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By: Jhorland Ayala-García
Sandy Dall'Erba

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The impact of preemptive investment on natural disasters*

Jhorland Ayala-García†

Sandy Dall'Erba§

Abstract

Extreme rainfall events are expected to become more frequent and more intense in the future. Because their mitigation is a challenge and their cost to human life is large, this paper studies the impact of preemptive investment against natural disasters on the future occurrence of landslides and the losses associated with it. Based on a panel of 746 Colombian municipalities with medium and high risk of landslides and an instrumental variable approach, we find that preemptive public investment can reduce the number of landslides, the number of people who die, are injured, or disappear after a landslide, as well as the number of people affected. However, we do not find any effect on the number of houses destroyed. The results reveal that local governments focus their preventive measures on saving the lives and the physical integrity of their citizens, but they pay less attention to the direct market losses of natural disasters. These results are relevant in the presence of imperfect private insurance markets and increased informal settlements.

Keywords: landslides, preemptive investment, disaster risk reduction, natural disasters.

JEL Classification: H1, H4, H5, C26, D6.

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† Banco de la República, Cartagena, Colombia. Email: jayalaga@banrep.gov.co.
§ University of Illinois at Urbana-Champaign, USA. Email: dallerba@illinois.edu.

El impacto de la inversión en prevención sobre los desastres naturales*

Jhorland Ayala-García♦

Sandy Dall'Erba•

Resumen

Se espera que los eventos de lluvias extremas sean más frecuentes e intensos en el futuro. Debido a que su mitigación es un desafío y su costo para la vida humana es alto, este documento estudia el impacto de la inversión en prevención contra desastres naturales en la ocurrencia futura de deslizamientos de tierra y las pérdidas asociadas a los mismos. Con base en un panel de 746 municipios colombianos con riesgo medio y alto de deslizamientos de tierra y un enfoque de variable instrumental, encontramos que la inversión pública en prevención puede reducir la frecuencia de los deslizamientos de tierra, la cantidad de personas que mueren, resultan heridas o desaparecen después de un deslizamiento de tierra, así como el número de personas afectadas. Sin embargo, no encontramos ningún efecto sobre el número de viviendas destruidas. Los resultados revelan que los gobiernos locales enfocan sus medidas preventivas en salvar la vida y la integridad física de sus ciudadanos, pero prestan menos atención a las pérdidas de activos como consecuencia de los desastres naturales. Estos resultados son relevantes en presencia de mercados de seguros privados imperfectos y un aumento de asentamientos informales.

Palabras clave: deslizamientos de tierra, inversión en prevención, reducción del riesgo de desastres naturales, desastres naturales.

Clasificación JEL: H1, H4, H5, C26, D6.

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♦ Banco de la República, Cartagena, Colombia. Email: jayalaga@banrep.gov.co.

• Universidad de Illinois en Urbana-Champaign, USA. Email: dallerba@illinois.edu.

1. Introduction

According to data from the National Administrative Department of Statistics (DANE, in Spanish), 71% of the Colombian population lives in municipalities with a medium or high risk of landslides. These natural events are defined as movements of soil or rocks in the direction of the slope of the mountainside that can be caused by earthquakes or rainfall. They are the main cause of death from natural hazards in Colombia (The World Bank Colombia, 2012) [1]. The National Unit for Disaster Risk Management (UNGRD, in Spanish) reports that between 2006 and 2017, up to 729,829 inhabitants were affected by landslide-related disasters, 2,141 people died, were injured, or disappeared, and 9,605 houses were destroyed. These disruptions demand effective preemptive measures from local and central governments to protect the lives, the assets, and the wellbeing of the population, more especially because future weather projections for the country indicate an increase in extreme rainfall events (Christensen *et al*., 2007; Rios *et al*., 2016). Examples of such measures are: monitoring hazards, building resilient infrastructure, and relocating the population living in risk-prone areas (The World Bank, 2010). Some studies, mostly cost-benefit analyses, try to evaluate the benefits of preemptive public investments against natural disasters (Kousky et al., 2019; Rose et al., 2007; Shreve and Kelman, 2014). However, this approach relies on strong assumptions about estimating both the costs and the benefits, especially when it comes to the non-market value of life.

Even with the accumulating evidence of their effectiveness, policymakers have few incentives to invest in preventive measures and prefer to focus on relief spending instead. There are two reasons for their choices. The first one comes from the optimal insurance literature (Goodspeed and Haughwout, 2012; Lohse and Robledo, 2013). It is based on the asymmetric information and moral hazard problems that can create a Samaritan's Dilemma, also called charity hazard (Buchanan, 1975; Raschky and Weck-Hannemann, 2007). Because central governments cannot credibly threaten to avert relief spending after a natural disaster, they unwillingly create incentives for local governments to underinvest in preventive measures (Goodspeed and Haughwout, 2012; Lohse and Robledo, 2013; Raschky and Weck-Hannemann, 2007). The second reason can be found in the public choice literature, according to which voters prefer politicians who favor post-disaster spending than those who spend more on preemptive measures (Healy and Malhotra, 2009).

[1] Excluding the volcanic eruption of the Nevado del Ruiz volcan in 1985 which caused more than 23,000 deaths (The World Bank Colombia, 2012).

Nevertheless, if more accurate information about the effectiveness of preemptive investment were available, politicians would be able to make more informed decisions on spending on preventive vs. post-disaster measures.

To our knowledge, the empirical evidence evaluating the effectiveness of preemptive public measures against natural disasters is scarce. The available studies have assessed the impact of preemptive investment but the methodology they use does not allow to establish causality. For example, Healy and Malhotra (2009) evaluate the impact of preemptive investments on natural disasters and they find that preparedness spending reduces the damages from natural disasters. Ji and Lee (2019) try to evaluate the effect of the Hazard Mitigation Grant Program on the reduction of economic losses from natural disasters in the United States. They find that counties that received grants to develop local mitigation projects experienced lower future economic losses from natural disasters. Finally, Anbarci *et al.* (2005) find that income and inequality are important determinants of natural disaster fatalities at the country level. They conclude that one of the mechanisms for this relationship is collective action and preparedness against natural disasters. However, they only rely on correlation tests to make their argument. In all cases, the authors do not control for institutional factors such as government stability, law enforcement capacity and corruption which are often considered important determinants of natural disasters (Kahn, 2005; Raschky, 2008; Strömberg, 2007). This omitted variable bias may affect their conclusions.

