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Natural disasters impact, factors of resilience and development: A meta-analysis of the macroeconomic literature

Sara Lazzaroni and Peter van Bergeijk

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Please address comments and/or queries for information to:

Institute of Social Studies
P.O. Box 29776
2502 LT The Hague
The Netherlands
or
E-mail: wpapers@iss.nl

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Abstract

We systematize recent macroeconomic empirical literature on the direct and indirect impact of natural disasters providing a meta-analysis of 20 studies published during 2002-2013. We show that the disagreement between these studies is caused by the empirical design, the estimation technique and the resilience factors included in the analyses. The meta-regression suggests that studies that analyse indirect costs have a 88% higher probability to find a positive significant disaster impact than studies of direct costs. If the impact of the disaster is modelled through a disaster indicator, the likelihood of finding a negative and significant disaster impact increases by 64%.

Keywords

Meta-analysis; natural disasters, growth, resilience.

Natural disasters impact, factor of resilience and development[1]
A meta-analysis of the macroeconomic literature

1 Introduction

Small to large scale natural disasters have always affected societies around the world. Still the economics of natural disasters is a fairly recent branch of the economic research (Okuyama, 2007; Pelling et al., 2002). Before the 2000s this topic was almost exclusively in the domains of other disciplines of social sciences and the technical sciences (Cavallo & Noy, 2010). Due to both the higher frequency and intensity of natural disasters and their relation to global warming, that changed and the empirical literature on the economic impact of natural disasters has grown substantially during the last decade (Raschky, 2008).

Hallegatte & Przyluski (2010: 2) define a natural disaster as "A natural event that causes a perturbation to the functioning of the economic system, with a significant negative impact on assets, production factors, output, employment, or consumption". The definition excludes endogenously initiated man-made disasters (Albala-Bertrand, 1993a: 8), but the intrinsic exogenous nature of natural disasters does not preclude that their impact is influenced by the socio-economic, demographic and institutional characteristics of the areas in which they occur. It is in this sense that the economics of natural disasters is intertwined with the study of determinants of poverty and development including the role of risk, shocks and vulnerability.

The quest whether disasters are a problem *of* or *for* development started with the seminal works of Albala-Bertrand (1993a; 1993b) who develops a model and provides empirical estimates that indicate that the long run growth impact of a disaster-induced capital loss is small, so that a moderate increase in expenditures may be sufficient to prevent the growth rate of output from falling. From this provocative starting point, the literature has developed into three strands. Initially the approach was micro-econometric and/or case-specific. According to Noy (2009) the case studies and micro-econometric analyses substantiated the relevance of some social, economic and institutional country-specific characteristics in determining the macroeconomic impacts of natural disasters, in particular through their influence on households' decisions, thus clearing the way for the more recent macroeconomic analyses. This third new strand in the literature starts in the mid-2000s, is macroeconomic in nature and studies the economics of disasters from multi-country and/or multi-event perspectives. The debate in this macroeconomic literature focuses on the sign (positive or negative) of the impact of natural disasters and on the factors that mitigate this impact. We have identified 22 macroeconomic studies in the last decade that empirically try to assess the effects of natural disasters. In Table 1

[1] We would like to thank Chiara Mussida, Mariacristina Piva and Mario Veneziani for helpful comments.

TABLE 1

Studies used in the meta-analysis and summary statistics for reported t-values

Study	Dependent Var.	Disaster Var.	N(max)	N	Mean	St.dev	Min	Max	Median	DVAR	Model type
			Collected t-statistics								
Rasmussen (2004)	Affected, damage	Count	149	12	-2.06	2.64	-6.881	1.41	-2.31	1	1
	Affected, damage	-	149	12	1.35	1.59	-0.24	4.99	0.88	0	1
Anbarci et al. (2005)	Killed	-	269	12	1.54	3.67	-2.63	5.88	1.37	0	1
Kahn (2005)	Deaths	Count	1438	9	-2.82	2.05	-7.07	-0.89	-1.71	1	1
		-	1438	39	1.53	3.17	-5.91	5.84	1.84	0	1
Escaleras et al. (2007)	Killed	-	344	16	0.05	1.73	-2.33	2.62	-0.63	0	1
Stromberg (2007)	Killed	-	4064	5	0.73	2.67	-2.33	3.25	2.33	0	1
Toya and Skidmore (2007)	Killed, damage	-	3893	24	4.99	4.83	-1.28	18.92	3.53	0	1
Kellenberg and Mobarak (2008)	Killed	Count	3271	30	-16.78	6.13	-30.46	-6.68	-17.36	1	1
	Killed	-	3271	60	-2.01	5.13	-14.84	8.49	-1.10	0	1
Raschky (2008)	Killed, damage	Affected	2792	6	-14.70	2.29	-16.83	-12.29	-14.78	1	1
	Killed, damage	-	2792	16	5.94	5.09	0.97	15.12	3.14	0	1
Padli and Habibullah (2009)	Killed	-	-	3	-1.24	6.55	-8.80	2.84	2.23	0	1
Padli et al. (2010)	Affected, killed, damage	-	73	27	4.20	12.94	-15.72	38.05	0.79	0	1
Toya and Skidmore (2013)°	Killed	-	2941	80	0.44	2.55	-7.72	4.64	0.26	0	1
Skidmore and Toya (2002)	GDP	Count	89	44	0.80	2.32	-3.09	3.91	1.65	1	2
Haeger et al. (2008)	GDP	Dummy, count, affected, killed, damage	363	11	-1.22	1.51	-3.65	1.02	-1.57	1	2
Tavares (2004)	GDP	Count	2418	45	-2.02	0.22	-2.24	-1.38	-2.13	1	2
Noy and Nualsri (2007)	GDP	Killed, damage	476	46	-0.75	1.14	-2.44	1.50	-0.83	1	
Noy (2009)	GDP	Dummy, damage	1574	41	-2.69	3.42	-11.04	8.90	-2.55	1	2
Jaramillo (2009)	GDP	Count, affected, killed, damage,	-	168	0.39	1.73	-3.34	5.29	0.45	1	2
Kim (2010)	GDP	Count	88	15	1.49	1.32	-1.32	2.97	2.06	1	2
Vu and Hammes (2010)	GDP	Affected, killed, damage	390	17	0.71	1.61	-3.17	3.13	0.86	1	2
Bergholt (2010)	GDP	Dummy, killed affected, damage	4279	41	-2.04	1.41	-5.78	0.57	-1.88	1	2
Strobl (2011)	GDP	Damage	14724	10	-1.93	1.94	-4.65	1.70	-2.52	1	2
Loayza et al. (2012)	GDP	Count	545	40	0.00	2.38	-4.05	5.53	-0.26	1	2
DVAR=0				291	1.17	5.76	-15.72	38.05	1.20		
DVAR=1				367	-2.52	5.42	-30.46	8.90	-1.71		
Model (1)				348	-0.86	7.75	-30.46	38.05	0.21		
Model (2)				310	-0.91	2.36	-11.03	8.90	-1.35		
Full Sample				658	-0.89	5.86	-30.46	38.05	-0.78		

Source: Authors' elaborations.

Note: Descriptive statistics for the studies on direct costs (Model type 1) are calculated changing the sign of the t-statistics reported in the original study to allow the same interpretation of the effects of disasters across model types. For example, if in the original study on direct costs a disaster indicator had positive t-value, it indicated an increase of disaster direct cost, that is a negative impact of the disaster, hence in our dataset we recorded that t-value with a negative sign. DVAR captures the nature of the collected parameter: it is 1 if the parameter corresponds to a disaster variable, 0 if it corresponds to a resilience factor variable. °See note below table 6.

we report the summary statistics of the collected t-values in the 22 studies in order to present an overview of the findings in the literature.[2] The median coefficient with respect to the ability of certain factors to mitigate disaster direct costs is positive in 9 cases and negative in 2 studies. Disaster frequency/severity worsens direct impact of a disaster in all the 4 studies that considered these indicators. The impact on growth is positive in 4 studies and negative in 7 studies. The average coefficient for direct costs studies is -0.86 and its standard deviation is 7.75, while the average coefficient for growth-disaster studies is -0.91, with a standard deviation of 2.36. Only one study (Tavares, 2004) reports consistent signs in all estimated equations (in this case the values are always negative and between -2.24 and -1.38. Overall, natural disaster have an average t-value of -0.89.

The disagreement between studies may be caused by methodological differences as suggested by the apparent heterogeneity in the data, the specifications and the estimation procedures. In such a context a meta-analysis of the reported results can be used to shed light on the impact of the methodology on the reported results. The first contribution of this paper is that we provide such a meta-analysis relating the reported test statistics to the respective methodological characteristics. Meta analysis is a relatively new research technique in economics but is well accepted in other fields such as medicine and psychology. Recent examples in development economics include: Doucouliagos & Paldam (2011), Havránek & Iršová (2010), and Mebratie & Bergeijk (2013). The parameters that build our meta-dataset have been derived from studies that were identified in an extensive search of macroeconomic published articles, books, book chapters, working papers and conference papers as detailed in Section 3.

In this article we focus on the macroeconomic analyses because this part of the literature is more homogeneous. The microeconomic literature, for example, is very heterogeneous in terms of the study-specific research questions that reflect the manifold contexts and/or the investigated household coping strategies. It would be difficult to combine the three strands of the literature because they use completely different indicators of disaster outcome. The case studies and the micro econometric analyses focus on sectoral losses or losses from individual events (Benson & Clay, 2004; Vos et al., 1999), consumption (Dercon, 2004; Kazianga & Udry, 2006) or health outcomes such as the Body Mass Index (Maccini & Young, 2008; Dercon & Krishnan, 2000), the macroeconomic studies concentrate on disaster damages in per cent of GDP, number of people affected and/or killed by the natural disasters and the effects of natural disasters on GDP.

[2] Note that for ease of discussion we report t-values always in a way that 'negative' impact means that the costs of the disaster are larger. In growth studies a negative t-value of the natural disaster variable indicates a growth slow down. However, if the original study investigates the direct costs of a disaster (disaster damages, affected or killed) then a negative t-value in the original study indicates smaller impact. Hence, to allow comparisons between the studies we changed the sign of the parameters for the studies on disaster direct costs (upper part of Table 1, model type 1)).

