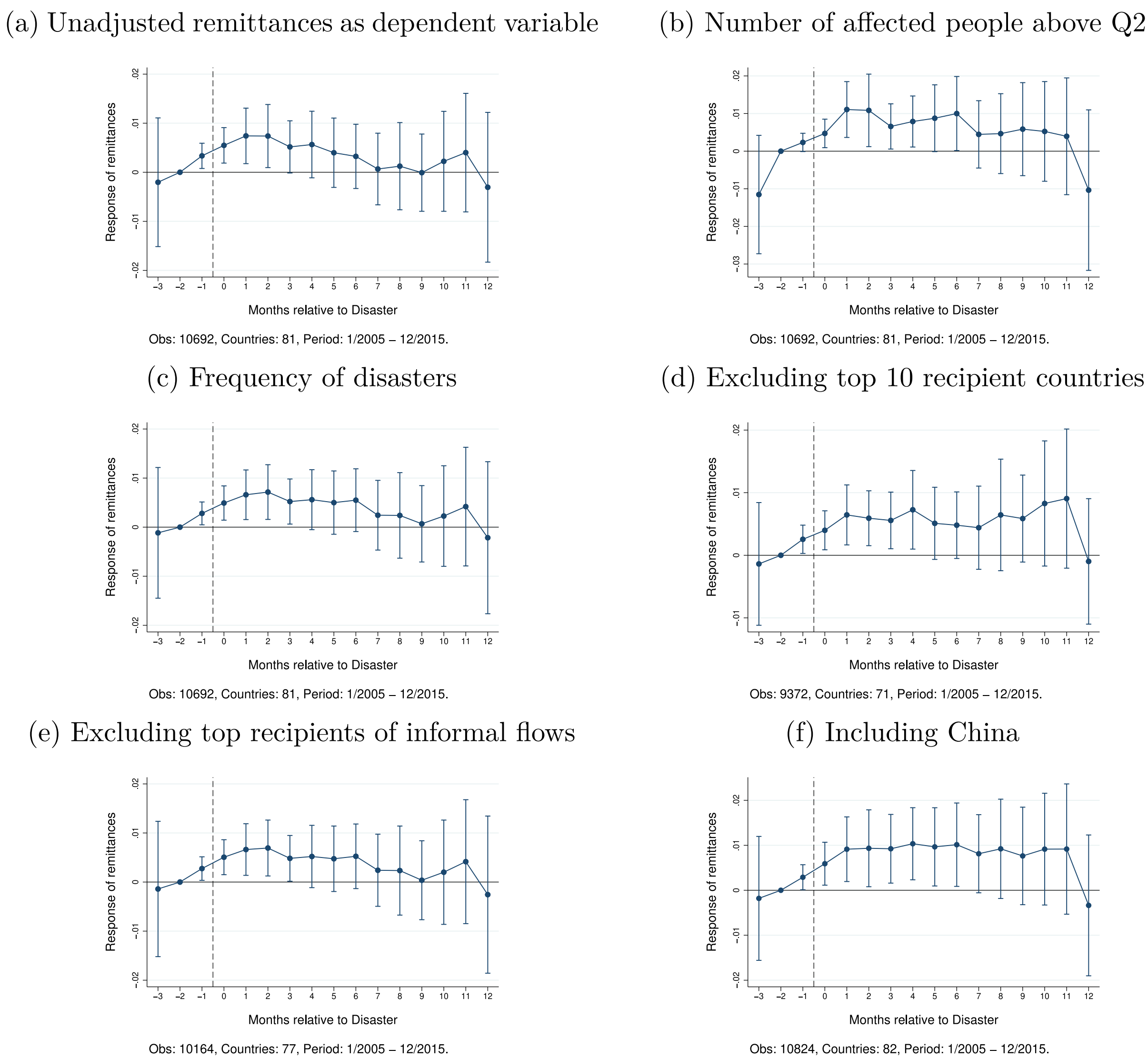

Fig. 4. Additional results and robustness checks.
Note: Panel (a) shows our baseline estimates of Eq. (2) with the logarithm of aggregate real remittances not seasonally adjusted as dependent variable. Panel (b) is estimated by considering disasters above the above 50th percentile of the distribution of the total number of people affected by the event. Panel (c) is estimated by replacing the disaster dummy with the number of disasters occurring in each country during a specific month. Panel (d) is estimated by excluding top 10 recipients of remittances from Italy: Romania, the Philippines, Morocco, Senegal and Bangladesh, Perù, Brazil, Ecuador, Albania and Ukraine. Panel (e) is estimated by excluding top recipients of informal remittances from Italy: Albania, Morocco, Romania, and Tunisia. Panel (f) is estimated including China in our estimation sample. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. Except for panel (a), the dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012). All specifications (a)–(e) include the following controls: terms of trade, exchange rate, unemployment rate and interest rate. Due to the peculiar nature of remittance flows from Italy to China discussed in Section 3, specification from panel (f) includes only destination country's controls.