In order to fill this gap in the literature, this paper combines satellite information with financial data at the subnational level to empirically evaluate the impact of preemptive investment against the occurrence and the damages of landslide-related disasters. We take advantage of a detailed public finance database for Colombian municipalities where we can obtain information about the preemptive investment against natural disasters. Examples of the preemptive measures taken by municipalities in order to reduce natural disasters are early alert systems to monitor weather, resilient infrastructure to prevent landslides such as protecting the side of mountains, deforestation control, and relocating the population living in risk-prone areas. Furthermore, we use an instrumental variable approach to capture the exogenous variation in preparedness spending and calculate how this variable affects future natural disasters. We focus on landslides because these events depend on local rainfall, as opposed to floods, which depend on rainfall or floods in upstream locations. The results show that current preparedness spending is positively affected by past rainfall across Colombian municipalities, and this higher investment significantly reduces the future occurrence of landslides, the total people affected, as well as the fatalities and injuries associated with landslides. However, preemptive investments do not have any significant impact on reducing the damages or losses of housing. These results provide novel, precise and important insights for policymakers as they indicate it is imperative to keep funding preemptive investments across Colombian municipalities. They protect the lives of the most vulnerable population even if further improvements are needed to also protect their assets (Fay and Ruggeri, 2005; Sawada and Takasaki, 2017). The remaining of the paper is organized as follows: the next section presents a review of the literature, while section 3 presents the data and the methodology. Section 4 reports the results. Finally, section 5 summarizes the main findings and offers some concluding remarks.

2. Literature review

The literature suggests different variables such as the level of economic development (Kahn, 2005; Toya and Skidmore, 2007), the quality of the local institutions (Raschky, 2008; Strömberg, 2007), and country size (Cavallo *et al.*, 2010) as the main factors affecting the vulnerability against natural disasters. For example, Kahn (2005) finds that the level of development is an important determinant of natural disaster damages, with richer countries experiencing the same amount of natural events but with fewer fatalities than poorer countries. Kahn (2005) also finds a negative relationship between higher-quality institutions and natural disasters. Toya and Skidmore (2007) expand the results in Kahn (2005) by considering socio-economic factors such as educational attainment, degree of openness, financial development, and the size of the government. They find that countries with higher income, a more educated population, more open to international trade, with developed financial systems, and smaller government sizes experience fewer losses associated with natural disasters. They hypothesize that richer countries can reduce losses by higher private self-insurance and stronger socio-economic infrastructure that reduces exposure to natural disasters.

In their work, Cavallo and Noy (2011) summarize the literature evaluating the determinants of the economic cost of natural disasters. They point out that most contributions estimate models where the direct damages of the natural disasters are a function of the magnitude and vulnerability of the disaster. The authors describe that direct damages include the economic value of the losses as well as mortality and morbidity. They state that the magnitude of a natural disaster can be measured depending on the type of natural event (Richter scale for earthquakes, wind speed for hurricanes, etc.). They conclude that vulnerability refers to the local physical or environmental characteristics that increase the susceptibility to a natural disaster.

While analyzing the determinants of nearly 2000 natural disasters, Cavallo *et al*. (2010) find that country size is positively correlated with the level of damages of a disaster. Contrary to the findings of Kahn (2005), Cavallo *et al*. (2010) conclude that economic development is positively correlated with the economic value of disaster losses. The difference may be explained in the fact that Kahn (2005) uses fatalities as the dependent variable while Cavallo *et al*. (2010) uses the economic value of the disaster losses and considers the number of fatalities as a control variable for the intensity of the natural disaster. Raschky (2008) uses two different measures of natural disasters: the number of fatalities and the economic value of losses. The author finds that economic development and institutional quality significantly reduce the damages of natural disasters. Similarly, Strömberg (2007) finds that government effectiveness, a measure of institutional quality, reduces natural disaster losses.

One element that has been surprisingly ignored in this literature is the effect of preemptive public investment or government's preparedness against natural disasters, although the effect of preventive measures has been studied in the private sector with a focus on earthquakes (Cardona et al., 2008; Shinozuka et al., 2003; Smyth et al., 2004; Sohn et al., 2003). One exception is Anbarci *et al.* (2005) who find that fatalities from natural disasters decrease with income but increase with inequality. They conclude that one of the mechanisms for this relationship is collective action and preparedness against natural disasters. However, they fail to test this hypothesis directly. As a result, their findings correspond to simple correlations and cannot be interpreted as actual causal relationships. Another exception is Healy and Malhotra (2009) who evaluate the impact of preemptive investments in the United States. The authors find a negative relationship between such investments and future damages related to natural disasters, but their results suffer from an omitted variable bias because they do not control for institutional characteristics and income. Our paper tries to fill this gap in the literature by using an instrumental variable approach that allows us to evaluate a causal relationship. Finally, Ji and Lee (2019) study the effect of the Hazard Mitigation Grant Program on the magnitude of natural disasters in the United States. They find that additional resources for mitigation purposes reduce losses from natural disasters, but they rely on the assumption that institutional characteristics at the county and state level are time-invariant. However, this assumption does not hold because it has been found that the declaration of a natural disaster in the United States, and the subsequent approval of Hazard Mitigation Grant Program funds, is correlated with institutional characteristics such as presidential and congressional relationships which may not be constant over time (Garrett and Sobel, 2003).