As we will see in Section 2, relevant heterogeneity exists even within the relatively homogeneous subgroup of macroeconomic studies as the macroeconomic empirical literature quantifies the effects of natural disasters in terms of determinants of either direct disaster costs and/or the short/long-run growth effects of direct, indirect and secondary impacts (Cavallo & Noy, 2010). For the purpose of our analysis it is important to note that while fundamentally different, the determinants are at the same time highly interrelated. For this reason the studies of direct and growth effects of natural disasters are seen to be complementary in the understanding of the role of disasters during the process of development. Indeed as pointed out by to Pelling et al. (2008: 258):

> […] there are many linkages between [direct, indirect and secondary] losses. Direct losses are incurred during the damage stages of a disaster but may lead to indirect losses resulting in secondary effects that continue to be felt throughout the recovery stage and may shape the preconditions of subsequent vulnerability. Reduced output and employment opportunities from direct and indirect damage in impacted activities or economic sectors create knock-on indirect and secondary costs through reduction in consumption and investment, reduced productive capacity and increased social costs (resettlement, health impacts).

The literature on indirect impacts of disasters frequently refers to the literature on direct costs when motivating the empirical design of the studies. First, indirect and secondary effects of disasters ultimately derive from the frequency, magnitude and incidence of natural events, so that an indicator for disaster direct impact is always included in the empirical analysis. Second, findings of direct costs mitigation factors are often used to justify the inclusion of similar variables in the empirical model of the indirect impact. For example, Noy (2009) refers to Rasmussen (2004), Kahn (2005) and Toya & Skidmore (2007) to support the inclusion of political economy and income level variables. The second contribution of this paper is that we clarify where the methodologies differ and how this affects the results reported in the literature.

The paper is structured as follows. Section 2 explores the existing macroeconomic literature on natural disasters and provides a classification of the 22 studies that make up our sample according to the main research questions and approaches in the analysis of disaster impacts. Section 3 describes the construction of the meta-dataset and introduces the dependent and explanatory variables as well as relevant descriptive analysis. Section 4 presents and discusses a multinominal logit analysis of the 658 regressions that form our dataset. The empirical results show that the empirical design of the studies is highly relevant for the sign and level of significance of estimated disaster impact. In particular, when a disaster indicator is included in the model there is a higher probability that the study reports a negative and significant impact. The use of the EM-DAT dataset, the inclusion of more recent years and of countries belonging to specific regions of the world also influence the reported marginal impact of disaster outcome and of some resilience factors. Section 5 concludes giving suggestions about the direction that future research in this field will have to take to better understand the economic impact of natural disasters.

2 Review of the macroeconomic literature on natural disasters

The macro econometric analyses focus on the effects of series of natural disasters investigating their 'mean' costs (Hallegatte & Przyluski, 2010). According to the ECLAC methodology, costs from disasters can be direct, indirect or secondary (Zapata-Marti, 1997: 10-11).

- Direct costs are represented by damages at the moment of the event: market losses such as damages to assets, goods and services for which a price is observable, and non-market losses like losses of lives or number of people affected by the disaster (Hallegatte & Przyluski, 2010).
- Indirect costs account for losses induced by disasters in terms of flows of goods, services and business revenues that will not be generated due to destructions or business interruptions (Hallegatte & Przyluski, 2010).
- Secondary effects are effects on the performance of the overall economy, quantifiable through the most relevant macro-economic variables in one or more years after the disaster occurred (Zapata-Marti, 1997: 10-11).

According to Albala-Bertrand (1993a: 11), a disaster impact is a sudden and sharp imbalance between the forces of the natural system and the counteracting forces of the social system. In this vision the magnitude of the natural event is an important input to the system but the outcome in terms of vulnerability of people and activities and the severity of the disequilibrium would be determined by on the one hand, geophysical and/or biological processes and on the other hand, social processes. Rasmussen (2004) emphasizes the importance of both systems in transforming a natural event in a natural disaster. His analysis of the Caribbean context suggests that decreasing number of disasters per capita and increasing per capita income levels reduce both the number of affected and the economic damages from natural disasters[3].

Kahn (2005) was the first to consider the role of institutions in mitigating disasters. His findings suggest that more democratic countries experience lower death counts. Accounting for corruption and government effectiveness, respectively, Escaleras et al. (2007) and Raschky (2008) find similar results. In contrast, Strömberg (2007) and Toya & Skidmore (2013) show a negative but non-significant effect of increasing democracy and political rights and a positive but non-significant effect of civil liberties levels, while other institutional characteristics (government effectiveness and decentralization) showed a positive effect in disaster deaths reduction. Similar deaths reductions

[3] Similar results for population and income are found in the studies in our sample, indicating robustness of income and population effects to differences in sample countries and time span. Raschky (2008) is the only author showing positive correlation between population and disaster deaths and damages.

could be brought about by increasing education and openness (Padli et al., 2010; Toya & Skidmore, 2007, 2013). Despite the increasing recognition of the role of institutions in fostering growth and development, institutions seem to have been rather neglected in the growth-disaster analysis, although some studies acknowledge their potential to mitigate the impact of disasters (Noy, 2009; Noy & Noualsri, 2007). Loayza et al. (2012) introduce institutions in the analysis claiming that their effects would be embedded in GDP initial level, share of investments, financial depth, government consumption to GDP, education and openness, but this would imply a redefinition of the concept of institutions in a too broader sense (in Section 3 and Table 5 we clarify the difference between institutions and institution quality indicators). Only one study of direct costs (Rasmussen, 2004) accounts for the share of investment in GDP as investments in preventive measures may help to mitigate disaster impacts. In contrast investments do appear frequently in the analysis of the (direct and indirect) effects of disasters on growth, often proving to be a positive and significant determinant of growth (see for example Kim (2010) or Skidmore & Toya (2002)).

Temporal and spatial distributions of natural events determine disaster incidence, and therefore it is important to consider the criteria used to decide on the country and disaster samples in the studies. Some studies claim that some regions are more prone to disasters. For example, Rasmussen (2004) and Heger et al. (2008) analyzed the Caribbean economies because the Caribbean is highly affected by natural hazards. Cavallo & Noy (2010) and Padli & Habibullah (2009) identify the Asia-Pacific region as the area with more disasters. In contrast, Strömberg (2007) argues that exposure to natural hazards is the same for high and low income areas. UNDP (2004: 3) proposes that the impact of natural disasters also depends on the type of disaster. Earthquakes would affect more countries where urbanization is increasing, tropical cyclones more harmful for countries with higher arable land and floods those with higher population density. Hence, again it is the combination of both natural and physical-socio-economic systems that ultimately determined the severity of the disaster-induced imbalance and a meta-analysis is needed to better grasp the contribution of each factor to shape the empirical results.

TABLE 2

Model type in the studies included

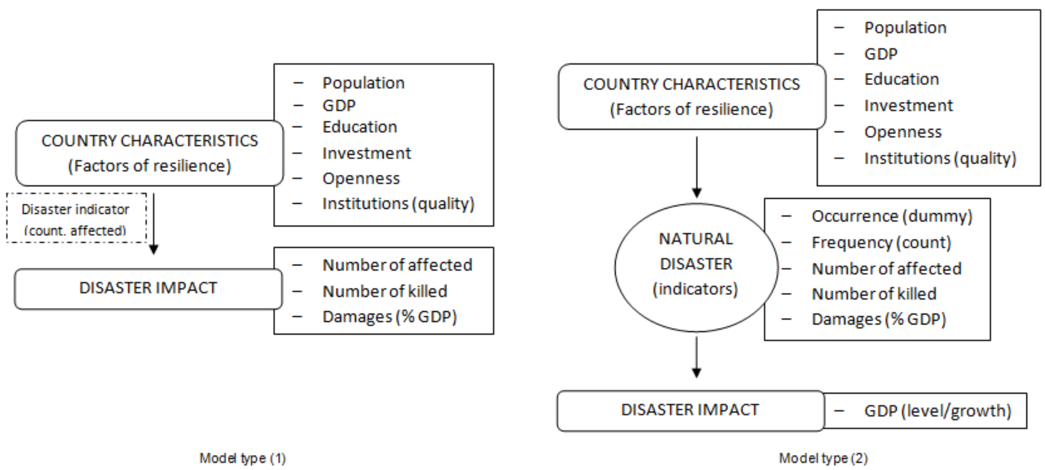
Model		Research question
(1)	$DI_{it} = \alpha + \delta FR_{it} + u_{it}$	Disaster direct costs and resilience
(2)	$G_{it} = \alpha + \beta DV_{it} + \gamma FR_{it} + u_{it}$	Disaster indirect/secondary costs
i	Index to countries	
t	Index to time	
DI_{it}	Disaster damages, affected or killed	
G_{it}	GDP (level/growth rate)	
DV_{it}	Disaster variable (dummy, count, killed, affected, damages)	
FR_{it}	Factors of resilience	
u_{it}	Residuals	

Note: Greek letters are used to denote the estimated coefficients.
Source: Authors' elaborations.

Building on the review above, we classify the studies according to the main research questions and approaches in the analysis of disaster impacts (Table 2). The first approach (Model 1) deals with direct costs of disasters, studying the role of socio-economic factors in mitigating or enhancing the adverse effects of disasters. Model 1 type studies study only periods in which disasters actually occurred and therefore do not have a disaster variable in the equation. (Four of these studies control for disaster frequency/severity: Kahn (2005); Kellenberg & Mobarak (2008), Raschky (2008) and Rasmussen (2004). The second approach studies the impact of natural disasters on GDP. It uses a specific 'disaster variable' that accounts for the occurrence of the phenomenon. The disaster variable can be a dummy, a disaster frequency or a variable describing the number of people affected or killed or the damages reported in case the disaster occurred (direct costs).

FIGURE 1

Chain of causality in the models in the selected studies.