5.2.5. Treatment-effect heterogeneity and anticipation effects

An increasing number of studies highlight that the use of standard two-way fixed-effects difference-in-differences and event-study estimators in settings with staggered treatments (such as ours) and heterogeneous treatment effects across groups and time periods can lead to biased estimates and fail to identify the average treatment effect on the treated (de Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Borusyak et al., 2024; Gardner et al., 2024). Furthermore, in this setting the estimated coefficients on the treatment leads from the event study may be different from zero even when the parallel trend assumption is actually verified (Sun and Abraham, 2021).

To address these concerns, we adopt the two-stage difference-in-differences (2SDD) estimator proposed by Gardner et al. (2024).[27] Precisely, the 2SDD procedure as applied to the event-study model of the remittance-disaster relationship in Eq. (2) works as follows:

(i) in the first stage, remittances are regressed on fixed effects and covariates for untreated observations (i.e., at the country–month–year level) without disaster leads and lags to obtain estimated values for $\hat{\lambda}_i$, $\hat{\tau}_t$ and $\hat{\delta}$

$$Y_{it} = \lambda_i + \tau_t + \sum_{z \in Z} \delta_z X_{Z_{it}} + \varepsilon_{it}; \tag{4}$$

[27] The estimator has been implemented in Stata and R with the packages DIDS2 and dids2 developed by Butts (2021) and Butts and Gardner (2022), respectively.

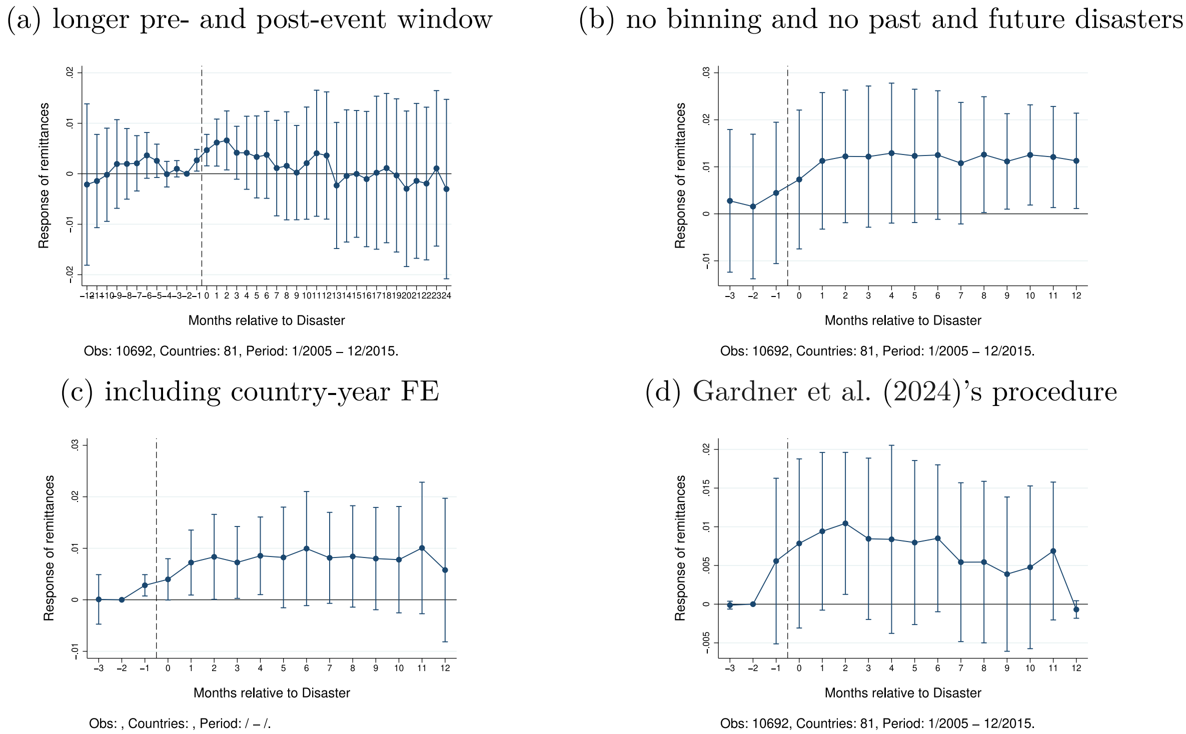

Fig. 5. Additional results and robustness checks.
Note: Panel (a) shows our baseline estimates of Eq. (2) with 12 leads and 24 lags. Panel (b) is based on the estimates of Eq. (1) with 3 leads and 12 lags, without account for past and future disasters and without binning the endpoints. Panel (c) shows our baseline estimates of Eq. (2) with a different set of fixed effects: country–year and month FE. Panel (d) shows estimates obtained through the Stata routine `dids2` developed by Butts and Gardner (2022) based on (Gardner et al., 2024). Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. In panel (b), all dummies are included as no reference period is needed when estimating the baseline model without binning the endpoints. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012). All specifications (a)–(d) include the following controls: terms of trade, exchange rate, unemployment rate and interest rate.

