Volcanic Risk and Social Behaviors: Evidence from Ecuador

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Preliminary Draft

Abstract

This paper investigates the impact of a volcanic eruption on social capital and formally tests several transmission channels. In this aim, we conducted a survey in Ecuador around Tungurahua volcano, and we use ash thickness from the November 2015 eruption as an exogenous measure of the shock intensity. We find an heterogeneous impact on bilateral cooperation conditional on the level of wealth inequality in the community. In the most homogeneous communities the shock negatively affects bilateral cooperation, supporting the hypothesis of an aftermath moral hazard, while the eruption has a positive effect in the most heterogeneous communities. In addition, the shock intensity unconditionally promotes the willingness to contribute to public goods, and trust toward public authorities.

Keywords: Natural Disaster; Social Capital; Moral Hazard.
JEL codes: D71; H41; O12; Q12; Q54

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1 Introduction

Social capital is the cornerstone of several economic mechanisms such as growth (Algan and Cahuc 2010), risk-sharing (Ambrus et al. 2014), informal borrowing (Karlan et al. 2009), among many others. While it has long been considered as fixed by economists, recent evidence suggest that social capital have both long-term and short-term determinants, and therefore can either increase or decrease in response to changes in the environment. Instances of short-term determinants highlighted in the literature are expansion in formal financial access (Comola and Prina 2015), conflicts (De Luca and Verpoorten 2015, Voors et al. 2012), or natural disasters. Yet, despite the growing threat represented by natural disasters in developing countries (CRED 2015), their impact on social capital is poorly understood.

Existing studies on the effects of natural disasters on social capital remain ambiguous as they either conclude to positive (Cassar et al. 2017), or negative effects (Fleming et al. 2014). In both cases, several mechanisms have been proposed as potential transmission channels. On the one hand, the reconstruction process in the aftermath of a shock may increase the time spent with others and therefore strengthen ties between people. Also, since social capital is known to be negatively correlated with inequality (Alesina and La Ferrara 2000), a decrease in wealth inequality following a shock could foster social capital. In addition, the occurrence of a natural disaster may change the risk perception of affected people about future shocks (Cameron and Shah 2015), who may, in turn, strengthen their network to better cope with future disasters. Finally, trust can increase toward people providing help during the recovery process (Andrabi and Das 2010). On the other hand, by heterogeneously affecting individuals in a community, the shock may create an asymmetric information regarding damages suffered and income losses providing excuses to break previously-established social contracts between agents. Social capital may also decrease due to rivalry generated by disputes to obtain scarce relief and recovery resources. Finally, social capital can be adversely affected by movements of individuals within or between communities in the aftermath of a disaster (Fleming et al. 2014). These mechanisms remain, however, to be formally tested.

The present paper empirically investigates the impact of a volcanic eruption on social capital and proposes a formal test of several potential mechanisms. To do so, we conducted a survey in June 2016, in Ecuador, around Mount Tungurahua, one of the most active volcanoes of the country. The sample consists in 225 farm households living in nine communities in the affected area. We measured social capital through survey questions which allows us to investigate a much wider spectrum of social capital than what would be possible with experimental games. Indeed, we are able to measure trust toward different kinds of people like relatives and neighbors, but also toward institutions such as the Geophysical Institute, local and national authorities. We also measure the willingness of people to cooperate with each others, to lend money, to contribute to collective goods, and their network size. Our survey occurred few months after the eruption of November 2015 which severely affected farm households living in neighboring communities due to the large quantity of ash released worsened by unfavorable climatic conditions. In fact, farm business is particularly vulnerable to ash fall which may incur severe damages on crops, livestock, and infrastructures, and which may also affect individuals' health (Le Pennec et al. 2012). Since the whole sample has been affected by the eruption, our identification strategy does not rely on the comparison of an affected group with a non-affected population as it is often the case in the literature. Rather, we use data on ash thickness at the community level as a proxy for the shock intensity and we exploit its variation between the sampled communities. The exogenous source of variation used to identify the causal effect comes from the fact that the quantity of ash received by a community depends on its relative position to the ash cloud and that ash dispersion heavily depends on a mix of volcanic and climatic conditions at the time of eruption (Le Pennec et al. 2012).