Source: Authors' elaborations

As illustrated in Figure 1, type (1) models only deal with disaster periods or situations, use the disaster variable as the dependent variable and focus on the factors that influence the disaster's impact (the dashed rectangle represents the studies that include also a disaster frequency/severity indicator). In contrast model type (2) compares periods or situations in which disasters occur with periods or situations in which no disaster occurs. So the variables accounting for number of affected or killed and damages are a disaster impact variable in model type (1) and a disaster indicator in model type (2), the two models use common sets of explanatory variables.

One purpose of the meta-analysis is to correct for the differences in methodology and their impact and to distil the evidence that is in the 22 studies despite these differences.[4] This is highly useful, first, because in practice cross referencing regularly occurs in the literature and therefore it is important to investigate the merit of the research strategies and, secondly because the combined analysis sheds light on the role of considered resilience factors in determining disasters impacts in the short- to long-run. In particular the control variables (resilience factors) in models of type (2) (or model type (1) if the t-value refers to a disaster frequency/severity indicator) contribute to both the magnitude and the level of significance of the disaster variable coefficient to the extent they are correlated with it and with the dependent variable. If they are correlated with the disaster variable but not included as explanatory variables in the equation, the internal validity of the model will be compromised (due to underspecification) and the OLS estimators will be biased. Indeed, if the disaster impact and the factor of resilience are correlated, there is a bias in the coefficient of the disaster variable (Wooldridge, 2009: 90). In order to investigate this issue we collected t-values for the disaster variable for models type (2) and in our meta analysis we account for selected resilience factors included in the specifications. With respect to model type (1) analysis the approach is straight forward and we collected the t-values corresponding to the selected resilience factors. If a study using model type (1) was including a disaster frequency/severity indicator in the explanatory variables, we recorded the t-value accounting for the selected resilience factors included in the specifications as we did for disaster variables in studies using model type (2). For example, Strobl (2011: 584) analyzing the growth impact of hurricanes from specification 2, reports the following equation (t-values in parenthesis)

$$GROWTH_{i,t-1\to t} = \alpha - \underset{(-2.509)}{0.0451} HURR_t - \underset{(-28.640)}{0.0523}\, log(INITIAL)_{t-1} \qquad \text{(Ex.1)}$$

Based on this equation we record in our meta dataset the t-value (-2.509) corresponding to the disaster variable (in this case $HURR_t$ a proxy of hurricanes damages), a value 1 for the dummy for model type (2) (TYPE2=1) and for the dummy accounting for the use of a disaster variable (DVAR=1). As the specification includes initial income $log(INITIAL)_{t-1}$, we recorded value 1 in the meta dataset for the income resilience factor variable (GDP). The same procedure was applied to all other specifications in the tables in the article. The procedure is similar for studies with model type (1) except that in this case the dummy accounting for model type of course takes value zero (TYPE2=0) while the t-value recorded and the value of DVAR depend on the specifications estimated in the study. For instance, in the work by Kellenberg and Mobarak (2008: 796) specification (1) in their Table 1 is (robust standard errors in parenthesis)

[4] We also present separate results for the two groups of studies depending on the nature of the coefficient reported in the original study (disaster variable or resilience factor).

$$ln(KILLED_t + 1) = \underset{(0.023)}{-0.126} ln(GDPpc)_t + \underset{(0.024)}{0.325}\, ln(Tot.Pop)_t + \underset{(0.037)}{0.442}(\#ND)_t \quad \text{(Ex.2)}$$

In this case we calculate the t-value of the disaster count variable $\#ND_a$ as 0.442/0.037 = 11.9, we change its sign to allow comparison with growth studies (see note 1) and record DVAR=1 and GDP=1 since the regression is accounting for GDP as a possible resilience factor as in the study by Strobl (2011). We also calculate the t value (again with opposite sign) of the resilience variable $ln(GDPpc)_t$ and record in the respective row DVAR=0 and GDP=1.

3 Meta analysis and meta dataset

We derive the parameters for our meta-dataset from 22 studies that we identified in an extensive search using Econlit and Google Scholar and deploying broad keyword listings with the following terminologies: 'natural disasters', 'impact', 'growth', 'economic development', 'development', 'killed', 'affected', 'institutions'. Literature reviews were not included. Moreover, since we are interested in collecting coefficients and/or t-statistics of the variables considered, empirical works using vector autoregressive models and input-output analyses could not be included since the former reported the impulse response functions only and not the short and long-term coefficients while the results of the input output analyses by design do not provide the standard errors or t values that we need in our meta analysis. Finally, we excluded the studies of Padli et al. (2009) and Jaramillo (2009) because they were not reporting the number of observations in the estimations presented. The 20 studies provide us with a total of 658 t-values divided more or less equally across Type 1 regressions (348 t-values) and Type 2 regressions (310 t-values).

This section first discusses the variables included in the meta dataset and then sets out the econometric approach that we follow in the meta analysis.

3.1 Dependent variable: t-values of direct and indirect disaster effects

Since both the research question and the model specification (log-log, linear-log, log-linear, linear) used across the studies are different and because the necessary information to derive comparable elasticities is often not reported in the studies, we conduct our analysis on the reported t-statistics. This has the advantage that t-values are dimension-less and hence more comparable. Since the major discussion in the literature is about sign and significance the focus on t statistics is appropriate.[5]

[5] This is a common nuisance encountered by other meta analyses as well; see Moons and Van Bergeijk (2012).

Table 1 lists the studies included in the meta-dataset.[6] The variability in the number of observations and level of significance of the mean/median collected t-statistic across the selected studies is evident. As noted before this variability could be the result of different choices in the model specification such as number of countries considered, length of the reference period of time, panel structure of the data, model type and estimation methodology, resilience factors etc. Before discussing in depth the meta-analysis' empirical strategy in Section 4, we take a closer look at the dependent variable. We compute composite t-statistics for some of the variables that we will use as moderator variables (sources of heterogeneity in the results of the studies). In doing this we follow the approach of previous meta-analysis (Sinani & Meyer, 2009; Havránek & Iršová, 2010 and Mebratie & van Bergeijk, 2013) and calculate the composite t-statistic as

$$t_C = \frac{\Sigma t_i}{\sqrt{N}} \sim N(0,1) \qquad (1)$$

Indeed the precision of a population parameter increases in sample size. So by broadening the sample and using the information contained in their samples, the combination of the individual studies is expected to generate a more significant result (a t-value that differs more from zero, either positively or negatively). In light of the variability of the number of observations in the selected studies, it is important to follow Diebel & Wooster (2010), Djankov & Murrell (2002) and Mebratie & van Bergeijk (2013), and calculate a weighted composite statistic

$$T_{WC} = \frac{\sum_{k=1}^{n} w_k t_k}{\sqrt{\sum_{k=1}^{n} w_k^2}} \sim N(0,1) \qquad (2)$$

where w_k is the weight assigned to the nth t-value in the meta-dataset calculated as the reciprocal of the number of observations in the regression from which the t-value was taken. Table 3 presents the aggregated and weighted t-statistics. Calculations were also conducted excluding extremely high t-values (>10) for a remaining number of 606 t-values.

The unweighted and weighted statistics presented in Table 3 suggest that looking at more than one weighting scheme can give more insights on the analysis of the reported t-statistics. For example, we can see that the weighted statistics are always lower than the composite ones, however, this especially applies for the categories that are more likely to present significant results (panel studies and studies using EM-DAT). More generally, the aggregate t-statistics are always statistically significant, even in the case we exclude outliers while they decrease substantially when we use the median.

[6] The studies that do not report the number of observations and are therefore not included in the meta-dataset are highlighted in grey.

TABLE 3
Aggregate t-statistics of the selected studies

	Using median t-statistics from each study		All observations		Excluding outliers		Weighted all observations		Weighted excluding outliers	
	TC	N	TC	N	TC	N	TW	N	TW	N
All studies	7.98	20	90.59	658	57.68	606	63.18	658	42.44	606
Variable type										
Disaster (DVAR=1)	5.16	10	67.05	367	39.56	335	44.46	368	32.15	335
Resilience (DVAR=0)	6.12	10	60.93	291	42.26	271	45.06	291	29.17	271
Type of data										
Panel	7.74	16	83.09	548	53.86	503	54.46	549	41.46	503
Cross-section	2.34	4	36.11	110	20.88	103	33.31	110	15.82	103
EM-DAT	27.20	16	89.07	598	54.52	546	63.44	599	38.96	546
Non EM-DAT	8.47	4	18.83	60	18.83	60	16.88	60	16.88	60

Source: Authors' elaborations.

3.2 Explanatory variables

The heterogeneity in the results of the studies on the impact of natural disasters could be due to three methodological choices: empirical design (database, disaster type, period and space choices to delimitate the subsample for the analysis), resilience factors included in the study, model type and econometric estimation technique.

Disaster data

Four studies (Strobl, 2011; Anbarci et al., 2005; Escaleras & Anbarci, 2007; Skidmore & Toya, 2002) used other databases (see Table 4 for further details on the different databases). Since the database used could have influenced the result of the study, we include a dummy in our meta-equation that assumes the value 1 if the study was conducted using EM-DAT, and 0 otherwise.

TABLE 4
Databases with information on natural disasters used in the selected studies.

	Studies by model type	
Database	(1)	(2)
EM-DAT	Rasmussen (2004) Kahn (2005) Stromberg (2007) Toya and Skidmore (2007) Kellenberg and Mobarak (2008) Rascky (2008) Padli et al. (2010) Toya and Skidmore (2013)	Skidmore and Toya (2002) Tavares (2004) Noy and Noualsri (2007) Heger et al. (2008) Noy (2009) Bergholt (2010) Kim (2010) Vu and Hammes (2010) Loayza et al. (2012)
HURDAT	0	Strobl (2011)
Davis (1992)	0	Skidmore, Toya (2002)
NGDC	Escaleras, Anbarci (2007) Anbarci et al. (2005)	0
Total	10	10

Source: Authors elaborations on the selected studies.