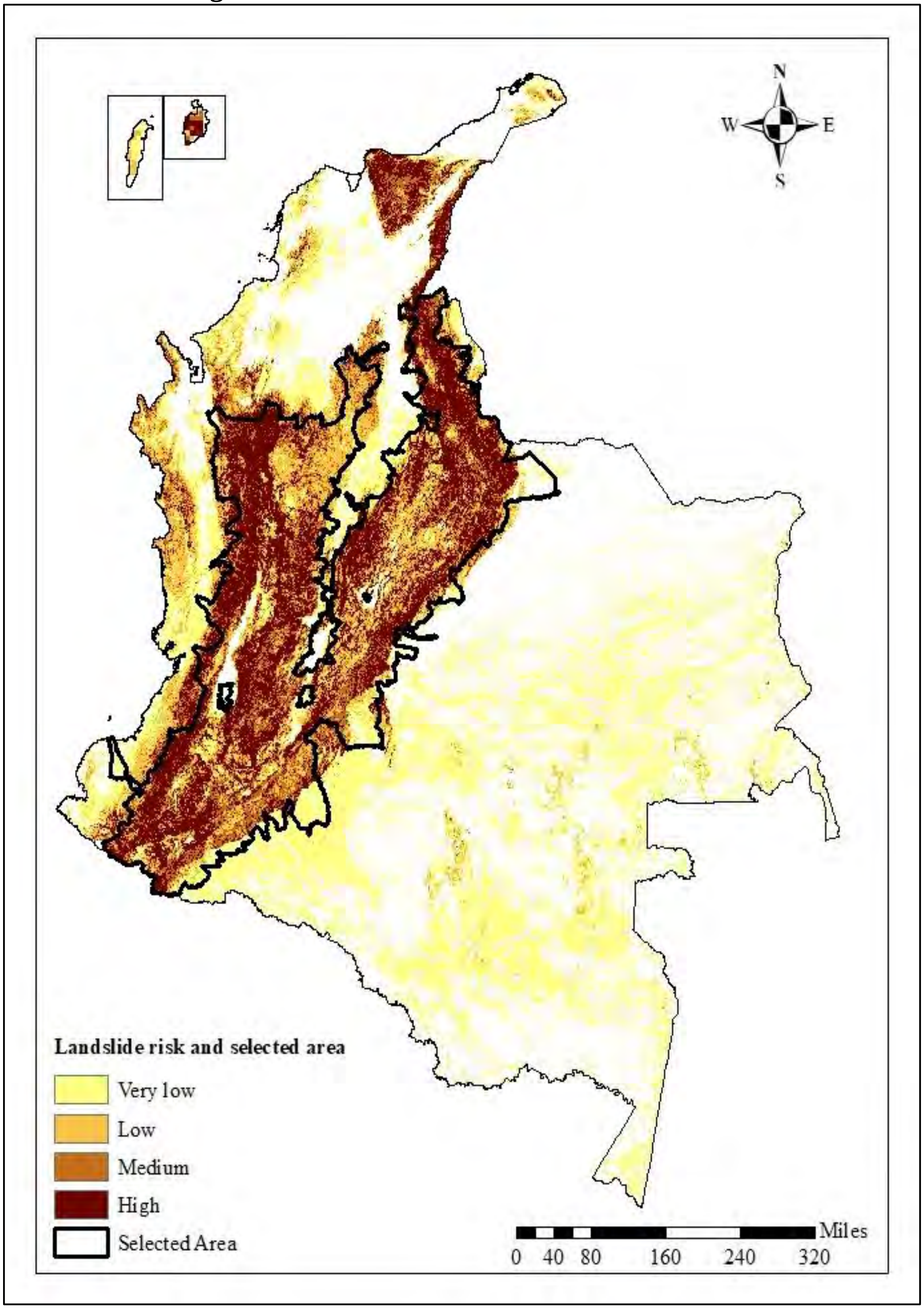
3. Data and Methodology

3.1. Data

This paper combines satellite information with public finance data across Colombian municipalities to evaluate the impact of preemptive investment on natural disasters. We use the Global Landslide Susceptibility Map from the Global Facility for Disaster Reduction and Recovery (GFDRR) and InnovationLab GeoNode (GFDRR-InnovationLab, 2019) to identify the municipalities at risk of landslide-related disasters. This map classifies landslide risk in four categories: very low, low, medium, and high. We then match the landslide map with the Colombian elevation map (DIVA-GIS, 2019) to select municipalities with a medium and high risk of landslide and with an elevation of more than 500 meters above the sea level (m.a.s.l.), which results in a sub-sample of 746 municipalities with 71% of the total population. The reason for this selection is that landslides depend on local precipitation, whereas floods depend not only on local rainfall but also on rainfall from upstream locations, which makes the identification strategy problematic. Because landslides take place more frequently in high-elevation municipalities and those at lower elevations suffer more frequently from floods, we can assume that preemptive investment in the former is expected to be mainly focused on preventing landslides, while in the latter the main problem to address is floods. Indeed, it can be seen in Figure 1 below that the risk of landslide in Colombia is higher in the selected area (municipalities above 500 m.a.s.l.). Figure 2 shows that landslides in Colombia have occurred mainly in the selected municipalities and that the occurrence of floods is in general higher in low elevation municipalities according to data from the National Unit for Disaster Risk Management (UNGRD, in Spanish). This argument is consistent with the empirical evidence that shows that hazard risk is an important determinant of preemptive investment in subnational governments (Karim and Noy, 2020).

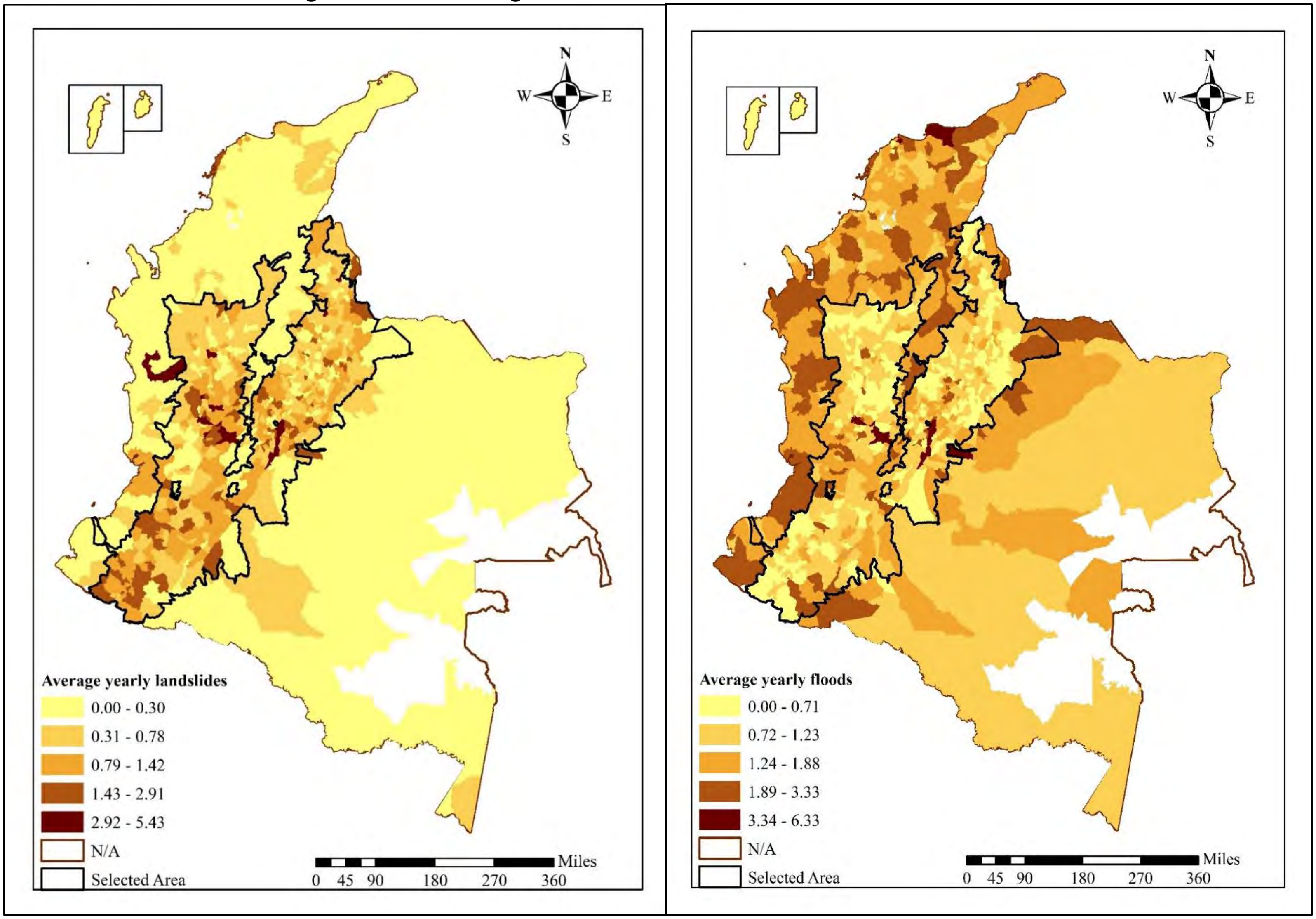
This paper uses the reports of national emergencies from the National Unit for Disaster Risk Management (UNGRD in Spanish). The database covers the period 2006-2017. It contains information about the occurrence of landslide-related disasters and three different measures of their intensity. Following the classification proposed by the Economic Commission for Latin America and the Caribbean (ECLAC), we use the total number of houses destroyed as a measure of direct market losses and the total people affected to capture the indirect market losses. Direct non-market losses are captured by the number of total deaths, injured and disappeared (ECLAC, 2003). These three measures are commonly used in natural disaster databases (Cavallo and Noy, 2011). We also consider the frequency of landslide-related events as a measure of the occurrence of natural disasters. In addition, we have satellite information about rainfall from the Tropical Rainfall Measuring Mission (TRMM) (GES-DISC, 2011). Satellite rainfall information has been suggested as an appropriate source of rainfall information for Colombia, given the limited coverage of monitoring stations at the municipality level in the country (Dinku *et al*., 2010). We use two different measures for the rainfall: i) the rainfall for the month of December, considering that this is the month when most of the municipal financial budgets are approved, ii) the average presipitation for the rainfall season (September – November) which is also close to the time when the future budget decisions are made. Figure 3 shows the evolution of our two measures of rainfall for the Colombian municipalities in our selected sample. It can be seen that both measures show the same trends over the studied period.