(ii) in the second stage, adjusted remittances – $\hat{Y}_{it} = Y_{it} - \hat{\lambda}_i - \hat{\tau}_t - \sum_{z\in Z} \hat{\delta}_z X_{Z_{it}}$ – are regressed on the set of leads and lags for the treated observations (at the country–month–year level):

$$\hat{Y}_{it} = \sum_{m=\underline{m}}^{\bar{m}} \beta_m \mathbb{B}_{it}^m + v_{it}. \tag{5}$$

Following Gardner et al.'s (2024) suggestion, in order to take into account the one-month anticipation effect identified in our baseline estimates and test for the parallel trend assumption, we redefine the disaster event and the treatment leads and lags as occurring one month before the actual date they occurred.

The results are reported in panel 5(d). Both the pattern and the magnitude of remittance response to disaster are very similar to the ones of the baseline model, even if point estimates become less precise. At the same time, however, estimation results are reassuring in terms of robustness to potential violations of the parallel trends assumption.

5.3. Heterogeneity

5.3.1. Type and nature of disasters

In this Section, we explore the heterogeneity of remittance response based on the type and nature of disaster events. As discussed in Section 3.2, we classify disasters into three main categories: climatic, geophysical, and meteorological. Results are reported in Fig. 6.

As expected, by analyzing the types of events separately the precision of the estimates is significantly reduced; countries not treated for one type of disaster could be treated for another, thus generating an attenuation bias. That said, the temporal dynamics of the response of remittances to the three types of disasters are clearly different. For climatic disasters in Fig. 6(a), post-disaster coefficients are broadly in line with our baseline estimates in terms of magnitude. The response peaks two months after the disaster; however, the contraction in remittance flows is rather rapid and around six to seven months after the event, remittances return to the pre-disaster level. The response of remittances to meteorological disasters displayed in Fig. 6(b) is on average much stronger in terms of magnitude, although the estimated coefficients are never statistically significant, and during the first six months it is steadily increasing before collapsing in the following months.

The dynamics of remittances associated with geophysical disasters is radically different. The impact of disasters such as earthquakes or tsunamis is likely to be localized, often having severe consequences on existing infrastructure and information and telecommunications services, thereby disrupting the channels through which remittances are usually sent home. This could help explain the negative response of remittances illustrated in Fig. 6(c) to this type of events. Although our results are not immediately comparable to previous literature, given the differences in disaster classification and empirical methodology, they are only partially consistent with those by David (2011), who finds a significant response of remittances to both climatic and geological disasters, and Yang (2008), who finds that poor countries exposed to hurricanes register an increase in remittance inflows.

Second, we distinguish natural disasters between sudden-onset and slow-onset events based on the length of time needed before the full scale of the disaster event is realized. Results are displayed in Fig. 7.

Remittances promptly respond to sudden-onset disasters, with a significant increase on impact that lasts up to the end of the second month after the disaster. In addition, the significant coefficient for the $t-1$ lead suggests that there is an anticipation effect for this type of disasters. In fact, although the definition of sudden-onset disasters includes events that can be considered exogenous and that occur in a very limited period of time, we cannot rule out the fact that some of