Our case study allows to test for three transmission channels, namely the role of risk perception, the impact of temporary displacement, and the role of moral hazard. While the study of the former two mechanisms is relatively straightforward to implement, empirically investigating the role of moral hazard appears, at first sight, more challenging. Therefore, to guide the empirical analysis, we present a simple theoretical model that highlights the impact of a natural disaster on cooperation in a community when the shock has two opposite effects: it increases the need for reconstruction and therefore the benefits of cooperation on the one hand, and creates an asymmetry of information on the post-disaster income on the other. Given the difficulty of measuring such an "intangible" asset as social capital, our theoretical analysis follows La Ferrara (2002) and concentrates on one of its most important components, which is particularly straightforward to measure: membership in a group. Our baseline framework is as follows. We consider a community populated by two types of individuals who differently value cooperation. Each individual is endowed with an heterogeneous income level. We consider that one individual is affected by an idiosyncratic negative shock and needs help to recover. In this aim, she sets up a club, and invites some other members of the community to participate. Once they have been invited, people can either accept or decline the invitation. In response, the initiator of the club can decide to punish them by refusing any future cooperation. In the absence of natural disasters, the optimal strategy for the initiator of the club is to focus on individuals whose income is above a certain threshold that guarantees the participation of prosocial individuals. Turning to the impact of a natural disaster we show that, by increasing the need for reconstruction and therefore the benefits from cooperation, a natural disaster increases the incentive to cooperates which induces an increase of the number of participants. On the other hand, by heterogeneously affecting people in the community, it creates a situation of asymmetry of information where the initiator of the club does not directly observe the post-disaster incomes of individuals but only their distributions, allowing members of the community to pretend to be poorer than they actually are, in order to refuse cooperation and avoid punishment. We show that whether one effect dominates the other depends on the level of wealth inequality in the community. If the level of inequality is low, the shock leads to a pooling equilibrium in which the initiator of the group is unable to distinguish between "rich" and "poor" individuals. Despite the increased benefit drawn from cooperation, if the initiator of the group is unable to punish, people are better off not participating and the richest individuals have thus no incentive to signal themselves. On the other hand, if the level of inequality is high, the initiator of the group is still able to distinguish "rich" and "poor" individuals, and to punish the former if they deny cooperation. Then, while inequalities are considered as an impediment to cooperation in normal times (Alesina and La Ferrara 2000), our model predicts that by reducing the impact of the asymmetry of information, the level of inequality, coupled with an increase of the benefits from cooperation, has a positive effect on social capital in the wake of natural disasters.

Our empirical results are strongly supportive of the theoretical predictions. In fact, we find that in the most unequal communities, an increase of the shock intensity increases bilateral cooperation, while an increase of the shock intensity in the least unequal communities leads to a decline of bilateral cooperation. Consistently with our model, according to which these mechanisms may only affect social capital in the community, the impact on trust toward institutions like the Geophysical Institute, local authority or national authority is not conditional on the level of inequality in the community. Interestingly, the shock intensity has a positive but unconditional impact on people's willingness to contribute to collective goods, suggesting an absence of moral hazard behavior. We also test for two other potential transmission channels highlighted in the literature: namely risk perception about future disasters and temporary displacement. Risk perception was measured as the perceived likelihood of a future eruption in the next two months using a Likert scale, but empirical results do not suggest any evidence of its role as a transmission channel. Finally, to investigate temporary displacement, we use the fact that the government implemented a relocation program for some households living the affected area, but due to the lack of business opportunities in the resettlement area, people keep living in their lands in the affected area. Some of our sample households have therefore the opportunity to temporarily move out of the affected area in the case of eruptions. Results suggest that having a house in the non-affected area only lowers the magnitude of the effect of the shock intensity on trust toward the Geophysical Institute and local authority, which remains nevertheless positive.