Disaster type

The type of the disaster investigated could have influenced the results across the studies in the sample since different studies accounted for different types of disasters. For example, according to the multi-country analysis of Bergholt (2010), hydrometeorological events such as floods, wet mass movements and storms would reduce short term growth more than geophysical disasters like earthquakes and volcano eruptions (-0.5% and -0.1% respectively). Similarly, Rodriguez-Oreggia et al. (2010) analyzing the case of Mexico, found that on average droughts would reduce the human development index by 1.3% while other disasters (avalanche, eruption, hailstorm, surge, snowstorm, earthquake, electric storm, tornado and strong winds) would reduce it by 1.0%. We classified the disasters in three broad categories, the third one accounting for non-natural disasters that were included in the analyses. Table 5 reports the list of disasters that we grouped in each category, while a dummy in the meta-dataset was created to track which kind of disaster was analyzed in the different studies. Note that the descriptive statistics reported in the table for the disaster type in the studies are calculated if at least one of the equations estimated in the study considered one of the three disaster types.[7]

[7] For the summary statistics concerning the t-values we refer to Table 7.

TABLE 5
Classification of the disasters per sources and frequency in the studies

		Studies			
Disaster type	Description	Mean	St.D.	Min	Max
Climatic	floods, droughts, extreme temperature events, wind storms, mass movements wet	0.90	0.30	0	1
Geologic	earthquake, landslides, volcano, dry mass movements	0.95	0.22	0	1
Other	Famine, Epidemics, wildfires, economic disasters	0.47	0.51	0	1
N		20			

Source: Authors's elaborations on the selected studies.

Sample size

The samples used in the studies account on average for 1581 observations but the variability in the number of observations is very high: the standard deviation is 1866 observations, with a minimum of 36 and a maximum of 14,724 observations. The number of observations could have a specific effect on the likelihood to obtain a certain sign and/or level of significance for the t-statistics reported in the studies, hence we included this variable in the meta equation.

Period

We set up a set of dummies to account for the period of time covered by the study by decades levels ('60s, '70s, '80s, '90s and 2000s). In fact, according to Cavallo & Noy (2010: 9-10) analysing the EM-DAT dataset, the incidence of natural disasters has increased in time in the last four decades, independently from the area of the world considered, especially due to an improved recording of smaller disasters. Hence, once we account for the period of time considered by the study, the non significance of the estimated impact of natural disasters could be due to the higher frequency of smaller disasters in the sample as time approaches more recent years. Note that the overall length of the period considered should also incorporate part of this change in the composition of the disaster dataset, then we will use these two different strategies to assess if the hypothesis of correlation between the time period considered and magnitude and significance of results is confirmed. A dummy for the length of the disaster impact analysis (short, medium or long) is also introduced.

Countries and regions

The countries included in the analysis could influence the results. As Cavallo & Noy (2010) pointed out concerning the EM-DAT dataset, the reported direct damages and number of killed and affected are lower for advanced economies and higher for developing countries. In particular, in the developing world the Asia-Pacific region would be the region where disasters bite more, followed by Africa and Latin America. We include in our meta-analysis dummies for six regions, namely, Africa, Asia, Europe, Latin America and the Caribbean, North America and Oceania, and, alternatively, we provide the classification between

OECD and non-OECD to consider if the t-values resulted from a specification including one or both of the categories mentioned.

Resilience factors

As we have discussed in the previous sub-sections, the models used in the empirical macroeconomic literature on the effects of natural disasters account in turn for different factors that can influence the impact of these phenomena on the outcome variable. However, in the selected studies we could find six main factors: the lagged GDP (in level or growth rate), indicators of the level of education in the country, the investment share of GDP, indicators of the degree of openness, indicators of institutional/democracy qualities and variables accounting for the population in the country. A dummy taking value one if the factor was included in the model specification and zero otherwise has been created for every factor aforementioned while in Table 6 the reader can find the different ways the factors were measured in the selected studies classified by model type.

Model type

We consider whether the study considers disaster situations only (Model type 1) or both disaster situations and non-disaster situations (Model type 2). In the meta-equation we consider the model type by means of a dummy variable named TYPE2. The dummy variable assumes the value 1 for model type 2, 0 otherwise. Furthermore, we include a dummy variable called DVAR to account for the nature of the collected t-value in the original study. If the t-value corresponds to a disaster indicator variable, the dummy takes value 1, while it takes value 0 if the t-value corresponds to a resilience factor variable.

Estimation technique

We already emphasized the advantages of an OLS estimation in understanding the impact of natural disasters and the mitigation role of certain factors of resilience in determining the results. Moreover, we generate a dummy accounting for the use of fixed effects models, these ultimately meant to consider time invariant fixed effects in a OLS model. On the other side, some studies chose the Generalized Method of Moments (GMM) estimation technique in order to avoid possible biases in the estimates due to potential correlation between explanatory variables and unobserved time invariant errors, thanks to the use of lagged variables (explanatory and dependent) as instruments (Loayza et al., 2012; Vu & Hammes, 2010; Heger et al., 2008; Noy & Noualsri, 2007). Note that the studies that used GMM in the meta-dataset are all of type (2), probably because for certain authors the impact of disasters on GDP is also the result of a certain GDP dynamic process. If we take model type (2) as the reference category in our meta-regression we can capture the relationship between the choice of using GMM and the magnitude and significance of the results. Finally, across the studies researchers chose to use panel or cross-sectional data, this feature is captured by a dummy.

TABLE 6
Factors of resilience and their measurement across the selected studies

Resilience factor	Indicator	Model type (1)	(2)
GDP	Lagged log per capita GDP growth rate (log/level)	0	3
	Lagged GDP growth rate	0	2
	Beginning of the period log real per capita GDP	0	6
	Current per capita GDP	10	1
Education	Illiteracy % population	0	1
	Years of secondary and higher schooling in the male population aged 15 and over at the beginning of the period	0	1
	Years of secondary and higher schooling in the total population aged 15 and over at the beginning of the period	2	1
	Log initial ratio of number of students enrolled in secondary school to the no. of persons of the corresponding school age	0	1
	School enrollment % population	0	1
	Years of school attainment	2	0
Investment	Lagged gross capital formation % GDP (WDI)	0	2
	Investment ratio over real GDP	1	4
	Growth in capital stock per capita (Kind Levine, 1994)	0	1
Openness	Import plus export over GDP (level/log)	2	4
	Open economy index (Sachs Warner, 1995): 1=open economy	0	1
	Exports of goods and services	0	1
Population	Number of inhabitants (level/log)	7	0
	Density (population/squared Km	3	1
Institutions	ICRG political risk rate: 0=bad, 100=good	0	2
	Democracy index POLITY 4: 0=low, 10=high	1	1
	Democracy index POLITY IV rearranged: 0=low, 20=high	1	0
	Regulatory quality (Kaufmann et al., 2003): 0=low, 1=high	1	0
	Voice and accountability (Kaufmann et al., 2003): 0=low, 1=high	1	0
	Rule of law (Kaufmann et al., 2003): 0=low, 1=high	1	0
	Control of corruption (Kaufmann et al., 2003): 0=low, 1=high	1	0
	ICRG investment climate: 0=bad	1	0
	Political rights: 1=bad, 7=good°	1	0
	Civil liberty: 1=bad, 7=good°	1	0
	ICRG corruption index: 0=most corrupted, 6=least corrupted	1	0
	Transparency International corruption index: 0=most c., 10=least c.	1	0
	World Bank government effectiveness index:	1	0
Total		10	10

Source: Authors elaborations from the selected studies.

Note: °The signs of the coefficients on political rights and civil liberties were changed to make the measurement scale increasing as in the other indicators for institutions.

Table 7 reports the definition and descriptive statistics of all the explanatory variables in the meta-dataset: empirical design, resilience factors and estimation technique variables.

TABLE 7

Definition of variables and descriptive statistics

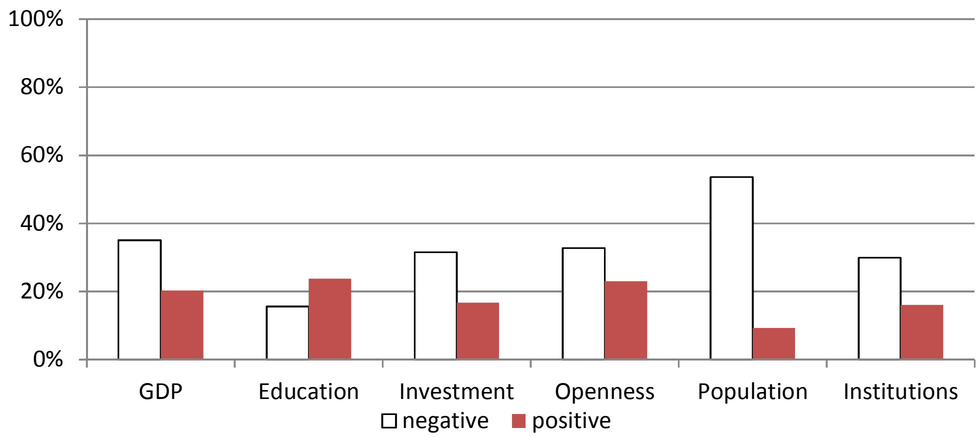
Variable	Description	N	Mean	St.D.
Empirical Design				
N observations	Number of observations in the original regression	659	362	830
EM-DAT	1 if data on disasters were taken from EM-DAT, else 0	659	0.91	0.29
Climatic disaster	1 if climatic natural disasters were included, else 0	659	0.84	0.36
Geologic disaster	1 if geologic natural disasters were included, else 0	659	0.81	0.40
Other disaster	1 if non-natural disasters were included, else 0	659	0.37	0.48
N years	Period considered in the estimation	659	29	10
1960s	1 if dataset was including disasters in the '60s, else 0	659	0.19	0.39
1970s	1 if dataset was including disasters in the '70s, else 0	659	0.67	0.47
1980s	1 if dataset was including disasters in the '80s, else 0	659	0.93	0.25
1990s	1 if dataset was including disasters in the '90s, else 0	659	0.97	0.16
2000s	1 if dataset was including disasters in the '00s, else 0	659	0.82	0.38
N countries	Number of countries in the sample	652	75.35	41
Africa	1 if African countries were included, else 0	602	0.86	0.35
Asia	1 if Asian countries were included, else 0	602	0.93	0.26
Europe	1 if European countries were included, else 0	602	0.80	0.40
LAC	1 if Latin American–Caribbean countries were included, else 0	602	0.95	0.21
North America	1 if North American countries were included, else 0	602	0.87	0.21
Oceania	1 if countries in Oceania were included, else 0	602	0.79	0.41
OECD	1 if OECD countries were included, else 0	647	0.79	0.41
Non OECD	1 if non-OECD countries were included, else 0	647	0.93	0.25
Long-run	1 if the study consider impact in the long-run, else 0	659	0.34	0.48
DVAR	1 if the t value corresponds to a disaster indicator, else 0	659	0.56	0.50
TYPE2	1 if the study is of model type (2), else 0	659	0.47	0.50
Estimation technique				
Panel	1 if dataset was panel (0=cross-section) , else 0	659	0.83	0.37
OLS	1 if the estimation is conducted with OLS, else 0	659	0.45	0.50
GMM	1 if the estimation is conducted with GMM, else 0	659	0.12	0.32
FE	1 if the estimation uses fixed effects, else 0	659	0.23	0.42
Resilience factors				
Population	1 if an indicator of population is included, else 0	659	0.21	0.41
GDP	1 if an indicator of income is included, else 0	659	0.68	0.47
Education	1 if an indicator of education level is included, else 0	659	0.24	0.43
Investment	1 if an indicator of capital formation is included, else 0	659	0.22	0.41
Openness	1 if an indicator of openness is included, else 0	659	0.26	0.44
Institutions	1 if an indicator of institute. quality is included, else 0	659	0.13	0.34

Source: Authors' elaborations.