Figure 1. Landslide risk and the selected area.



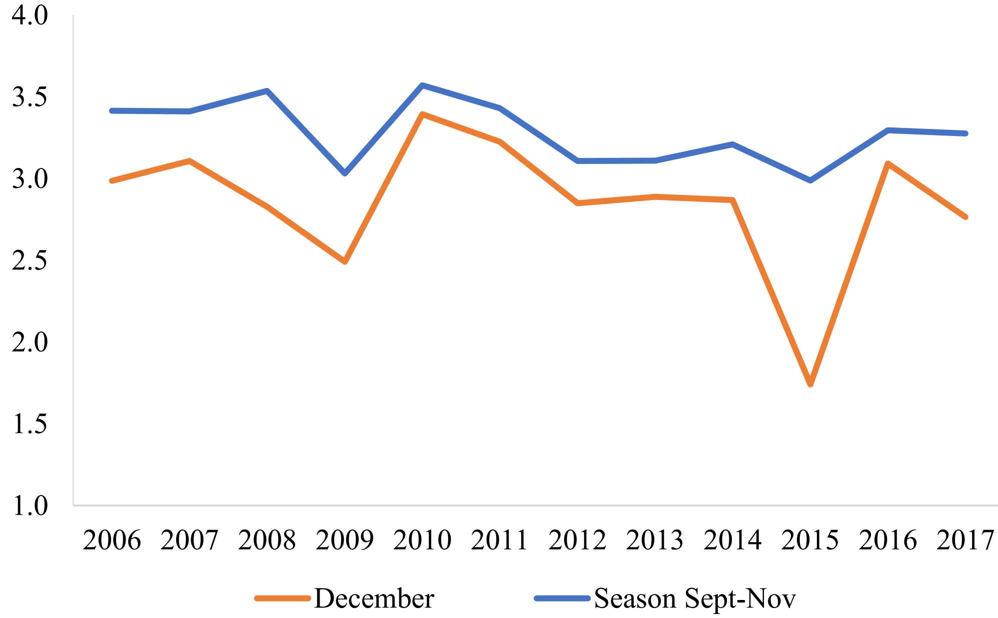
Source: the author with data from the Global Facility for Disaster Reduction and Recovery (GFDRR) and InnovationLab GeoNode and DIVA-GIS (2019)

Figure 2. The average number of landslides and floods, 1998-2018.



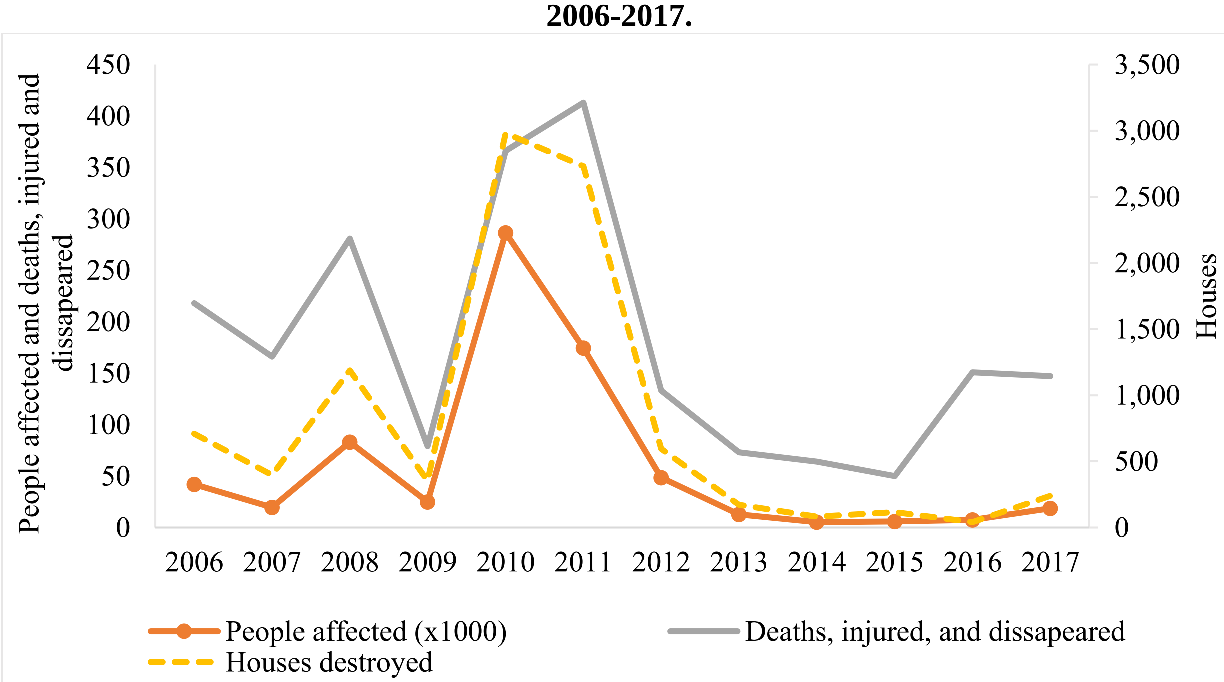
Source: the author with data from The National Unit for Disaster Risk Management (UNGRD, in Spanish), the Global Facility for Disaster Reduction and Recovery (GFDRR) and InnovationLab GeoNode, and DIVA-GIS (2019).

Figure 3. Rainfall (mm/h) in Colombian municipalities, 2006-2017.



Source: The authors with data from Tropical Rainfall Measuring Mission (TRMM) (GES-DISC, 2011).