In sum, this paper makes three contributions to the literature on the impact of natural disasters on social capital. Our main contribution lies in the formal empirical test of the economic mechanisms driving the effects of natural disasters on social capital, and to show the positive role of wealth inequality following the shock. Additionally, unlike some other studies that rely on an unaffected group as counter-factual, which may raise identification issues, we focus on the affected population only, using ash thickness from the November 2015 eruption as an exogenous measure of the shock intensity. Finally, by investigating several measures of bilateral cooperation, the willingness to contribute to collective goods, and trust in institutions, this paper explores a much wider spectrum of social capital than what has been done so far in the literature.

The remainder of this paper is as follows. Section 2 presents the related literature. Section 3 presents the theoretical framework. Data and descriptive statistics are presented in Section 4. Sections 5 and 6 discuss the empirical method and the results. Finally, Section 7 concludes.

2 Related Literature

Our paper is related to the burgeoning literature on the impact of natural disasters on social capital. Existing studies provide ambiguous results as both positive and negative impacts are highlighted. In fact, on the one hand, Becchetti et al. (2017) investigate the impact of the 2004 tsunami on generosity. They find that individuals affected by the tsunami give and expect less than non-damaged even seven years after the event. Similarly, Fleming et al. (2014) investigate, using trust games, the effect of the 2010 Chilean earthquake on trust and reciprocity. They find that the shock has no effect on trust but negatively impacts reciprocity. They explain their results through, what they call, aftermath moral hazard. They argue that a natural disaster affects the equilibrium within communities in terms of public knowledge or shared information about each other's household characteristics – especially wealth levels and recovery – increasing information asymmetries between fellow villagers in the aftermath of the disaster. This situation could be exploited by individuals in the community to reciprocate less and make a gain. Apart from this explanation, Fleming et al. (2014) also mention other mechanisms that could adversely affect social capital. For instance, rivalry generated by disputes to obtain scarce resources can negatively affect levels of trust and/or reciprocity inside communities. Similarly, they argue that migration or displacement of people within or between communities could also deteriorate social capital. In this vein, Barr (2003), who studies the impact of the relocation program set up after the civil war in Zimbabwe, finds that the level of trust between people is lower in resettled communities than in original communities.

On the other hand, Toya and Skidmore (2014) find a positive impact of natural disasters on trust at the macroeconomic level over the 1985-2004 period. Focusing on OECD countries, they find that volcanic eruptions are positively associated with changes in trust. Castillo et al. (2011) investigate the impact of a large negative shock on altruism, trust and reciprocity in 30 small Honduran communities diversely affected by Hurricane Mitch in 1998. Their estimates suggest that while negative shocks might promote cooperation, too large shocks might actually destroy cooperation. Cassar et al. (2017) analyze the case of the 2004 Indian Ocean tsunami in Thailand and find a positive link between affected people and trust. To explain their findings, Cassar et al. (2017) highlight fours potential transmission channels through which natural disasters can positively affect social capital. First, longer interactions during reconstruction foster familiarity among survivors and familiarity breeds trust. This hypothesis is supported by Buggle and Durante (2017) who examine the historical relationship between economic risk and the evolution of social cooperation. They argue that the need of subsistence farmers to cope with climatic risk triggered cooperation and increased trust. Second, receiving help from family and neighbors increases faith that others are similarly trustworthy. In this vein, Andrabi and Das (2010) investigate the 2005 earthquake in Pakistan and show that trust felt toward Europeans and Americans increased thanks to the greater provision of foreign aid and foreigner presence in affected villages. Third, the perceived probability that a similar event might occur in the future increases the potential for needing help from others in the future, which causes people to be more trustworthy. This argument echoes with the burgeoning literature suggesting that affected people tend to overweight the probability of future shocks in the wake of natural disasters (Cameron and Shah 2015, Samphantharak and Chantarat 2014). Fourth, natural disasters can lower the degree of income disparity in the community which may in turn increases trust. In fact, a large literature has highlighted the adverse role of inequality on cooperation. For instance, using individual level data from US localities, Alesina and La Ferrara (2002) find that trust is lower in metropolitan areas with an uneven distribution of income. Similarly, Bjørnskov (2007) finds that income inequality and ethnic diversity reduce trust. Leigh (2006) studies the impact of inequalities on trust at the macroeconomic level and reaches similar conclusions.