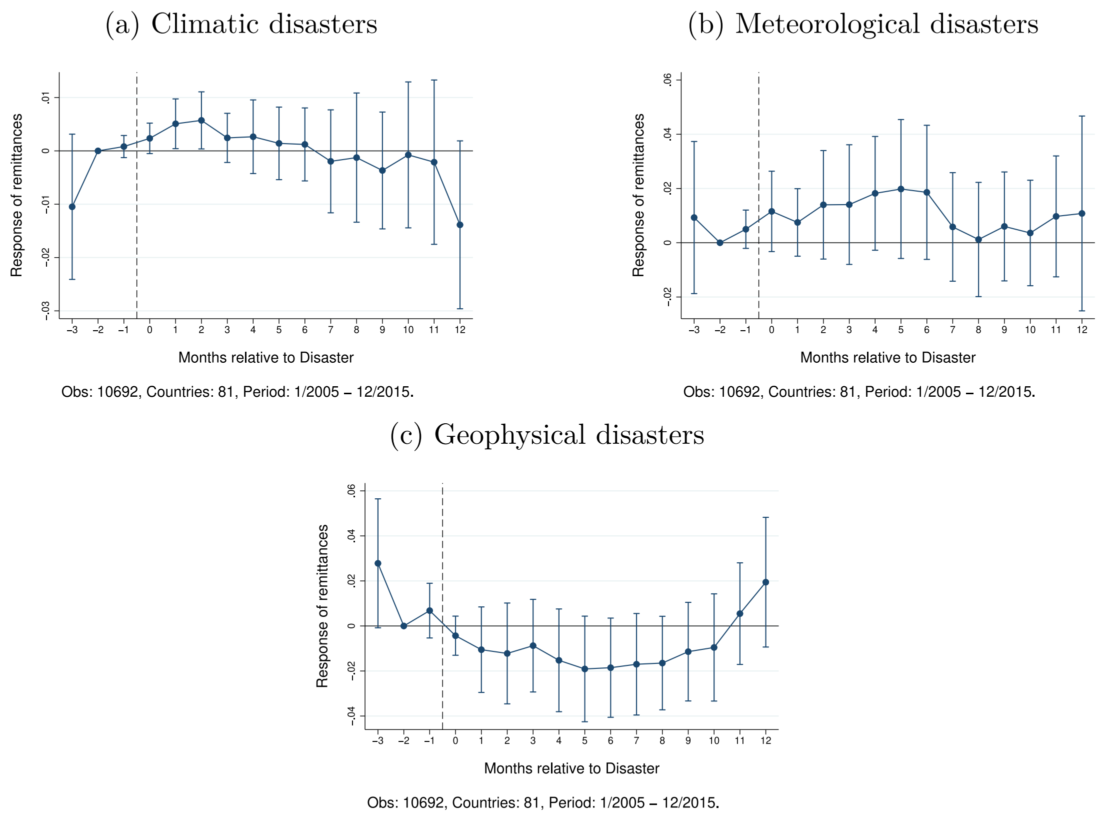

Fig. 6. Heterogeneity: type of disasters.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated by restricting the sample to climatic disasters: floods, droughts, wildfire and landslides. Panel (b) is estimated by restricting the sample to meteorological disasters: extreme temperatures and storms. Panel (c) is estimated by restricting the sample to geophysical disasters: earthquakes, volcanic activity and mass movements (dry). Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

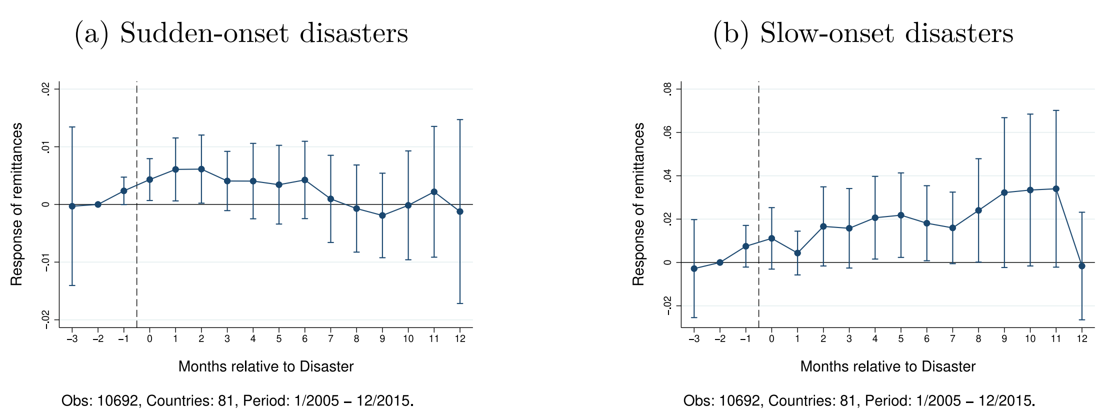

Fig. 7. Heterogeneity: nature of disasters.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated by restricting the sample to sudden-onset disasters: earthquakes, volcanic activity, mass movements (dry), storms, landslides and flooding. Panel (b) is estimated by restricting the sample to slow-onset disasters: extreme temperatures, wildfire and droughts. This classification is based on the Sendai Framework for Disaster Risk Reduction 2015–2030, adopted by UN Member States in 2015. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

them could be anticipated. In our estimation sample, the composition of sudden-onset disasters is dominated by floods and storms, together constituting about 85% of this subsample. Even if such events remain exogenous in terms of their precise occurrence time, they are likely to happen during a known time frame — the rainy season. This allows migrants and households to potentially anticipate and prepare for them. Therefore, it is not surprising that migrants, especially those with family and relatives in flood-prone areas, increase their remittances around the time when these events usually occur, in order to help households prepare for potential disasters. These funds could be used to invest in safeguarding measures to cope with the expected event, such as installing reinforced roofing, clearing waterways or improving drainage systems. Additionally, they could be allocated for immediate

(a) Countries with Italy among diaspora's top 20 destinations

(b) Countries with Italy outside diaspora's top 20 destinations

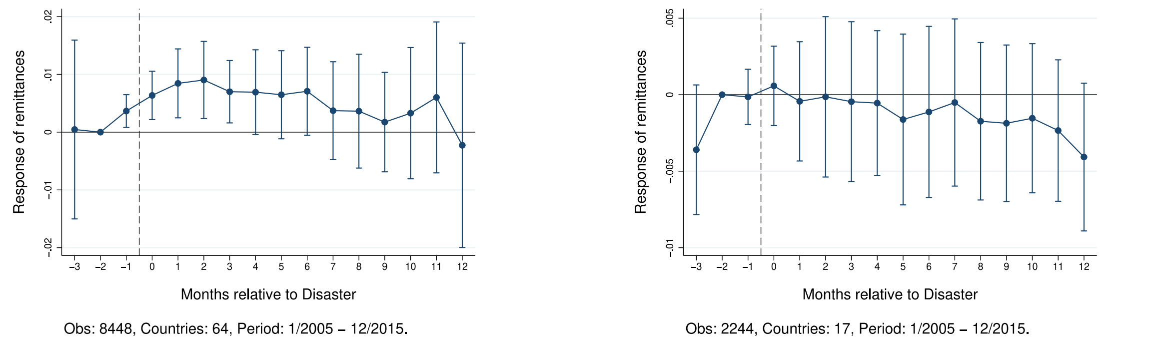

Fig. 8. Heterogeneity: Italy as top destination country.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated on the subsample of countries with Italy among their diaspora's top 20 destinations according to the average bilateral flow of migrants over the period 2005–2015. Estimates on bilateral flows are provided for 2005, 2010 and 2015 by Abel and Cohen (2022) through the Pseudo-Bayesian demographic accounting method. Panel (b) is estimated on the subsample of countries with Italy as minor destination for their diaspora abroad. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