Figure 2 classifies the t values that are reported in the 20 studies by means of the sign and significance level (Appendix table A1 reports the detailed counts). The top figure provides the results when we consider all 20 studies simultaneously. For example, in the 20 studies we recorded 447 t-values that were reported for the inclusion of a GDP indicator (as listed in Table A1 in the appendix). The t values are negative and significant in 35% of the cases positive and significant in 20% of the cases and insignificant in the remaining 45% of the cases. A negative result implies that the disaster has bigger direct and indirect costs: for higher GDP the impact of natural disasters is likely to be significantly negative.

FIGURE 2

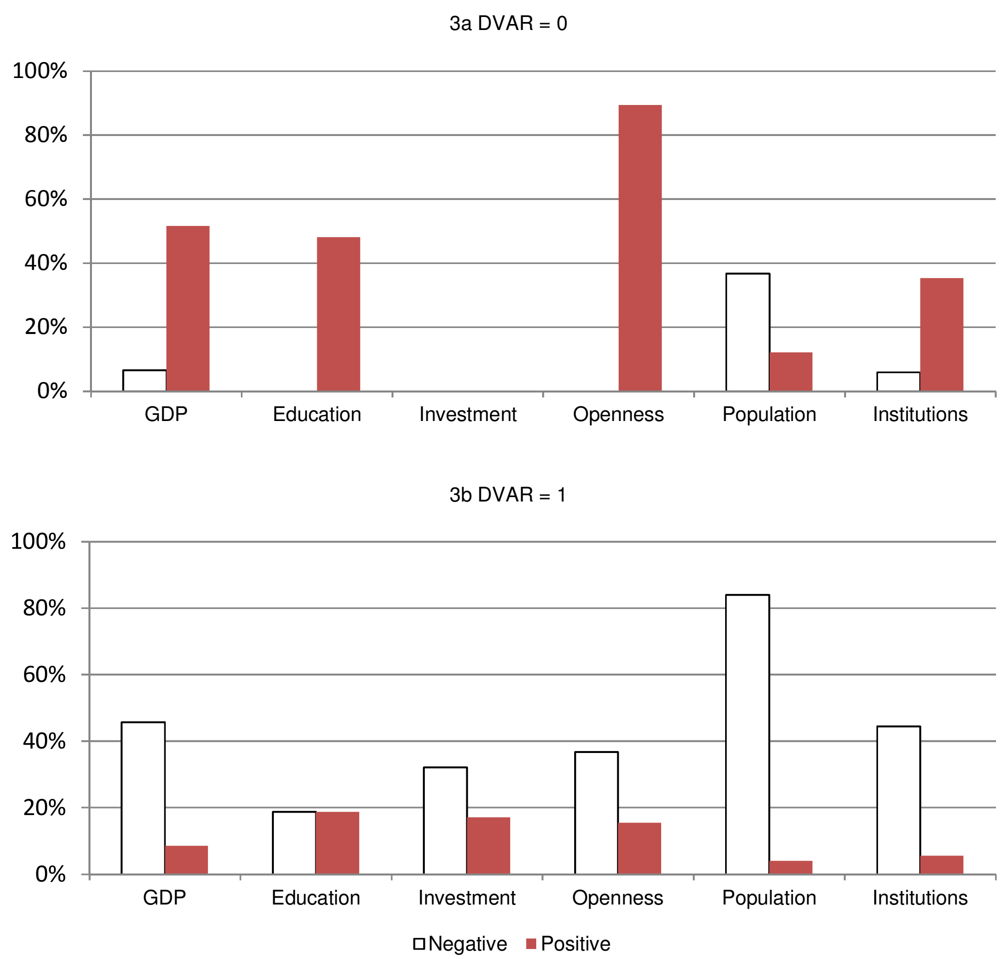
Effects of resilience factors on disaster impact
(total sample; share of significant t values)



Source: Authors elaborations

Next we analyze the t values according to the type of t-value collected: corresponding to a resilience factor variable (DVAR=0) or to disaster variable (DVAR=1) and according to the model type. Figure 3 and 4 allow us to make four observations. First, we find only agreement for population where – independent of variable type – the negative and significant t-values clearly outnumber the positive and significant t values. Only for the case the disaggregation is by model type positive and significant t-values reach the same percentage of negative and significant t-values if the model is of type 2. Second, for all other variables we find clear indications of disagreement in the aggregate. Third, this is driven by the fact that the t-value either belongs to a disaster or resilience variable and/or by the model type. It is striking that the evidence of resilience variable/model 1 type studies for GDP, openness and institutions is opposite to the evidence of disaster variable/model 2 type studies. A clear example is GDP. The t-values for GDP are significant and negative in 35% of the regressions including a GDP indicator that we collected from the 20 studies (23% of the overall t-values). This overall finding, however, is the result of different relationships for resilience variable/model 1 type studies and disaster variable/model 2 type studies. When the disaster impact is calculated using a disaster variable, its t value is negative and significant in 46% of the cases (it is insignificant in 45% of the cases). This suggests that higher GDP in general enlarges the direct and/or indirect costs of natural disasters impact. This may be due to the fact that a wealthier country could have more damages to its growth because a disaster can potentially destroy more productive capacity or income-generating activities. In particular, turning to the disaggregation by model type, the negative effect of higher GDP seems to take place through indirect costs, probably because in wealthier countries, in addition to the loss of existent production capacity and activities, a greater loss is triggered by the flows of goods, services and business revenues that will not be generated due to destructions or business interruptions. When, in contrast, disaster impact is calculated as percentage of population affected or killed or as percentage of damages over GDP, higher GDP results in a positive and significant result in 52% of the studies accounting for GDP (10% of the full sample of studies), possibly due to greater resilience. Fourth, the main conclusion of this section, however, is that no consensus appears to emerge regarding the possible factors of resilience. Clearly there is a need to pay attention to the way the model is theoretically and empirically built since authors' decisions about these aspects seem to be crucial in determining the sign and significance of natural disaster impacts.

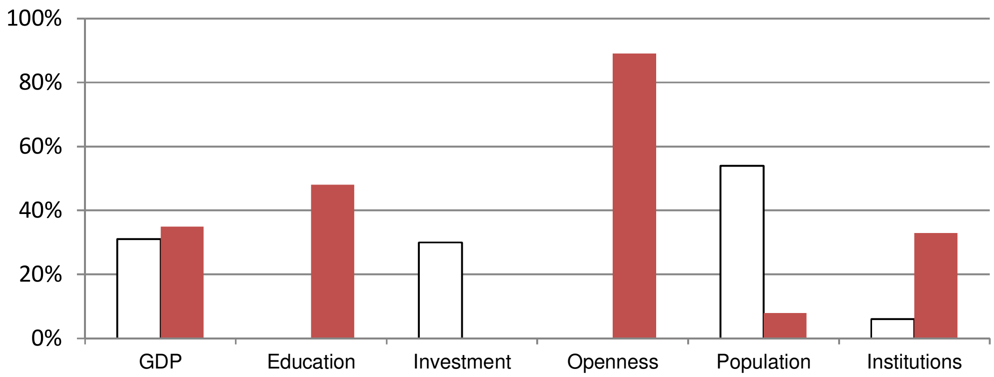
FIGURE 3
The effects of resilience factors on disaster impacts by variable (share of significant t values)