3 The Model

The aftermath moral hazard hypothesis is not directly testable empirically. The aim of this section is therefore to setup a theoretical model in order to highlight a variable that could be used in the empirical analysis to investigate this transmission channel. Given the difficulty of measuring such an "intangible" asset as social capital, our analysis follows La Ferrara (2002) and concentrates on one of its most important components, which is particularly straightforward to measure: membership in a group. The main features of the model are as follows. We consider a community in which one individual is affected by a negative shock and needs help to recover. Therefore, she sets up a club, and invites some other members of the community to participate. Once they have been invited, people can either accept or decline the invitation. In response, the initiator of the club can decide to punish them by refusing any future cooperation. We show that a natural disaster, by increasing the need for reconstruction, and by inducing an asymmetry of information on post-disaster income, may either increase or decrease the level of cooperation, depending on the level of inequality in the community.

Setup We consider a community formed by N individuals, indexed by z. Individual can be of two types, either prosocial ($\theta_z = \theta^h$) with probability p, or antisocial ($\theta_z = \theta^l$) with probability $(1-p)$. The type of each individual is a private information, but the distribution is known by the community. Each individual is initially endowed with an exogenous level of wealth, denoted w_z, publicly known, and drawn from a uniform distribution U$[w_{min}, w_{max}]$. Each individual generates an income, denoted y_z, from his wealth such that:

$$y_z = w_z \tag{1}$$

We assume that one individual, to whom we refer as "she" thereafter, suffered from a negative shock and needs help from the community to recover. She creates a restricted access club, in which she invites some members of the community to participate in order to produce a club good, denoted G. The provision of the club good is subject to congestion effects and is equal to:

$$G = gP - (1-\gamma)P^2 \tag{2}$$

where g is the fixed contribution given by each participant, P is the number of participants, and γ, the size of the project, lies in [0;1). Once he has been invited, an individual is free to participate or not. As stated above, participation is conditional on the payment of a contribution, denoted

g, which is assumed to be the same for all individuals. Whatever his participation choice, the remaining income is spent in the consumption of a private good. The budget constraint for an individual z belonging to the club is therefore:

$$y_z = x_z + g$$

where x_z is the level of consumption of the private good, and g is the contribution given by z for the production of the club good. We consider that the club good, G, only benefits to the initiator of the club, and that the incentive for an individual to participate only lies on future reciprocity. In fact, we consider that people are aware that, in the future, each of them may also need help, and that they value the discounted value of future cooperation, which we denote α. We consider that the benefits of future cooperation between two individuals i and j depends on their type. If both players are of type θ^h, each of them will draw a high benefit from future cooperation which we denote α^{hh}. If both players are of type θ^l, little or no cooperation will occur and both players will receive a payoff α^{ll}. Finally, if players are of different type, cooperation will be unidirectional, and will be beneficial for the θ^l player who may receive help without reciprocating, and therefore costly for the θ^h player. In sum, α can take four values such that $\alpha^{hh} > \alpha^{lh} > \alpha^{ll} \geq 0 > \alpha^{hl}$.

We assume that all individuals are characterized by the following utility function:

$$U_z = u(x_z) + \theta_z + \alpha \tag{3}$$

where $u(x_z)$ is concave and represents the utility derived from the consumption of x, θ_z is the individual's type and represents the joy derived from cooperation, and α represents the discounted value of future cooperation.