precautionary actions, such as purchasing essential goods in anticipation of price surges that may occur after the shock due to potential supply chain disruptions.[28] It is worth highlighting the importance of an anticipatory response of remittances to disasters given the difficulty of organizing timely humanitarian interventions after a shock (FAO, 2021; OCHA, 2022), and the role that pre-emptive actions have in substantially limiting the asset loss and damage to affected populations (Pople et al., 2024).[29]

On the other hand, the response of remittances to slow-onset disasters is not immediate and becomes statistically significant only from the fourth month after the event. The remittance response increases over time and peaks ten to eleven months after the onset of the disaster. Therefore, even though slow-onset disasters allow for an extended period of forewarning and a potential proactive response both at the local and international level, which could in principle reduce the need for support from the diaspora abroad, the gradual buildup of damages over time leads to a constant growth in the support from the diaspora abroad.

5.3.2. Diaspora and migrant community concentration in Italy

Given the crucial role played by diasporas in determining migration and remittance patterns in response to adverse shocks in the origin country (Mahajan and Yang, 2020; Galstyan and Ambrosini, 2023), we investigate how baseline results change according to both the importance of Italy as a top destination of a specific migrant community, and the spatial concentration of such community across Italian regions.

In Fig. 8, we show estimates obtained by splitting the sample according to whether or not Italy is among the top destinations of each country's diaspora abroad. By making use of bilateral flows estimates provided for 2005, 2010 and 2015 by Abel and Cohen (2022) through the Pseudo-Bayesian demographic accounting method, we established whether Italy on average ranked among the diaspora's top 20 destinations worldwide over the period 2005–2015, and split the sample of origin countries accordingly. Therefore, panel (a) is estimated on the subsample of countries with Italy among their diaspora's top 20 destinations whereas panel (b) refers to the subset of remaining countries. Compared to our baseline estimates for the entire sample, disaster lag coefficients are slightly greater for the subset of countries of origin with Italy among the top 20 destinations: the magnitude of the response of remittances comes close to 1% in the first months, and remains pretty stable above 0.5% up to 6 months after the event. The remittance response is equally persistent up to the third month and a cumulative increase twelve months after the disaster equal to 7% of the level prevailing before the disaster. For the sample of countries with Italy as a minor destination, remittances seem not to react positively to disasters. Overall, results are in line with the evidence on the important role that the presence of diaspora groups plays for the magnitude of remittance flows and for guaranteeing support to home country's communities (Mohapatra et al., 2012; Bettin et al., 2017).

Then, we consider whether spatial concentration of a same-country migrant community in Italy affects how remittances respond to natural disasters at home. A well established literature has documented that the spatial density of an immigrant ethnic population in the host country matters for the 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 influence (possibly in opposite directions) the ability and willingness to increase remittances in response to adverse shocks (Marcelli and Lowell, 2005; Bettin et al., 2012; Carling and Hoelscher, 2013). Migrant hometown associations and charities are likely to develop and operate in localities where migrants are concentrated (Chauvet et al., 2015). In this case, the financial support to the home country might be indirectly channeled through such associations rather than through direct remittances.[30] Given these contrasting mechanisms, the net effect of immigrant spatial concentration on remittance responses to natural disasters remains an empirical question worthy of investigation.

[28] Consistently, a pre-crisis survey conducted by OCHA (2022) in the Philippines reveals that 81% of respondents plan to use cash assistance received shortly before a typhoon strikes to purchase food products, essential items for children, or first aid kits, which are anticipated to be in short supply after the event. A randomized experiment conducted by IRC & IFPRI (2023) further shows that anticipatory cash transfers encourage recipient households to invest in productive assets and take proactive measures, such as early harvesting and stockpiling food.

[29] In light of this, humanitarian organizations such as Mercy Corps are exploring initiatives aimed at harnessing the potential of remittances for anticipatory action. These include for example providing clients of digital financial services, who frequently send remittances to regions forecasted to experience extreme events, with an early warning and a financial incentive to remit, in the form of reduced fees (Tesfaye and Reid, 2023).

[30] Due to the unavailability of data on support provided to home countries by hometown associations and charities in the event of adverse natural events, we are unable to investigate this channel further.