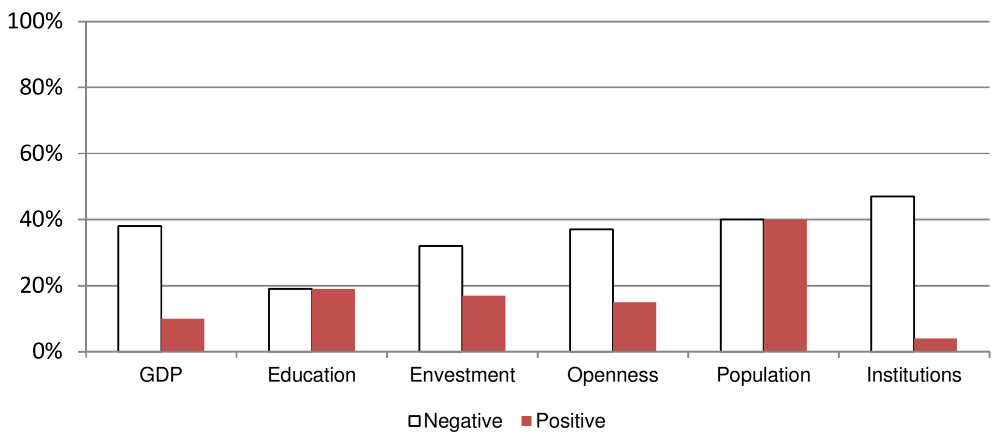
Source: Appendix Table A1

FIGURE 4
The effects of resilience factors on disaster impacts by model

4a Model type 1



4b Model type 2



Source: Appendix Table A1

4 Empirical results: The meta equation

To investigate the influence of study characteristics on the sign and level of significance of the t-statistic we use a meta-regression analysis. In particular, we use a multinomial logistic model since we are interested in establishing whether the probability that the recorded disaster impact is negative and significant, negative non-significant, positive non significant or positive and significant is influenced by the model design. We prefer a multinomial model to an ordinal model because, given the acknowledged potential negative impact of the phenomena analyzed and the fact that the recording of disaster data in time could have been influenced by changes in the public attention to the phenomena or improved recording techniques, the assumption of proportional odds[8] could be violated. Indeed, the test for the proportional odds assumption proposed by Wolfe & Gould (1998) rejects the null hypothesis that odds are proportional (p-value 0.000). Moreover, the use of a logit or probit model follows from a theoretical understanding and testing of the assumption underlying the two possible models in analyzing the problem at hand. A multinomial probit model assumes that the error terms follow a multivariate normal distribution and are correlated across choices (Hausman & Wise, 1978: 405). In contrast, a multinomial logit model assumes independence of irrelevant alternatives (IIA), that is, odds of one outcome should not depend on the other available outcomes (Long & Freese, 2006: 243). Given the exogeneity of natural disasters, the assumption of IIA seems the most likely to apply to our analysis. The Hausman test of IIA confirms that the multinomial logit model is appropriate for the first specification considered while the test for the second specification rejects IIA for outcome 3[9]. Moreover, both the Wald and Likelihood-ratio tests for combining alternatives reject the hypothesis that pairs of alternatives are indistinguishable, confirming that the four outcomes model chosen is correct. It is also important to consider the issue of potential endogeneity of the estimated disaster impact parameter (that is: the interaction of the natural event with the social system characteristics embedded in the empirical design of the studies): this suggests to cluster standard errors by study in order to obtain unbiased estimates. We will report the estimations of the model both without and with clustered standard errors. We assume that the log-odds of every response of the multinomial logit follow a linear model

$$y_{ij}^{(m)} = \theta_0{}^{(m)} + \theta_1{}^{(m)} ED_{ij} + \theta_2{}^{(m)} ET_{ij} + \theta_3{}^{(m)} RF_{ij} + \varepsilon_{ij}{}^{(m)} \qquad (3)$$

with the multinomial logit link

$$ln\,\Omega_{m|b}(\boldsymbol{ED}, \boldsymbol{ET}, \boldsymbol{RF}) = ln\frac{\Pr(y = m|\boldsymbol{ED}, \boldsymbol{ET}, \boldsymbol{RF})}{\Pr(y = b|\boldsymbol{ED}, \boldsymbol{ET}, \boldsymbol{RF})} \qquad (4)$$

where y is a categorical variable that can take the following values:

1 if the reported t-value in regression i in study j is negative and significant at least at 10% (lower or equal to -1.65),

2 if it is negative and non significant (between -1.65 and 0),

3 if it is positive and non significant (between 0 and +1.65) and

4 if positive and significant at least at 10% (greater or equal to +1.65).

[8] The proportional odds assumption in a logit model states that the explanatory variables have constant cumulative response probabilities across all the categories of the ordinal response (Wolfe and Gould, 1998: 24).

[9] Cheng and Long (2007) show through Monte Carlo experiments that this test has poor size properties, but the reasonable distinctiveness of the alternatives in this study further supports our choice of a multinomial logit (Amemiya, 1981; Long & Freese, 2006; McFadden, 1973).

$\boldsymbol{ED}$, $\boldsymbol{ET}$ and $\boldsymbol{RF}$ are vectors of empirical design, estimation technique and resilience factors respectively, $\boldsymbol{\varepsilon}$ is the error term. Estimations were robust to the inclusion or exclusion of the constant $\boldsymbol{\theta_0}$. The constant term is included and reported, because it "represents the random effect that control for the commonality and dependency of estimates within and across studies" (Sinani & Meyer, 2009).

Table 8-9 present the multinomial logit marginal effects and z-values resulting from the estimation of equation (4) for two different specification, the first more parsimonious, the second accounting for decades and regional disaggregation in the datasets used by the different studies. Tables 10-11 presents marginal effects of the two specifications resulting from estimations with clustered standard errors. Table 9 and 11 presenting the less parsimonious specification exclude the studies by Strömberg (2007) and Tavares (2004) due to missing number and list of countries respectively. In general, Tables 8-11 show the relation between the empirical design, the estimation technique and the resilience factors with the likelihood of finding negative/positive and statistically significant/non statistically significant coefficients for the impact of natural disasters. We report the average probability and relative standard deviation of every outcome and the marginal and discrete changes in the probability that the sign and significance of the outcome is the selected one when the considered explanatory variable is introduced in the model. We discuss first the non clustered and then the clustered results.

In Table 8 and 9 we can see that the probability to report a negative and significant outcome is on average higher than other outcomes (38% against 20, 16 and 26%) The model strategy doesn't seem to influence the probability to obtain a specific outcome. Similar results are found if we modify the specification to account for decades and regional disaggregations in the dataset used in the different studies. Model type and disaster variables do not seem to significantly determine the probability of particular outcomes, while number of observations and years considered are in some cases significant determinants of disaster outcome but their magnitude is very low. On the other side, using EM-DAT decreases the probability that disasters have a negative and significant impact by 21%, and increases the probability that the disaster has a positive insignificant and significant effect by 17% and 15% respectively, probably due to the fact that in EM-DAT there is a prevalence of less large disasters (Cavallo & Noy, 2010). If the study includes OECD countries the probability of experiencing a significant negative or positive outcome is lowered, while including non-OECD countries increases the probability of a disaster negative impact by 44%, in line with the assumption that richer countries would be less affected by disasters and poorer developing countries would be more vulnerable to disaster events (UNDP, 2004). The finding that geologic disasters are less harmful for the economies as claimed by Bergholt (2010) seem to be supported by the studies in the sample. Accounting for geologic disasters on average decreases by 22% the probability of reporting negative but not significant (significant at 1%). On the other side, if the model in the original study is designed to analyse long-term effects, on average the likelihood of obtaining a negative and non significant result is decreased by

20%, significant at 1%. Turning to estimation techniques, both OLS and GMM seem to decrease the probability of reporting a negative and significant outcome while using fixed effects would increase the probability of a positive and significant impact of natural disasters. Population seems to be the only resilience factor able to influence all the outcomes, suggesting that the likelihood that the impact is negative and significant (insignificant) is increased by 32% (9%) when the study accounts for population. Including education in the analysis would lower the probability of a negative and significant impact, enhancing the probabilities of the impact to be negative but insignificant, while including openness would increase the probability for the outcome to be negative and significant (+19% significant at 1%). When we include in the specification dummies for decades and regional country aggregations considered by the studies (Table 9), it seems that studies on data from more recent decades have greater probability to report a positive and significant outcome. Whether this is due to a progressive increase in the ability to mitigate disaster adverse effects or to the increasing number of milder disasters reported in the dataset (especially EM-DAT) used in the studies is still to be clarified. In support of the second hypothesis we can see that using EM-DAT decreases by 36% the probability of finding a negative and significant outcome, again coherently with the prevalence of less large disasters in the dataset revealed by Cavallo and Noy (2010). Moreover, the inclusion of African and Asian countries seems to increase the probability of a disaster positive impact while Latin America and Caribbean countries suggest a greater probability to report a negative but non-significant outcome. When controlling for regional composition of the dataset the fixed effect dummy for the estimation technique supports now negative and significant outcome while the importance of some resilience factors in determining disaster impact changes. Population remains significant in increasing the probability of a negative and significant outcome and decreasing the probability to report a positive insignificant and significant result (+36%, -18% and -24% respectively, significant at conventional levels). Accounting for GDP seems to increase the probability of having a positive and significant result by 10% while the probability to report a negative non significant result is lowered by 15%, both significant at conventional levels. On the other side, accounting for education seems now not to influence the likelihood of any outcome, while if investments is included in the analysis, there is a 11% more probability to find a negative and significant disaster impact. Finally, openness would increase the probability of a positive and significant result by 13% while institutions do not seem to influence disaster outcomes.

TABLE 8

Meta-regression analysis (multinomial logit), disaster impact marginal effects

Outcome (c)	Disaster Impact (DI)											
	(1)			(2)			(3)			(4)		
	Significant and negative			Negative but insignificant			Positive but insignificant			Significant and positive		
P(DI=outcome), (st.dev.)	0.38		(0.30)	0.20		(0.18)	0.16		(0.14)	0.26		(0.27)
N observ.	0.00	***	(3.61)	0.00		(0)	0.00	***	(-2.4)	0.00		(-0.36)
N years	-0.01	***	(-3.05)	0.00		(1.38)	0.00	**	(2.09)	0.11		(0.13)
Panel°	0.04		(0.55)	-0.12		(-1.47)	-0.04		(-0.49)	-0.10		(1.53)
EM-DAT°	-0.21	***	(-3.04)	0.14		(2.19)	0.17	**	(2.3)	0.15	*	(-1.79)
OECD	-0.18	***	(-2.67)	0.03		(0.56)	-0.01		(-0.18)	-0.04	**	(2.15)
Non-OECD	0.44	***	(2.63)	-0.36	***	(-3.78)	-0.04		(-0.48)	0.09		(-0.41)
Climatic°	-0.02		(-0.44)	-0.07		(-1.37)	0.00		(-0.03)	-0.13	*	(1.66)
Geologic°	-0.22	***	(-4.39)	0.32		(5.18)	0.04		(0.8)	-0.16	***	(-3)
Other°	0.20	***	(3.03)	-0.10		(-1.74)	0.06		(1.05)	0.14	**	(-2.15)
Long-run°	0.00		(-0.01)	-0.20	***	(-3.54)	0.07		(1.56)	-2.01	***	(2.67)
DVAR°	0.97		(0.03)	0.62		(0.02)	0.42		(0.02)	1.62		(-0.02)
TYPE2°	-0.70		(-0.02)	-0.47		(-0.02)	-0.45		(-0.02)	0.21		(0.02)
OLS°	-0.15	***	(-2.83)	0.03		(0.51)	-0.08	*	(-1.8)	0.14	***	(3.63)
GMM°	-0.26	***	(-2.73)	0.06		(0.7)	0.06		(0.79)	-0.25		(1.26)
FE°	0.07		(1.56)	0.03		(0.65)	0.14	***	(3.21)	-0.23	***	(-4.74)
Population°	0.32	***	(5.99)	0.09	*	(1.93)	-0.18	***	(-3.04)	0.03	***	(-4.78)
GDP°	0.10		(1.85)	-0.11	**	(-2.27)	-0.02		(-0.61)	0.07		(0.84)
Education°	-0.26	***	(-3.42)	0.13	***	(2.34)	0.06		(1.24)	-0.02		(1.43)
Investment°	0.00		(0.05)	0.03		(0.47)	-0.01		(-0.2)	0.00		(-0.36)
Openness°	0.19	***	(3.42)	0.03		(0.48)	-0.22	***	(-3.68)	-0.09		(-0.05)
Institutions°	0.03		(0.46)	0.07		(1.34)	-0.01		(-0.25)	0.00		(-1.47)
Pseudo R^2												0.32
N studies												20
N observations												646

Source: Autors elaborations.