Following the individual's decision to participate or not, the initiator of the club can decide to punish him. Punishment takes the form of no future cooperation between both players, but does not systematically follow a deny of participation. In fact, an individual decides to participate to the club as long as the utility derived from participation is greater than the utility derived from non-participation. More formally, an individual accepts to participate if:

$$u(y_z - g) + \theta_z + \alpha > u(y_z) \tag{4}$$

Then, there are two reasons for which a member may refuse to cooperate. First, he might be of type θ^l and therefore does not derive any joy from cooperation. Second, even though he is of type θ^h, the participation fee, g, might be too high relative to his income, making participation to the club too costly for him. However, he would have surely cooperated if his income was higher or, equivalently, g smaller. Punishing a good type agent who did not participate for economic reasons is therefore costly for the initiator of the group since it prevents any future cooperation with him. Consequently, because each individual's type is unknown, punishment is not always the best response to non-participation.

To sum up, the timing of the game is as follows:

1. The initiator of the club decides whether to invite one individual to join the club or not.
2. The individual decides to participate or not.
3. The initiator of the club decides to punish him or not.
4. Payoffs are realized.

Payoffs Payoffs for the initiator of the club are as follows:

1. (Ask; Cooperates; No punishment): $U = g - 2(1-\gamma)P + \alpha$

2. (Ask; Does not cooperate; Does not punish good type): $U = \alpha^{hh}$ or α^{lh}
3. (Ask; Does not cooperate; Punish bad type): $U = 0$
4. (Ask; Does not cooperate; Punish good type): $U = 0$
5. (Ask; Does not cooperate; Does not punish bad type): $U = \alpha^{hl}$ or α^{ll}

Payoffs for the other individuals of the community are as follows: Not being asked to participate or, equivalently, being asked but denying cooperation without punishment is the best possible outcome for any individual since he maximizes his consumption of the private good, and still benefits from future cooperation. As a second best, depending on his income level, the contribution amount, and his type, an individual may either prefer to cooperate and avoid punishment, or not to cooperate and suffer from punishment.

1. (Not Asked): $U = u(y_z) + \alpha$
2. (Asked, Does not cooperate, Not Punished): $U = u(y_z) + \alpha$
3. (Asked, Cooperates, Not Punished): $U = u(y_z - g) + \theta + \alpha$
4. (Asked, Does not cooperate, Punished): $U = u(y_z)$

Solution In this framework, where income is perfectly observable, there exists an income level, which we denote $y^\star$, above which any θ^h agent will accept to participate, and below which no agent, regardless of their type, cooperates. The optimal behavior for the initiator of the club is therefore to invite members whose income is above $y^\star$ since a refusal would automatically signal a θ^l individual that is costless or even beneficial to punish. The equilibrium is reached when the optimal number of participants is reached or when no additional player would accept to participate if invited.

The impact of a natural disaster Following the literature, we consider that the shock has two opposite effects. First, it increases the need for reconstruction, which translates into an increase of the size of the project, γ. Since the initiator of the club is more vulnerable in the wake of a natural disaster, we may consider that her willingness to reciprocate in the future is higher, increasing α for the participants, and lowering $y^\star$. Second, the natural disaster negatively and heterogeneously affects wealth of individuals and creates an asymmetry of information, such that the initiator of the group does not directly observe the true post-disaster income of an individual but only its distribution. More formally, the ex-post income level, denoted $\tilde{y}$, equals:

$$\tilde{y}_z = w_z - s \tag{5}$$

and $s = s_1$ with probability q, and $s = s_2$ with probability (1-q), and $s_1 > s_2$.

This leads to three situations: *(a)* There exists a wealth level which we denote $w^{'}$ such that, for any individual whose wealth belongs to $[w_{min}; w^{'}]$, the post-disaster income, $\tilde{y}$, will be lower than $y^\star$, regardless of the shock intensity (s_1 or s_2); *(b)* There exists a wealth level which we denote $w^{''}$ such that for any individual whose wealth belongs to $[w^{''}; w_{max}]$ the post-disaster income, $\tilde{y}$, will be higher than $y^\star$, regardless of the shock intensity (s_1 or s_2); *(c)* Individuals whose wealth lies in $[w^{'}; w^{''}]$ will have a post disaster income $\tilde{y}$ lower than $y^\star$ with probability q, and higher than $y^\star$ with probability $(1 - q)$.