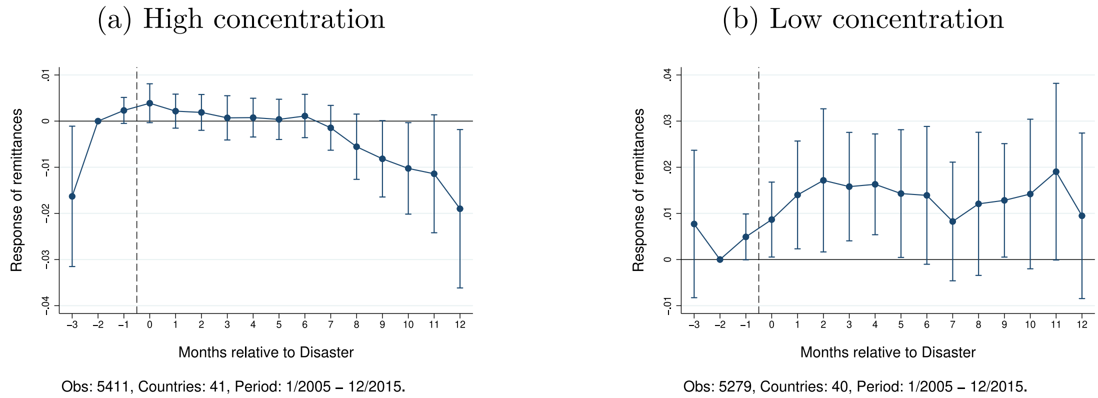

Fig. 9. Heterogeneity: spatial location of migrants in the host country.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated on the subsample of countries with high spatial concentration of migrants in Italy. Panel (b) estimated is estimated on the subsample of countries with low spatial concentration of migrants in Italy. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

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

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

We split our sample into two groups of national migrant communities with a spatial concentration in Italy above and below the median value of HHI.

Fig. 9(a) shows that remittances originating from migrant 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 and tend to become negative seven months after the disaster strikes. By contrast, the response of remittances sent by migrant groups more sparsely distributed across Italian regions is statistically and economically significant.

At first glance, this result may appear to conflict with the results presented in Fig. 8. When a country is the main destination for a specific diaspora, it is likely that many migrants from that community concentrate in a few specific regions of the host country. The differences we observe in the remittance responses between the two groups of countries – those with highly geographically concentrated communities in Italy and those for which Italy is a top destination – can then be explained by looking at the actual composition of these groups in our sample. In fact, 30 out of the 40 countries with more dispersed communities in Italy, including Albania, Bangladesh, Morocco, Romania and Ukraine, are also among those with Italy as a leading diaspora destination.

5.3.3. Home country's level of development

We further 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 strongly reduces both the precision and the power of our estimates, it is interesting to note that the overall response of remittances from Italy to natural disasters in migrants' home countries seems to be mostly driven by the diaspora from LICs and UMICs (Fig. 10(a) and (c)), with hardly any significant contribution by migrants from LMICs. This kind of U-shaped relationship between remittances' response to disasters and origin countries' average income level is partly in line with the evidence provided by Yang (2008), who found that remittances' response to hurricanes in developing countries was statistically significant only for the poorest ones.[31] At the same time, it may suggest complementarity between migrants' response to natural disasters via remittances and the probability of reconstruction in the home country. Richer countries (UMICs in this case), where the post-disaster reconstruction process is likely to be easier and faster, could also count on a larger and more rapid response of remittance flows from their migrant community abroad. Alternatively, we may interpret the origin country's level of development as a proxy for migrants' economic opportunities in Italy. People coming from UMICs such as Albania or Romania could integrate into the Italian labor market faster and this would make it easier for them to offer sizeable support when relatives and friends back home need assistance. Migrants from LICs, despite reacting significantly in the aftermath of disasters, would increase their transfer by significantly lower amounts due to their more precarious economic conditions.

5.3.4. Host country's economic conditions

Finally, we explore whether the economic conditions in the host country affect how remittances respond to natural disasters at home. To this end, we consider three different sub-periods: the pre-crisis period 2005–2008, the crisis period 2009–2012 and the post-crisis period 2013–2015. The results illustrated in Fig. 11(a) show that before the financial crisis, remittances increased on impact by approximately 1.1% compared to the level recorded two months before the disaster and by more than 2% six months later, and the response remained significantly greater than zero up to 9 months after the disaster. On average, during the pre-crisis period the cumulative increase in remittances over a 12-month horizon exceeds the level of remittances before the disaster by 22%.

In contrast, the ability of migrants to increase their remittances in response to a natural disaster in their country of origin was very limited during the years of the great financial crisis. During this period, the temporal dynamics of remittance outflows to countries affected by natural disasters mirrors the harsh economic conditions that most migrants were experiencing in Italy: a small increase in remittances between the first and second months after the event is followed by a strong negative rebound in the flow of remittances which brings them to a lower level compared to the pre-disaster period (Fig. 11(b)).

In the last period of our sample following the crisis (2013–2015), the response of remittances to natural disasters in the country of origin

[31] These partially different results are likely due to differences in the sample composition, in the types of disaster events and in the time period between the two analyses.