Note:° change from zero to one. Z-values in parenthesis. *, **, *** stands for 10, 5 and 1% level of significance.

TABLE 9

Meta-regression analysis (multinomial logit), disaster impact effects and dataset time and regional composition characteristics

	Disaster Impact (DI)											
Outcome	(1)			(2)			(3)			(4)		
	Significant and negative			Negative but insignificant			Positive but insignificant			Significant and positive		
P(DI=outcome), (St.Dev.)	0.34		(0.31)	0.22		(0.22)	0.17		(0.18)	0.27		(0.32)
N observ.	0.00		(-0.05)	0.00		(1.5)	0.00	*	(-1.95)	0.00		(0.02)
1960s	0.10		(1.02)	0.07		(0.74)	-0.19	*	(-1.7)	0.02		(0.23)
1970s	0.00		(-0.04)	0.01		(0.12)	0.22	**	(2.35)	-0.23	***	(-3.46)
1980s	-0.46	**	(-2.59)	-0.35	**	(-2.13)	-0.43	**	(-2.76)	1.23	***	(5.16)
1990s	-0.56	***	(-2.9)	-0.45	**	(-2.55)	-0.13		(-0.84)	1.15	***	(4.9)
2000s	-0.36	**	(-2.52)	-0.49	***	(-3.6)	-0.30	**	(-2.29)	1.15	***	(4.75)
N countries	0.00	***	(2.88v	0.00		(-1.09)	0.00		(-0.45)	0.00		(-1.3)
Panel°	0.60	***	(2.86)	0.41	*	(1.81)	0.68	***	(3.14)	-1.69	***	(-4.21)
EM-DAT°	-0.36	***	(-3.33)	0.27	**	(2.27)	0.11		(1.05)	-0.02		(-0.29)
Climatic°	0.00		(0.02)	-0.12	**	(-1.95)	-0.10		(-1.46)	0.21	***	(3.23)
Geologic°	-0.20	***	(-3.4)	0.29	***	(4.02)	0.01		(0.14)	-0.10	*	(-1.85)
Other°	0.08		(0.85)	-0.21	**	(-2.22)	0.03		(0.38)	0.10		(1.06)
Africa	-0.14		(-0.84)	-0.42	**	(-2.67)	0.20	*	(1.63)	0.36	**	(2.84)
Asia	-0.76	***	(-2.79)	0.30		(0.81)	-0.76	***	(-3.22)	1.22	***	(3.28)
Europe	-0.23		(-1.46)	0.24		(1.36)	-0.16		(-1.02)	0.15		(0.93)
LAC°	0.31		(1.24)	1.51	***	(4.52)	0.08		(0.44)	-1.90	***	(-5.68)
North America	-0.06		(-0.37)	-0.42	*	(-1.8)	0.03		(0.24)	0.45	**	(2.12)
Oceania	0.20		(1.59)	-0.26	*	(-1.79)	0.30	**	(2.23)	-0.24	*	(-1.92)
Long-run°	0.02		(0.21)	-0.16		(-1.51)	0.21	***	(3.07)	-0.06		(-0.63)
DVAR°	0.64		(0.05)	0.53		(0.04)	0.37		(0.02)	-1.54		(-0.04)
TYPE2°	-0.42		(-0.03)	-0.23		(-0.02)	-0.24		(-0.01)	0.88		(0.02)
OLS°	-0.28	***	(-2.99)	-0.03		(-0.38)	0.07		(0.76)	0.25	***	(3.03)
GMM°	-0.24	*	(-1.96)	0.07		(0.59)	0.07		(0.54)	0.11		(0.62)
FE°	0.11	**	(2.11)	0.05		(0.87)	0.04		(0.69)	-0.20	***	(-3.3)
Population°	0.36	***	(5.48)	0.06		(1.14)	-0.18	**	(-2.88)	-0.24	***	(-4.77)
GDP°	0.08		(1.32)	-0.15	**	(-2.56)	-0.04		(-0.84)	0.10	***	(2.78)
Education°	-0.11		(-1.29)	0.07		(1.1	-0.01		(-0.24)	0.05		(1.1)
Investment°	0.18	***	(2.76)	0.08		(1.09	-0.11		(-1.62)	-0.16	*	(-1.94)
Openness°	-0.02		(-0.24)	0.00		(-0.02	-0.11	*	(-1.67)	0.13	**	(2.38)
Institutions°	0.04		(0.07)	0.08		(1.27)	0.01		(0.09)	-0.12		(-1.77)
Pseudo R^2												0.40
N studies												18
N observations												594

Source: Author's elaborations

Note:° change from zero to one. Z-values in parenthesis. *, **, *** stands for 10, 5 and 1% level of significance.

One problem with the analysis in Tables 8 and 9 is that correlation can be expected between the t-values that are reported within the same study and therefore Tables 10 and 11 cluster standard errors for studies. Average probabilities for different outcomes remain equal, however, the crucial difference is that the level of significance of some variable in determining the outcome of the study changes. Both the magnitude and the level of significance of DVAR in both specifications with clustered standard errors vary while clustering allows probably to disentangle the effect of regional disaggregation combined with model type on the likelihood of different outcomes in the second specification. Our earlier findings are confirmed: the use of EM-DAT further decreases the probability of obtaining a negative and significant result while accounting for geological disasters increases the probability of reporting a negative but non-significant impact. The marginal effects of other empirical design and estimation technique factors are also confirmed, while for resilience factors the influence on the likelihood of finding a positive or negative, significant or insignificant t-value for disaster impact reduces. When considering clustered standard errors and period of time and regional disaggregations using a disaster indicator increases the probability to find a negative and significant outcome by 64% while choosing model type 2 increases the probability to find a positive and significant outcome by 88%. The variables accounting for resilience factors experienced a general decrease in the level of significance. Education, openness and institutions do not appear to influence the likelihood of any outcome while investments suggest a higher probability of a negative impact, contradicting the hypothesis that higher investments should help to mitigate disaster negative effects as in the non-clustered estimations. The population dummy remained significant in determining significant negative and positive outcomes (+36% and -24% respectively, significant at 1%). The comparison of results of different specifications finally suggests a (internal) correlation between study design, resilience and regional distribution of the countries. If worldwide some factors of resilience can influence the sign and significance of the impact of natural disasters, these mitigation effect are likely to be country or regional specific (depending on how many countries in the region have strongest factors of resilience) and depending on the model type/variables chosen by the author of the study.

TABLE 10

Meta-regression analysis (multinomial logit), disaster impact effects, standard errors clustered by studies

Outcome (c)	Disaster Impact (DI)											
	(1)			(2)			(3)			(4)		
	Significant and negative			Negative but insignificant			Positive but insignificant			Significant and positive		
P(DI=outcome), (st.dev.)	0.38		(0.30)	0.20		(0.18)	0.16		(0.14)	0.26		(0.27)
N observ.	0.00	***	(2.71)	0.00		(0)	0.00	***	(-3.31)	0.00		(-0.16)
N years	-0.01	***	(-2.7)	0.00		(0.97)	0.00	**	(2.26)	0.11		(0.07)
Panel°	0.04		(0.47)	-0.12		(-1.16)	-0.04		(-0.56)	-0.10		(0.67)
EM-DAT°	-0.21	**	(-2.26)	0.14		(1.45)	0.17	*	(1.84)	0.15		(-1.08)
OECD	-0.18	*	(-1.87)	0.03		(0.56)	-0.01		(-0.13)	-0.04		(1.29)
Non-OECD	0.44	**	(1.96)	-0.36	***	(-4.38)	-0.04		(-0.34)	0.09		(-0.38)
Climatic°	-0.02		(-0.33)	-0.07		(-1.1)	0.00		(-0.02)	-0.13		(0.78)
Geologic°	-0.22	***	(-4.06)	0.32	***	(6.93)	0.04		(0.9)	-0.16		(-1.46)
Other°	0.20	**	(1.99)	-0.10		(-1.18)	0.06		(0.81)	0.14		(-0.88)
Long-run°	0.00		(-0.01)	-0.20	***	(-2.91)	0.07		(1.47)	-2.01		(1.33)
DVAR°	0.97	***	(5.54)	0.62	***	(2.78)	0.42	***	(2.85)	1.62	***	(-7.17)
TYPE2°	-0.70	***	(-3.82)	-0.47	**	(-2.32)	-0.45	***	(-3.08)	0.21	***	(4.93)
OLS°	-0.15	**	(-2.06)	0.03		(0.32)	-0.08	*	(-1.8)	0.14		(1.33)
GMM°	-0.26	**	(-2.11)	0.06		(0.5)	0.06		(0.83)	-0.25		(0.76)
FE°	0.07	*	(1.77)	0.03		(0.72)	0.14	***	(4.28)	-0.23	***	(-4.61)
Population°	0.32	***	(4.76)	0.09		(0.84)	-0.18	**	(-2.01)	0.03	**	(-2.07)
GDP°	0.10		(1.31)	-0.11		(-1.53)	-0.02		(-0.67)	0.07		(0.34)
Education°	-0.26	***	(-2.72)	0.13		(1.45)	0.06		(1.17)	-0.02		(1.08)
Investment°	0.00		(0.06)	0.03		(0.4)	-0.01		(-0.19)	0.00		(-0.23)
Openness°	0.19	***	(2.97)	0.03		(0.38)	-0.22	***	(-3.97)	-0.09		(-0.02)
Institutions°	0.03		(0.38)	0.07		(0.79)	-0.01		(-0.19)	0.00		(-0.61)
Pseudo R^2												0.32
N studies												20
N observations												646

Source: Autors elaborations.