Strategy for the initiator of the club The initiator of the club first invites people whose wealth belongs to $[w^{''}; w_{max}]$. If there are enough people accepting to participate, the game stops. Otherwise, the initiator of the group invites people whose wealth belongs to $[w^{'}; w^{''})$. In this category, an individual may refuse to cooperate for three reasons: *(i)* he might be of type θ^l; *(ii)* his post-disaster income $\tilde{y}$ might actually be below $y^\star$; *(iii)* he might try to strategically use the asymmetry of information to refuse cooperation and avoid punishment. Then, punishment does not systematically follow a deny of participation since it may result in punishing a good type individual which would be costly for the initiator of the club. To avoid to signal his own type to the rest of the community, the θ^l initiator of the group has an interest to behave as if he were a θ^h type. Therefore, more formally, the initiator of the club decides to punish if the expected benefits from punishment exceed the expected costs, that is:

$$p\alpha^{hh} + (1-p)\alpha^{hl} < 0 \tag{6}$$

Strategy for the invited individual The game is solved by backward induction. The invited participant knows what the initiator of the club will play if he does not cooperate. If he knows that punishment is too costly for the initiator of the club he will not participate. On the contrary, if he knows that punishment will occur, depending on his post-disaster income and his type, he will chose the optimal move which may be either to participate or not.

Discussion The model highlights that in the wake of a natural disaster, an individual requiring help from the rest of the community faces three types of people: those for whom she knows that they are too poor to help, those for whom she knows with certainty that their post-disaster income is sufficiently high for θ^h individuals to help; and those for whom post-disaster income might be either above or below the threshold. While a deny to participate from the second group automatically signal a θ^l type, that the initiator of the club has an interest to punish, this is no more the case for the latter group. Under the fairly reasonable assumption that the cost of punishing a good type individual exceeds the benefit from punishing the bad type, the optimal behavior for the initiator of the group is therefore not to punish individuals refusing cooperation. Knowing that, the invited players whose wealth lies in $[w^{'}, w^{''}]$ will all deny cooperation. Consequently, the initiator of the group is left with the richest members of her community to get help. Therefore, the key variable that determines the number of participants in the club following a shock is the distance between their ex-ante income level (or, equivalently, their wealth) and the income level $y^\star$ which insures cooperation of θ^h individuals. Empirically, this may translate into the level of wealth inequality in the community.

In sum, the model predicts that in the most homogeneous communities, cooperation decreases following a natural disaster since this latter creates an asymmetry of information on post-disaster income allowing invited individuals to refuse cooperation and avoid punishment. On the contrary, in the most heterogeneous communities, the noise created by the shock is not sufficient for individuals to pretend to be too poor to cooperate. Also, if the initiator of the club offers a higher payoff of future cooperation, α, cooperation may even increase. Finally, one may worry that this framework does not take into account aversion for inequality, a feature which has been widely documented in the literature. Introducing aversion for inequality between the initiator of the club and participants, would lead the initiator of the club to restrict to a thinner range the set of potential participants, but would not change our conclusions.

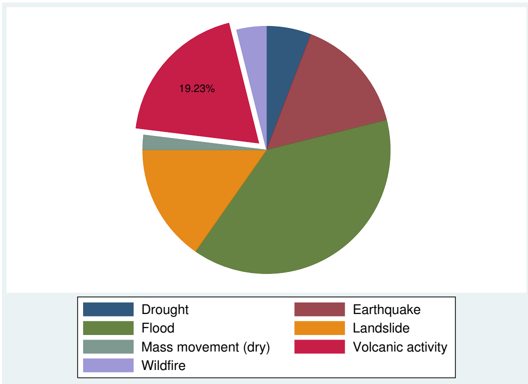
4 Data and Descriptive statistics

After presenting the context of the study in Section 4.1, we expose the data in Section 4.2 and we present descriptive statistics in Section 4.3.