Figure 4. Landslide-related natural disaster losses in selected municipalities, yearly average 2006-2017.

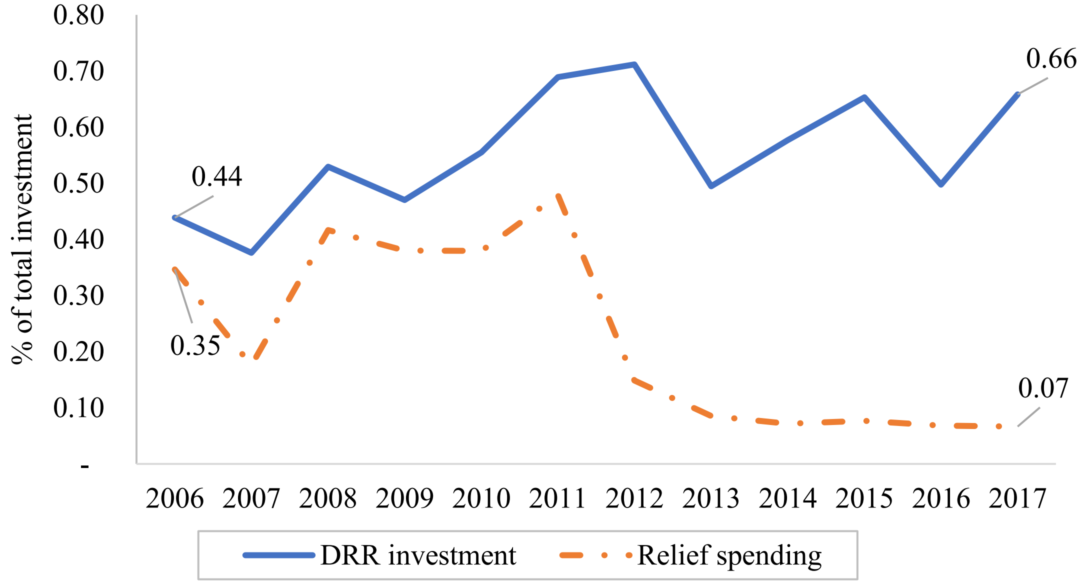


Source: The author with data from the National Planning Department.

Figure 4 shows that the three different measures of natural disaster losses follow the same pattern for the period 2006-2017. The spike in 2010-2011 corresponds to a greater occurrence of natural disasters following a severe *La Niña* event in that period. The average total rainfall in 2010-2011 was 46% higher than the average for 2006-2009 in the selected sample. This weather shock increased the average landslides from 190 in 2006-2009 to 674 in 2010-2011. Likewise, the yearly average number of people affected soared from 42,329 to 230,448, whereas the average number of dead, injured and disappeared increased from 186 to 390, and the average houses destroyed rose from 662 to 2,856 respectively.

The information regarding preemptive investments against natural disasters comes from the Unique Territorial Form dataset. This comprehensive dataset contains detailed financial information about revenue and expenditures at the municipality level. The preemptive investment covers the following groups of expenditures: i) information systems to monitor weather conditions, ii) building resilient infrastructure to protect human settlements and public and private infrastructure, iii) relocating population living in risk-prone areas to safer locations, and iv) educational programs about natural disaster's risk. Figure 5 shows the evolution of the share of preemptive and relief spending on total public investment between 2006 and 2017. The former represented only 0.38% of the total investment in 2006 and increased to 0.66% in 2017 while relief spending dropped from 0.35% to 0.07% over the same period. Additionally, we use data from the National Information Network (RNI, in Spanish) about the number of victims of the Colombian armed internal conflict. This variable can be used as a measure of vulnerability, given that the internal conflict has created a problem of forced displacement in the country. In general, forcibly displaced populations do not have enough assets to buy or rent a house in a safe place, so they are forced to build informal settlements on available free land, which is usually in the high-risk prone area (Fay and Ruggeri, 2005).

Figure 5. Evolution of preemptive and relief spending in selected municipalities, 2006-2017.



Source: The author with data from the National Planning Department.

Table 1. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Total landslides	0.46	1.13	0	28
People affected	82.21	515.89	0	14305
Houses destroyed	12.61	98.14	0	3642
Dead, Injured, or Disappeared	0.24	2.19	0	92
Preventive investment (thousands COP$)	5.97	17.98	0.0	715.4
Rainfall (in logs)	2.87	0.64	-2.15	4.6
Vulnerable population	0.42	3.25	0.0	158.3
Income per capita (millions COP$)	0.17	0.22	0.0	4.4
Population density	0.16	0.66	0.0	13.9
Population (in 100,000)	0.41	3.07	0.0	80.8

Source: The authors with data from the National Administrative Department of Statistics (DANE, in Spanish), The National Unit for Disaster Risk Management (UNGRD, in Spanish), and The Global Landslide Susceptibility Map.

Table 1 shows the descriptive statistics of the 746 municipalities of the selected sample over the period 2006-2017. We consider four different measures of natural disaster registered in the emergencies database: i) the total number of landslides, ii) the total number of people affected, iii) the total number of houses destroyed and iv) the total number of dead, injured, or disappeared after a landslide related event. Preemptive investment and income are measured in per capita units for every municipality. Rainfall is our measure of exogenous variation, which will allow us to make a causal argument. We obtain the yearly rainfall information for every municipality from the TRMM. We use the total number of internally displaced people as a measure of the vulnerable population as a control variable for vulnerability while population density and total population are control variables for the level of exposure.

3.2. Methodology

To evaluate the impact of preemptive investment on future natural disasters in Colombia, we use four different measures that capture direct and indirect market losses, as well as non-market losses from landslide-related events. Local governments' investment decisions regarding preventive measures against natural disasters may be correlated with institutional characteristics such as law enforcement capacity and expenditure efficiency where the latter shows significant regional variation across spending sectors and regions (Ayala and Dall'erba, 2020). Indeed, more control over the spread of informal settlements can reduce the need for preventive spending and less efficient municipalities would require more resources to effectively prevent natural disasters. There is evidence that higher-quality institutions are important determinants of natural disasters, possibly because better institutions are associated with more political accountability (Kahn, 2005). However, law enforcement capacity at the subnational level is not observed and efficiency measures for preemptive expenditure are not available. This generates an endogeneity problem as law enforcement capacity and expenditure efficiency are unobservable time-variant characteristics. In addition, measurement error is common in developing countries (Brückner, 2012), especially at the subnational level, which is the second source of endogeneity of public investment. As a result, we need to use an empirical strategy that allows us to obtain an exogenous variation of preemptive investments at the municipality level.