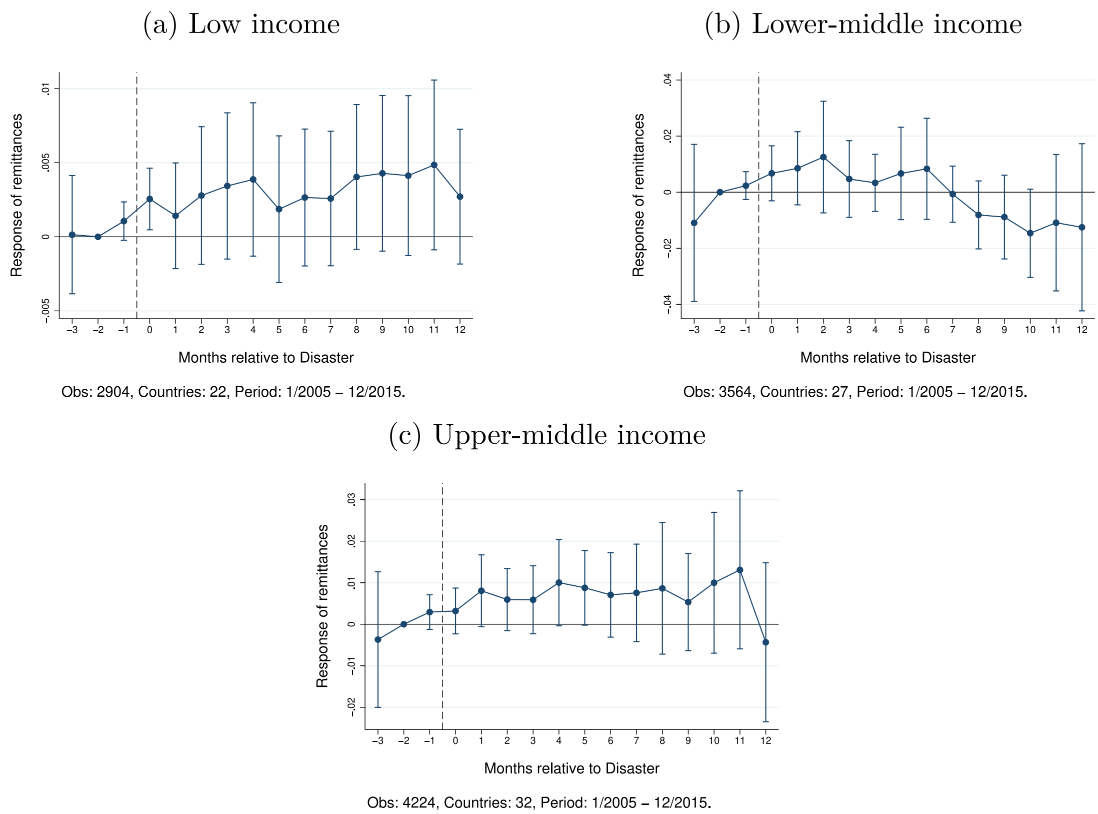

Fig. 10. Heterogeneity: home country's income level.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated for low-income (LIC) countries: Benin, Burkina Faso, Burundi, Central African Republic, Chad, Congo Dem. Rep., Ethiopia, Guinea, Guinea-Bissau, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Sierra Leone, Tanzania, Togo, Uganda. Panel (b) is estimated for lower-middle-income (LMIC) countries: Angola, Bangladesh, Bolivia, Cambodia, Cameroon, Cape Verde, Congo, Cote d'Ivoire, Egypt, El Salvador, Ghana, Honduras, Indonesia, Kenya, Kyrgyzstan, Mauritania, Moldova, Mongolia, Morocco, Nicaragua, Nigeria, Philippines, Senegal, Tunisia, Ukraine, Vietnam, Zambia. Panel (c) is estimated for upper-middle-income (UMIC) countries: Albania, Algeria, Argentina, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, Colombia, Costa Rica, Dominican Republic, Ecuador, Gabon, Georgia, Guatemala, Jamaica, Jordan, Kazakhstan, Lebanon, Malaysia, Mauritius, Mexico, Paraguay, Peru, Romania, Russian Federation, South Africa, Sri Lanka, Thailand, Turkey, Venezuela. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

returns to being positive, even if the effect of disasters is on average lower[32] compared to the pre-crisis period and less precisely estimated (Fig. 11(c)). In addition to the shorter estimation period, this can be explained by the fact that the effects of the economic slowdown that followed the double financial and sovereign debt crisis were not transitory and Italy experienced for several years a tense labor market and a persistent increase in poverty rates.

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. The inconclusive evidence sometimes provided by cross-country studies may indeed be explained by the fact that annual data fail to account for the actual response in migrants' transfers. Based on our estimates, this response is relatively quick, peaking within the first few months after the disaster. It generally tapers off within six to seven months at most. Following this period, remittance flows typically return to their pre-disaster levels and never become significantly lower. A similar exercise based on annualized data failed to reveal any significant response of remittances to natural disasters, due to both the short-term dynamics of the actual response and to the irregular and mostly unpredictable nature of different types of natural disasters over a standard calendar year.

The effect is driven by disasters occurring in countries where Italy is among the top destinations for the diaspora. At the same time, when migrant communities are more concentrated geographically in the host country, they tend to be less responsive to the occurrence of disasters back home. Additionally, poor socio-economic conditions faced by migrants abroad hinder their ability to send remittances, which explains the lack of a significant increase in international transfers following natural disasters during the double financial and sovereign debt crisis. 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 reaction to slow-onset events is apparently delayed and somewhat 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 with a large diaspora abroad that are increasingly exposed to such events. Migrant remittances can serve as immediate financial aid for households affected by disasters, often

[32] In 2013–2015 the cumulative increase in remittances in the 12 months following a disaster exceeds the level of remittances before the disaster by 4.4%.