4.1 Context

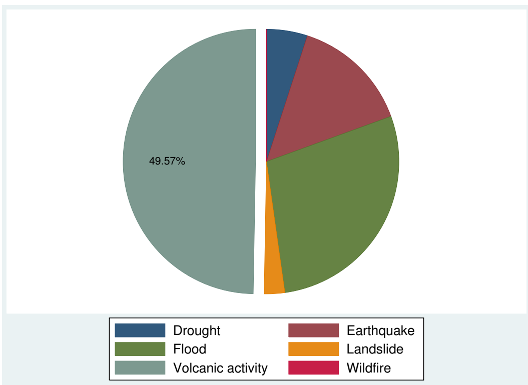
Ecuador suffers from extreme vulnerability and high exposure to natural hazards. In fact, approximately 96% of the urban population lives in coastal and mountainous regions that are exposed to seismic, volcanic, flood, landslide and El Niño hazards (WorldBank 2012). According to the EM-DAT database, over the 1990-2016 period, volcanic eruptions appear as the second most frequent event in Ecuador behind floods (Figure 1). Depending on their place of living, inhabitants are not exposed to the same risk. For instance, flooding mainly affects the coastal zone, while volcanic eruptions affect the central zone, and droughts have been recorded in some provinces in the northern coastal and central regions. Nevertheless, with 35 volcanoes, and more than 4 millions people living within 30km from a volcano, which represent around one third of the national population, Ecuadorians are particularly exposed to volcanic risk.[1] As a matter of fact, according to the EM-DAT database, over the 1990-2016 period, half of the total number of people affected by natural disasters were threatened by volcanic eruptions (Figure 2).

Figure 1: Frequency of Natural Disasters in Ecuador over 1990-2016.



Source: Author's elaboration on EM-DAT database.

Figure 2: Affected People by Natural Disasters in Ecuador over 1990-2016.



Source: Author's elaboration on EM-DAT database.

This paper focuses on Mount Tungurahua, one of the most active volcano of the country. After approximately 80 years of quiescence, Mount Tungurahua entered a new phase of activity in the fall of 1999 (Hall et al. 1999). The volcano has remained active throughout this period

[1]Source: https://www.preventionweb.net/countries/ecu/data/

and has frequently deposited ash on the surrounding landscape and constantly threatened neighboring communities. Neighboring communities are mainly populated by smallholding farmers as 80-90% of farms in the region are estimated to be less than 10 hectares. Locally grown crops mainly include maize, beans, potatoes and onions, and livestock activities include dairying and intensive chicken farms (Leonard et al. 2005). Due to the equatorial location and climate of Ecuador, the growing season is continuous throughout the year. That is, plants are harvested at any time of the year, and therefore, ashfall represent a permanent threat regardless of the time of eruption. Eruptions may also affect livestock, causing stress or even deaths of animals. Finally, ashfall has caused a variety of health issues for individuals such as skin, abdominal, digestive, psychological and respiratory problems (Sword-Daniels et al. 2011).

Contrary to what one would expect, despite the recurrent negative shocks, households did not migrate out of the affected area. Without being exhaustive, we can shed light on some reasons. First, moving to close urban areas would mean to switch from their farm activity to a non-farm business for which they have no qualification. In addition, the beginning of the eruptive phase coincides with the economic crisis in Ecuador, increasing the difficulty of finding a job in urban areas. Third, most of their capital is anchored to location, and unless they could sell it, migration would represent a dramatic wealth loss. Finally, as we noticed during the interviews, people still hope for the volcano to stop.

In order to help local people to cope with volcanic risk, public authorities implemented a procedure for emergency management which involves a three-step process presented in Sword-Daniels et al. (2011). The monitoring of volcanoes is carried out by scientists of the Geophysical Institute, the main research centre in Ecuador for the diagnosis and monitoring of seismic and volcanic hazards. The Geophysical Institute is based in Quito, the capital of the country, and monitors seventeen volcanoes, including Mount Tungurahua, using decentralized observatories. The Tungurahua observatory provides daily reports on volcanic activity. When unrest manifests at the volcano, the Geophysical Institute informs the National Secretariat of Risk Management (also known as the "National Secretariat") and provides hazard scenarios for the likely progression of activity. Based on them, the National Secretariat makes contingency plans which are then given to the local governments. Finally, it is the decision of the local governments to assign the alert level, and to give evacuation orders if necessary. In practice, it has been noted that alert levels are inconsistent across municipalities.