In this paper, we rely on an instrumental variable approach. We propose to use past rainfall as the exogenous instrumental variable in this case. More precisely, we use rainfall from year $t - 1$ as an instrument for the current preemptive investment. This time lag reflects the traditional approach according to which expenditure decisions are taken over the year before their implementation. As a result, a first-stage regression will assess how last year's rainfall level determines the current year's preemptive spending which can be written as follows:

$$\text{First stage: } \mathrm{I}_{\mathrm{it}} = \alpha \mathrm{R}_{\mathrm{i,t-1}} + \mathrm{X'}_{\mathrm{it}}\gamma + \mu_{\mathrm{i}} + \epsilon_{\mathrm{it}},$$

where I_{it} is the current preemptive investment, $\mathrm{R}_{\mathrm{i,t-1}}$ is the rainfall in $t-1$, $\mathrm{X'}_{\mathrm{it}}$ is a vector of control variables that include measures for economic development, exposure, and vulnerability, μ_i are municipalities fixed effects (FE) and ϵ_{it} is the error term. In the second stage, we will measure how the current preparedness investments affect the future occurrence and damages of natural disasters. Given the high variability and the presence of zeros in our measures of natural disaster, we use two different specifications: i) linear logarithmic transformations in the form $\ln(1+x)$ as in Kahn (2005) and ii) FE Poisson estimation with a control function approach following the method proposed by Lin and Wooldridge (2019). Therefore, our second stage can be written as follows:

Linear transformation: $\ln(\mathrm{D}_{\mathrm{i,t+1}}+1) = \beta\hat{\mathrm{I}}_{\mathrm{it}} + \mathrm{X'}_{\mathrm{it}}\omega + \lambda_{\mathrm{i}} + \varepsilon_{\mathrm{i,t+1}}$,

FE Poisson: $\mathrm{E}(\mathrm{D}_{\mathrm{i,t+1}} | I_{\mathrm{it}}, \mathrm{R}_{\mathrm{i,t-1,}} \mathrm{X'}_{\mathrm{it}}, \hat{\epsilon}_{\mathrm{it}}, \delta_{\mathrm{i}}) = \delta_{\mathrm{i}} \exp(\theta I_{\mathrm{it}} + \hat{\epsilon}_{\mathrm{it}}\rho + \mathrm{X'}_{\mathrm{it}}\emptyset)$,

where $\mathrm{D}_{\mathrm{i,t+1}}$ is the natural disaster in $t+1$, $\hat{\epsilon}_{\mathrm{it}}$ are the residuals from the first stage, λ_{i} and δ_i are municipality fixed effects and $\varepsilon_{\mathrm{i,t+1}}$ is the error term assumed to be normally distributed. Past rainfall is expected to be uncorrelated with the current municipality's institutional quality but strongly correlated to the municipality's decision of current preemptive investment. We take advantage of panel data to control for time-invariant municipal characteristics such as terrain conditions (slope, soil characteristics, elevation, etc.). Because we use the within transformation, only deviations from each municipality's average rainfall level are expected to display a significant effect on investments and disasters. This approach differs from a cost-benefit analysis because it does not rely on assumptions about the monetary value of the market and non-market losses (Kousky et al., 2019; Shreve and Kelman, 2014) and because it establishes an actual causal relationship. The results of our study can be taken as a complementary policy tool for the cost-benefit literature.

4. Results

The results of the first stage are shown in Table 2. Colum (I) presents the results using the cumulated rainfall for the month of December and Colum (II) considers the average cumulated rainfall for the rainy season September-November. In both cases, there is a strong and statistically significant relationship between rainfall in December of $t-2$ and preemptive investment in $t-1$. It means that, on average, municipalities invest more in preemptive measures if they observed a higher level of rainfall in the previous year. The *Cragg-Donald Wald F* statistic (Donald and Cragg, 1993) is significant at 10% for the Stock-Yogo weak ID test (Stock and Yogo, 2005) when using December rainfall and it is significant at 15% level when using the rainy season (September-November), which means that the instrument satisfies the relevance condition. However, rainfall for the month of December results in a stronger instrument. For the exogeneity assumption, we rely on the fact that rainfall at $t-1$ cannot affect disasters at time $t+1$. As a result, any remaining effect of rainfall at $t-1$ on landslides at time $t+1$ can only take place through mitigation or preventive measures. Since lansdlides are a recurrent event in Colombia because of the geographical characteristics of the Andean Region (The World Bank Colombia, 2012; UNGRD, 2018), it is unlikely that a natural disaster in $t-1$ impacts the occurrence and magnitude of a disaster two years later. In addition, we can discard the possibility that private preemptive measures act as a confounding factor for two reasons. First, most of the people affected by a landslide live in very vulnerable conditions. They are forced to live in risk-prone areas because they do not have the means to buy private insurance or to make preemptive investment when rainfall increases (Ratnadiwakara and Venugopal, 2020). Second, even if private investment were to take place as a result of higher rainfall, this private investment would affect the losses, but not the frequency of landslide occurrences.

The results of the first stage show that preemptive investment in $t-1$ is higher for municipalities that experienced a higher level of rainfall in $t-2$. A one percent increase in rainfall of December in $t-2$ increases the average current investment in $t-1$ by COP$1,860 and a one percent increase in the average rainfall in the rainy season September-November in $t-2$ increases preemptive investment in $t-1$ by COP$3,720. This is the average result for all municipalities with an elevation higher than 500 meters.

Table 2. First stage, preemptive investment and rainfall in municipalities over 500 m.a.s.l.

Dependent variable: preemptive Investment (*t-1*)	(I)	(II)
Rainfall *(t-2)*	**1.862*****	**2.678*****
	(0.344)	(0.836)
Rainfall *t*	-0.322	-0.407
	(0.879)	(0.936)
Time trend	**0.515*****	**0.536*****
	(0.064)	(0.076)
Vulnerable population	-0.013	0.012

	(0.027)	(0.024)
Per capita tax revenue	**7.813*** **	**8.635*** **
	(2.774)	(2.833)
Population density	-0.420	-0.337
	(3.599)	(3.615)
Total population	**-2.125*** **	**-2.001*** **
	(0.330)	(0.318)
Constant	-1,034.66***	-1,081.56***
	(127.78)	(154.073)
Observations	8,794	8,794
Number of municipalities	746	746
F(7, 745)	24.23	20.01
Cragg-Donald Wald F	26.55	7.99
Stock-Yogo weak ID test: maximal IV size	(10%) 16.38	(15%) 6.66

Standard errors clustered at city level. City fixed effects included. *** p<0.01, ** p<0.05, * p<0.1.

Source: Elaborated by the authors.

Table 3 presents the results of the second stage on our four measures of natural disaster with the log transformation while table 4 shows the FE Poisson results. In both cases, we consider the cumulated rainfall for the month of December as an instrument for preemptive investment given that this is a stronger instrument. Our findings indicate that one more unit of preemptive investment (COP$ 1,000 per capita) reduces the future occurrence of landslides by 2%, the number of people affected by 5.1%, and the number of dead, injured and disappeared by 1%. Using the FE Poisson results from table 4, we find that, ceteris paribus, one more unit of preemptive investment reduces the number of landslides by 5.3% (exp(0.054)-1) while the number of people affected is reduced by 12.6% and the number of dead, injured and disappeared is reduced by 17%. Although the marginal results are significantly different between the two specifications, the general conclusions are the same: preemptive investment reduces the frequency and losses of landslides. Finally, our results indicate that investments do not have any significant effect on the number of houses destroyed. This finding meets our expectations as (most) people move when a landslide is expected but their property does not. In addition, one should not count on past disasters as a means to prevent new families to be located in risk-prone areas. These are very poor families who do not have other options.