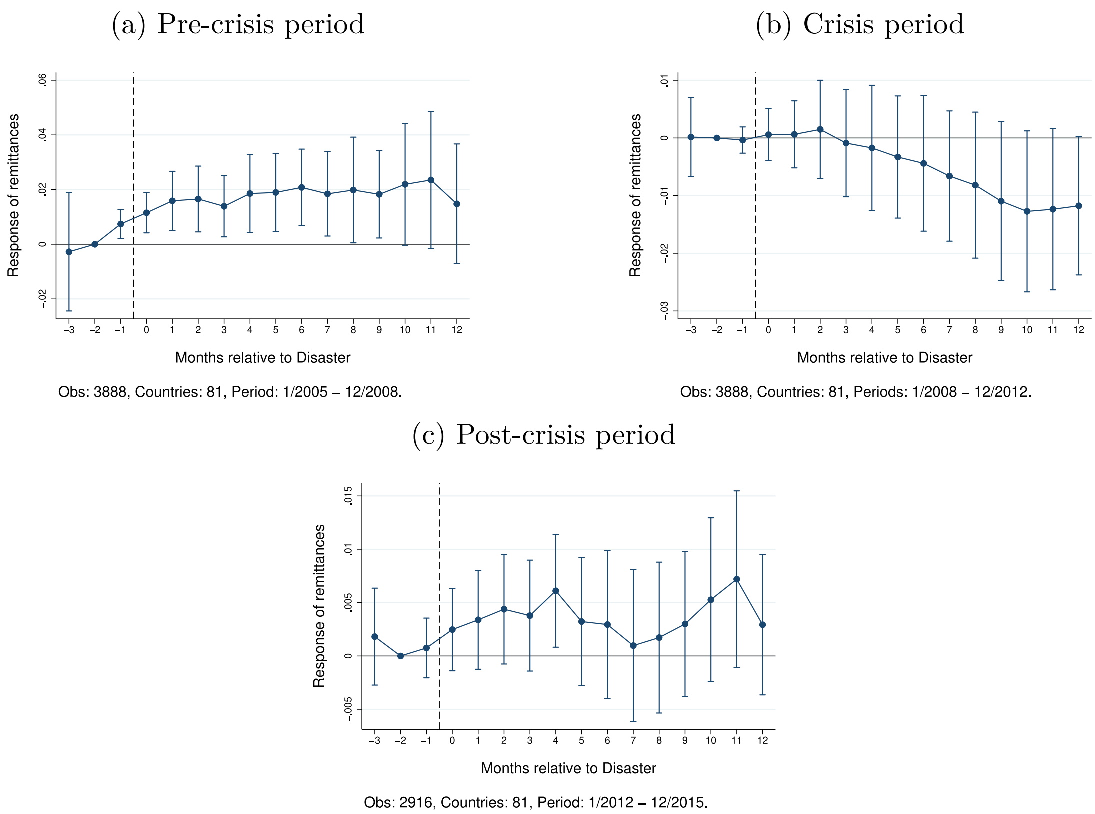

Fig. 11. Heterogeneity: host country's economic conditions.
Note: baseline estimates of Eq. (1) with 3 leads and 12 lags and the following control variables: terms of trade, exchange rate, unemployment rate and interest rate. Panel (a) is estimated by restricting the sample to the pre-crisis period 2005–2008. Panel (b) is estimated by restricting the sample to the crisis period 2009–2012. Panel (c) is estimated by restricting the sample to the post-crisis period 2013–2015. Plots are based on 90% confidence intervals. The dummy in $m = -2$ is set to zero for each disaster and serves as the reference point. The dependent variable is the logarithm of aggregate real remittances adjusted by applying the X-12-ARIMA seasonal-adjustment method of the U.S. Census Bureau with Stata (Wang and Wu, 2012).

compensating for the delayed arrival of official assistance, if available. Cash transfers may also provide affected households with greater flexibility compared to in-kind official assistance.

However, remittance effectiveness after a disaster depends on two key factors. First, individuals without access to remittance-receiving technology would remain extremely vulnerable in case of natural disasters, given that the diaspora abroad could hardly play any mitigating role. Second, high transaction costs may limit migrants' altruistic responsiveness in the aftermath of a disaster. Even though the capacity to remit is closely linked to migrants' economic circumstances in their host countries, a substantial reduction in the costs of international transfers would free up additional resources that may prove critical during humanitarian emergencies. Achieving the Sustainable Development Goal of reducing remittance costs to less than 3% by 2030 could thus represent a useful instrument not only to enhance the social and economic development of poorer countries but also to increase their resilience to extreme natural events.

CRediT authorship contribution statement

Giulia Bettin: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Amadou Jallow:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Alberto Zazzaro:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2024.103413.

Data availability

Data will be made available on request.

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