Note: ° change from zero to one. Z-values in parenthesis. *, **, *** stands for 10, 5 and 1% level of significance.

TABLE 11

Meta-regression analysis (multinomial logit), disaster impact effects and dataset time and regional composition characteristics. St. err. clustered by studies

Outcome	Disaster Impact (DI)							
	(1)		(2)		(3)		(4)	
	Significant and negative		Negative but insignificant		Positive but insignificant		Significant and positive	
P(DI=outcome), (St.Dev.)	0.34	(0.31)	0.22	(0.22)	0.17	(0.18)	0.27	(0.32)
N observ.	0.00	(-0.08)	0.00 *	(1.75)	0.00 **	(-2.22)	0.00	(0.02)
1960s	0.10	(1.09)	0.07	(0.73)	-0.19 **	(-2.02)	0.02	(0.21)
1970s	0.00	(-0.05)	0.01	(0.16)	0.22 **	(2.19)	-0.23 ***	(-3.34)
1980s	-0.46 ***	(-4.01)	-0.35 **	(-2.12)	-0.43 **	(-2.02)	1.23 ***	(3.6)
1990s	-0.56 ***	(-6.07)	-0.45 ***	(-3.23)	-0.13	(-0.54)	1.15 ***	(3.28)
2000s	-0.36 ***	(-3.48)	-0.49 ***	(-3.04)	-0.30 **	(-1.36)	1.15 ***	(3.17)
N countries	0.00 ***	(2.64)	0.00	(-1.26)	0.00	(-0.51)	0.00	(-0.9)
Panel°	0.60 ***	(5.1)	0.41 *	(1.7)	0.68 *	(1.74)	-1.69 ***	(-2.67)
EM-DAT°	-0.36 ***	(-4.13)	0.27 ***	(6.64)	0.11	(0.64)	-0.02	(-0.23)
Climatic°	0.00	(0.02)	-0.12	(-1.56)	-0.10 **	(-2.09)	0.21 *	(1.7)
Geologic°	-0.20 ***	(-4.58)	0.29 ***	(5.77)	0.01	(0.18)	-0.10	(-1.28)
Other°	0.08	(1.03)	-0.21 ***	(-3.25)	0.03	(0.23)	0.10	(0.78)
Africa	-0.14	(-1.06)	-0.42 ***	(-3.58)	0.20	(1.24)	0.36 ***	(2.66)
Asia	-0.76 ***	(-2.9)	0.30	(1.32)	-0.76 **	(-2.2)	1.22 *	(1.93)
Europe	-0.23 *	(-1.81)	0.24 ***	(2.9)	-0.16	(-0.97)	0.15	(1.14)
LAC°	0.31 *	(1.83)	1.51 ***	(5.97)	0.08	(0.33)	-1.90 ***	(-4.15)
North America	-0.06	(-0.46)	-0.42 ***	(-2.9)	0.03	(0.28)	0.45 *	(1.86)
Oceania	0.20	(1.59)	-0.26 ***	(-3.19)	0.30 *	(1.96)	-0.24 *	(-1.75)
Long-run°	0.02	(0.22)	-0.16 ***	(-3.3)	0.21 **	(2.02)	-0.06	(-0.74)
DVAR°	0.64 ***	(3.97)	0.53 ***	(2.91)	0.37 ***	(3.18)	-1.54 ***	(-7.97)
TYPE2°	-0.42 ***	(-2.67)	-0.23	(-1.43)	-0.24	(-1.3)	0.88 ***	(2.81)
OLS°	-0.28 ***	(-2.72)	-0.03	(-0.37)	0.07	(0.7)	0.25	(1.31)
GMM°	-0.24	(-1.64)	0.07	(0.51)	0.07	(0.53)	0.11	(0.46)
FE°	0.11 ***	(4.59)	0.05	(0.81)	0.04	(0.81)	-0.20 **	(-2.18)
Population°	0.36 ***	(3.97)	0.06	(0.8)	-0.18	(-1.48)	-0.24 ***	(-2.91)
GDP°	0.08	(1)	-0.15 *	(-1.66)	-0.04	(-0.83)	0.10	(1.54)
Education°	-0.11	(-1.26)	0.07	(0.69)	-0.01	(-0.26)	0.05	(1.13)
Investment°	0.18 **	(2.26)	0.08	(1.05)	-0.11	(-1.2)	-0.16	(-1.33)
Openness°	-0.02	(-0.41)	0.00	(-0.02)	-0.11	(-1.49)	0.13	(1.45)
Institutions°	0.04	(0.58)	0.08	(0.91)	0.01	(0.08)	-0.12	(-0.95)
Pseudo R^2								0.40
N studies								18
N observations								594

Source: Author's elaborations

Note:° change from zero to one. Z-values in parenthesis. *, **, *** stands for 10, 5 and 1% level of significance.

5 Conclusions

The debate on the impact of natural disasters and the possible mitigation strategies has become lively during the last decade due to an increase in the occurrence of natural hazards. This study attempted to re-organize the recent macroeconomic empirical literature and investigates whether the relationship between the likelihood of a disaster to generate high/low negative or positive effects in the country that has experienced it is influenced by country, regional, time characteristics or resilience factors implemented or featuring the context at hand. This meta-analysis supports some of the observations already revealed by literature reviews, namely, that some characteristics of the dataset used for the empirical analysis, such as period of time and countries considered, can influence the results of the model elaborated. In particular, the meta-analysis suggests that part of the heterogeneity in the results is related to the empirical model on which the analysis is based. Hence, in the process of estimating the impact of natural disasters, researchers should compare the results of different model types to better understand the sign and significance of the natural hazard's effects. Population seems to be a key variable in determining the sign and level of significance of disaster impacts probably due to its importance in enhancing or reducing the number of vulnerable (and consequently more prone to be affected) people in the case the disaster occurs. On the other side, other factors that are usually considered crucial in disaster effects mitigation seem to really assume this role depending on the context analyzed. Following this observations, future studies should pay higher attention to the regional and countries aggregations that they use for the estimations of macroeconomic impacts of natural disasters.

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Appendices

APPENDIX TABLE A1

The effects of resilience factors on disaster impacts (total and by variable/model type)

Variable	Negative and significant		Negative and non significant		Positive and non significant		Positive and significant		Total	DVAR	Model type
GDP	157	35%	112	25%	88	20%	90	20%	447	All	All
Education	25	16%	56	35%	41	26%	38	24%	160	All	All
Investment	45	31%	51	36%	24	16%	23	17%	143	All	All
Openness	57	33%	52	30%	25	14%	40	23%	174	All	All
Population	75	54%	46	33%	6	4%	13	9%	140	All	All
Institutions	26	30%	28	32%	19	22%	14	16%	87	All	All
GDP	8	7%	10	8%	41	34%	63	52%	122	0	-
Education	0		8	30%	6	22%	13	48%	27	0	-
Investment	0		2	50%	2	50%	0		4	0	-
Openness	0		1	5%	1	5%	17	89%	19	0	-
Population	33	37%	40	44%	6	7%	11	12%	90	0	-
Institutions	2	6%	7	21%	13	38%	12	35%	34	0	-
GDP	149	46%	102	31%	47	14%	27	8%	325	1	-
Education	25	19%	48	36%	35	26%	25	19%	133	1	-
Investment	45	32%	49	35%	22	16%	23	17%	139	1	-
Openness	57	37%	51	33%	24	15%	24	15%	155	1	-
Population	42	84%	6	12%	0	0%	2	4%	50	1	-
Institutions	24	45%	21	40%	6	11%	2	4%	53	1	-
GDP	55	31%	16	9%	45	25%	63	35%	179	-	1
Education	0		8	30%	6	22%	13	48%	27	-	1
Investment	3	30%	3	30%	4	40%	0	0%	10	-	1
Openness	0		1	5%	1	5%	17	89%	19	-	1
Population	73	54%	45	33%	6	4%	11	8%	135	-	1
Institutions	2	6%	9	25%	13	36%	12	33%	36	-	1
GDP	102	38%	96	36%	43	16%	27	10%	268	-	2
Education	25	19%	48	36%	35	26%	25	19%	133	-	2
Investment	42	32%	48	36%	20	15%	23	17%	133	-	2
Openness	58	37%	52	34%	25	16%	24	15%	155	-	2
Population	2	40%	1	20%	0		2	40%	5	-	2
Institutions	24	47%	19	37%	6	12%	2	4%	51	-	2

Source: Authors' elaborations based on the 20 selected studies.

APPENDIX TABLE A2
The effects of resilience factors on disaster impacts. T values DVAR=1 by Model type

Variable	Negative and significant		Negative and non significant		Positive and non significant		Positive and significant		Total by DVAR	DVAR	Total by modell	Model type
GDP	47	15%	6	2%	4	1%	0		325	1	57	1
	102	31%	96	29%	43	13%	27	8%		1	268	2
Education	0		0		0		0		133	1	0	1
	25	19%	48	36%	35	26%	25	19%		1	133	2
Investment	3	2%	1	1%	2	1%	0		139	1	6	1
	42	30%	48	34%	20	15%	23	17%		1	133	2
Openness	0		0		0		0		155	1	0	1
	57	37%	51	33%	24	15%	24	15%		1	155	2
Population	40	80%	5	10%	0		0		50	1	45	1
	2	4%	1	2%	0		2	4%		1	5	2
Institutions	0		2	4%	0		0		53	1	2	1
	24	45%	19	36%	6	11%	2	4%		1	51	2

Source: Authors' elaborations based on the 20 selected studies.