When comparing these estimates with the OLS results reported in Appendix 1, we hypothesize that the endogeneity problem is driven by a measurement error given that we find a bias toward zero in the main coefficients. The results are robust to the selection of municipalities over 1,000 m.a.s.l. (Appendix 2). Moreover, the main conclusions do not change if we consider the average rainfall for the rainy season for the Colombian Andean region for the months of September-November as an instrument for preemptive investment (Appendix 3). The results are also consistent with the exclusion of presumably exogenous covariates (Appendix 4). We also consider the possibility that our findings are affected by the spike in natural disasters observed during 2010-2011. As a result, we estimate the same regressions for the years 2012-2017 and our main results remain consistent (Appendix 5).

Table 3. Second stage, log transformation, preemptive investment and natural disasters

Dependent variable (in logs)	Total Landslides	People affected	Houses destroyed	Deaths, Injured, and Disappeared
Preemptive investment *t-1*	**-0.020*** **	**-0.051** **	-0.002	**-0.010** **
	(0.006)	(0.020)	(0.005)	(0.004)
Rainfall	**0.122*** **	**0.510*** **	**0.091*** **	**0.036*** **
	(0.019)	(0.057)	(0.012)	(0.011)
Time	**0.020*** **	-0.016	**-0.011*** **	0.002
	(0.003)	(0.011)	(0.003)	(0.002)
Vulnerable population *t-1*	0.000	-0.005	0.002	0.006
	(0.003)	(0.007)	(0.003)	(0.007)
Per capita tax revenue *t-1*	**0.170** **	**0.654** **	0.082	**0.138*** **
	(0.080)	(0.281)	(0.063)	(0.052)
Population density	**-0.422*** **	**-1.271*** **	**-0.250* **	-0.176
	(0.100)	(0.350)	(0.149)	(0.269)
Total population	**-0.091*** **	**-0.222*** **	**-0.130*** **	**-0.223*** **
	(0.020)	(0.078)	(0.040)	(0.028)
Observations	8,794	8,794	8,794	8,794

Standard errors clustered at city level. City fixed effects included. *** p<0.01, ** p<0.05, * p<0.1.
Source: Elaborated by the authors.

Table 4. Second stage, Poisson FE estimation, preemptive investment and natural disasters

Dependent variable (at time t):	Total Landslides	People affected	Houses destroyed	Deaths, Injured, and Disappeared
Preventive investment *t-1*	**-0.054** **	**-0.135** **	-0.153	**-0.187** **
	(0.021)	(0.067)	(0.114)	(0.079)
Rainfall	**0.680*** **	**1.193*** **	**1.295*** **	**0.976*** **
	(0.059)	(0.190)	(0.316)	(0.255)
Time	**0.071*** **	**-0.066** **	-0.053	0.029
	(0.010)	(0.033)	(0.054)	(0.041)
Vulnerable population *(t-1)*	0.003	-0.000	**-0.018*** **	-0.015
	(0.003)	(0.013)	(0.006)	(0.009)
Per capita tax revenue *(t-1)*	0.262	-1.442	-2.484	1.815
	(0.381)	(1.360)	(1.985)	(1.309)
Population density	**-1.417*** **	0.019	-0.377	-1.998

	(0.385)	(0.985)	(0.761)	(1.409)
Total population	**-0.125*** **	-0.260	-0.196	**-0.452*** **
	(0.046)	(0.166)	(0.254)	(0.158)
Observations	7,102	6,187	4,078	2,709

Standard errors clustered at city level. City fixed effects included. *** p<0.01, ** p<0.05, * p<0.1.
Source: Elaborated by the authors.

Taking the coefficients of the FE Poisson model of table 4, increasing per capita preemptive investment by 1% from the average would reduce the expected number of landslides by 0.3%, the number of people affected by 0.8% and the number of dead, injured and disappeared by 1%. It means that with respect to the average values, a 1% increase in per capita preemptive investment could save up to 2,2 lives. Our results show a higher elasticity than the one that has been found in Healy and Malhotra (2009) whose findings indicate an elasticity of 0.13. The difference may be explained by the omitted variable bias in their results caused by omitted factors such as corruption and expenditure efficiency. All the regressions include a linear trend in order to control for the improvements in the collection and reporting of disaster events over time in the municipalities, as it has been done in the literature (Cavallo *et al*., 2010). As expected, the results indicate that current rainfall is a key determinant of landslides related to natural events and it is positively correlated with all our measures of natural disasters. No significant relationship is found between vulnerability and landslide-related losses. In contrast to what has been found at the country level by Kahn (2005), our results indicate that richer municipalities experience a higher number of people affected and a higher level of mortality and morbidity. The measures of exposure indicate that higher exposure decreases the losses from natural disasters after controlling for preemptive investment and income as it is suggested by The World Bank (2012). Municipalities with a higher population density experience lower market losses and larger municipalities in terms of population experience lower losses in all measures of natural disasters.

5. Conclusion

Climate change is increasing extreme rainfall events that will affect the probability of natural disasters. Colombia is a country highly prone to the occurrence of landslides which are the main cause of death from natural disasters in the country. This reality demands effective measures to protect the lives and assets of the most vulnerable population. However, the existing empirical evidence evaluating the effectiveness of public preparedness spending against natural disasters does not allow us to make causal arguments. This paper fills this gap in the literature. With data from Colombian municipalities, we use an instrumental variable approach to evaluate the impact of preemptive investment against natural disasters using past rainfall as an instrument for current preemptive investment.

We combine satellite information with public finances at the municipality level to evaluate the relationship between current preemptive investment and future natural disasters at the sub-national level. This paper focuses on the most elevated municipalities to identify the singular effect of landslides and it relies on a rich and detailed dataset of rainfall and local investments. We take advantage of panel data to control for unobserved time-invariant heterogeneity. In the first stage, we use past rainfall as a determinant of current preemptive investment. This variable works as a relevant and exogenous instrument determining the level of current investment against future natural disasters. In the second stage, we regress measures of occurrence of landslides and their magnitude to evaluate the effectiveness of exogenous preemptive investment. We focus on landslides because these natural disasters depend on local rainfall only. Floods, on the other hand, depend on the sum of local and upstream precipitation.

Based on the exogenous variation obtained in the first stage, our results indicate a negative impact of preemptive investment on the number of fatalities and injuries at the local level. The results show that preemptive investments reduce the future occurrence of landslides, the total people affected and the fatalities and injuries associated with landslides, but they fail to protect against direct market damages. Specifically, we find that an increase of 1% in preemptive investment per capita reduces the future occurrence of landslides by 0.3%, the total people affected by 0.8% and the number of deads, injured and disappeared by 1%. We do not find a statistically significant effect of preemptive investment on the future number of houses destroyed.

Our findings should increase the awareness of policymakers regarding the importance of preemptive investments. Colombian municipalities already allocate a higher portion of their budget for preemptive investments than for relief spending. Yet, we show that preemptive investments are not helping families protect their assets and this is particularly true for the most vulnerable population as they do not have the means to live anywhere else than in risk-prone areas. As a result, investments could be even more effective if they could also focus on reducing the asset losses through means such as highly-subsidized or fully-paid private insurance contracts. Another option could be fund large-scale, deeply subsidized, housing programs as this experience seems to have worked in several developing countries (Buckley et al., 2016). Furthermore, improvements in governance at the municipality level should prevent the spread of informal settlements in risk-prone areas (The World Bank Colombia, 2012).

Future research should focus on the impact of preemptive investments against floods, which is the second most important source of damages from natural disasters in Colombia, according to data from the UNGRD. This question would oblige us to consider additional elements such as private-public partnership, large infrastructures such as levees, dams and diversion canals and to develop intermunicipal upstream and downstream covariance matrices (Peterson *et al*., 2007; Peterson and Ver Hoef, 2014).

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7. Appendix

Appendix 1. OLS results.

Log transformation

Dependent variable (at time t):	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Disappeared
Preventive investment *t-1*	0.000	-0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Rainfall	0.134***	0.539***	0.093***	0.042***
	(0.008)	(0.034)	(0.011)	(0.006)
Time	0.012***	-0.038***	-0.012***	-0.002*
	(0.001)	(0.006)	(0.002)	(0.001)
Vulnerable population	0.000	-0.005	0.002	0.006
	(0.004)	(0.007)	(0.003)	(0.007)
Per capita tax revenue	0.008	0.238	0.064	0.060**
	(0.049)	(0.175)	(0.042)	(0.028)
Population density	-0.411***	-1.242***	-0.249	-0.171
	(0.097)	(0.393)	(0.152)	(0.279)
Total population	-0.050***	-0.119	-0.126***	-0.203***
	(0.015)	(0.076)	(0.039)	(0.028)
Constant	-23.685***	76.475***	24.013***	3.702*
	(2.823)	(11.363)	(3.349)	(2.210)
Observations	8,794	8,794	8,794	8,794
R-squared	0.037	0.037	0.019	0.021
Number of id	746	746	746	746

Standard errors clustered at city level. City fixed effects included. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

FE Poisson estimation

Dependent variable (at time t):	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Disappeared
Preventive investment *t-1*	0.000	-0.008**	-0.018*	-0.004
	(0.001)	(0.004)	(0.010)	(0.009)
Rainfall	0.745***	1.333***	0.888***	1.332***
	(0.063)	(0.191)	(0.196)	(0.245)
Time	0.061***	-0.062***	-0.043**	-0.028
	(0.006)	(0.012)	(0.017)	(0.022)
Vulnerable population	0.005**	-0.001	-0.016	0.020***
	(0.002)	(0.009)	(0.024)	(0.002)
Per capita tax revenue	0.103	-2.300**	-1.981**	1.546
	(0.327)	(0.943)	(0.900)	(1.147)
Population density	-1.586***	-0.850	-0.453	-1.302
	(0.332)	(0.827)	(0.744)	(1.405)
Total population	-0.015	0.054	-0.020	-0.216***

	(0.023)	(0.066)	(0.089)	(0.079)
Observations	7,862	6,934	6,730	3,080
Number of id	666	587	570	262

Standard errors clustered at city level. City fixed effects included. *** *p*<0.01, ** *p*<0.05, * *p*<0.1.

Appendix 2. Preemptive investment and natural disasters in municipalities over 1,000 m.a.s.l.

First Stage	
Dependent variable:	Preemptive investment (t)
Rainfall *(t-2)*	**1.987*****
	(0.374)
Cragg-Donald Wald F	25.31
Stock-Yogo weak ID test: 10% maximal IV size	16.38

Second Stage				
Dependent variable:	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Disappeared
Preemptive investment *t-1*	**-0.0204*****	**-0.062*****	-0.003	**-0.011****
	(0.007)	(0.022)	(0.005)	(0.004)
Observations	7,671	7,671	7,671	7,671

Standard errors clustered at city level. City fixed effects included. *** *p*<0.01, ** *p*<0.05, * *p*<0.1. We control for all the covariates of the original model.

Appendix 3. Second stage, log transformation, preemptive investment and natural disasters (Seasonal rainfall).

Dependent variable (in logs):	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Disappeared
Preemptive investment *t-1*	**-0.022****	-0.023	-0.024	**-0.020****
	(0.010)	(0.038)	(0.015)	(0.010)
Rainfall	**0.305*****	**1.614*****	**0.264*****	**0.083*****
	(0.028)	(0.109)	(0.044)	(0.026)
Time	**0.025*****	-0.008	0.002	**0.008***
	(0.005)	(0.017)	(0.006)	(0.004)
Vulnerable population *t-1*	0.000	-0.005	0.002	0.006
	(0.003)	(0.006)	(0.002)	(0.007)
Per capita tax revenue *t-1*	0.179	0.415	**0.262***	**0.219****
	(0.110)	(0.375)	(0.150)	(0.101)
Population density	**-0.396*****	**-1.129*****	**-0.243***	-0.175
	(0.103)	(0.345)	(0.140)	(0.262)
Total population	**-0.097*****	-0.168	**-0.175*****	**-0.243*****
	(0.025)	(0.110)	(0.046)	(0.032)
Observations	8,794	8,794	8,794	8,794

Standard errors clustered at city level. City fixed effects included. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Elaborated by the authors.

Appendix 4. Second stage, FE Poisson estimation with one endogenous covariate

Dependent variable:	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Disappeared
Preventive investment *t-1*	**-0.246*** **	0.092	-0.070	**-0.219***
	(0.041)	(0.126)	(0.203)	(0.122)
Observations	8,797	8,797	8,797	8,797

Standard errors clustered at city level. City fixed effects included. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix 5. Second stage, preemptive investment and natural disasters, 2012-2017 (December rainfall).

Log transformation

Dependent variable (at time t):	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Dissapeared
Preventive investment *t-1*	**-0.034*** **	**-0.085*** **	**-0.010***	-0.005
	(0.010)	(0.029)	(0.005)	(0.005)
Observations	4,383	4,383	4,383	4,383

Standard errors clustered at city level. City fixed effects included. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We control for all the covariates of the original model.

FE Poisson estimation

Dependent variable (at time t):	Total Landslides	People affected	Houses destroyed	Deaths, Injured and Dissapeared
Preventive investment *t-1*	**-0.098*** **	-0.149	**-0.317** **	-0.086
	(0.021)	(0.096)	(0.132)	(0.088)
Observations	3,031	2,239	1,107	820

Standard errors clustered at city level. City fixed effects included. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We control for all the covariates of the original model.