Apart from the monitoring activity, public authorities also intervene during and in the wake of eruptions. In the words of the National Secretariat, the Emergency Plan of Action aims to provide to the population the necessary supplies to reduce the effects of ashfall such as: water, food, masks, scarfs, eye drops for the eyes, and to distribute information about the precautions to take for their protection and that of their goods. For the case of animals, fodder for its diet will be delivered and/or transfer to less affected zones. Regarding ashfall clean-up, in general, brooms are used for clean-up of streets if the grain size of the ash allows. Once swept up, a truck provided by the local mayor will collect the ash. The National Secretariat assists the local level authorities by providing bags for ash collection; ask mask supplies, and goggles and brooms to assist the clean-up. Groups of the local population called 'mingas' generally maintain infrastructure and roads within the community, and will clear ash within their neighborhood. However for the clearance of roads that run between villages, the provincial level are responsible for the clean-up. The municipality and the National Secretariat share the cost of clean-up, by an agreed proportion that depends on the situation; the cost is split so that 50% is paid by the Municipality and 50% by the National Secretariat for routine maintenance (this may include landslides or mudflows), but in emergencies the National Secretariat will pay 80% of the total cost, with the municipality making up the remaining 20% of the cost.

4.2 Data

Our study site is the province of Chimborazo which is situated to the south of the Tungurahua volcano. Using the hazard map provided by the Geophysical Institute of Ecuador, we identified the areas at risk and we conducted a survey of 225 households, living in nine communities, situated in three parishes (Puela, Bilbao and Cotalo). The survey was conducted in June 2016, and we investigate the impact of the November 2015 eruption.

4.2.1 Measuring Social Capital

Social capital is a broad concept that is often represented along two dimensions: cognitive and structural. While the cognitive component is less tangible and captures perceived support, trust, social cohesion and perceived civic engagement, the structural component refers to networks, connectedness, associational life and civic participation. In addition, trust is multidimensional as it can be delivered to different types of agents (Morrone et al. 2009). Consequently, the evolution of someone's trusting behavior may not be the same toward relatives or neighbors for instance. Taking into account this heterogeneity is difficult using trust games. For this reason, we measure social capital through survey questions following Grootaert (2004).

Trust: To measure trust, each of the 225 household heads was asked: "*In general, how much do you trust [name]?*", where [name] was replaced by: "relatives", "other persons of the community", "geophysical institute", "local authority", and "national authority" in this order. For each of them, respondents could answer: "to a very great extent", "to a great extent", "to a small extent" or "to a very small extent".

Cooperation: To measure cooperation, each of the 225 household heads was asked four questions. First, "*In general, how many persons in your community contribute time or money toward common development goals, such as repairing a road or 'mingas'?*". Respondents could answer one of the five following propositions: "everybody", "more than half", "about half", "less than half", or "no one". Second, we asked: "*Suppose a serious illness happened to someone in the community. How likely is it that some people in the community would get together to help them?*". Respondents could answer: "very likely", "somewhat likely", "somewhat unlikely" or "very unlikely". Then, we ask each of the 225 household heads to what extent they agree with the following propositions: "*Most people in this community are willing to help you if you need it.*", and "*In this community, people generally do not trust each other in matters of lending and borrowing money.*". For each of these two latter propositions, the respondent could answer: "agree strongly", "agree somewhat", "neither agree nor disagree", "disagree somewhat", or "disagree strongly".

Network Size We measure the size of the network through two questions. To capture the size of the network people can count on in case of small problems we asked: "*If you suddenly needed a small amount of money (enough to pay for expenses for your household for one week), how many people beyond your immediate household could you turn to who would be willing to provide this money?*". To measure the size of the network able to help in case of severe problems, we asked: "*If you suddenly faced a long-term emergency such as harvest failure, how many people beyond your immediate household could you turn to who would be willing to assist you?*". Respondents were asked to provide a number.

4.2.2 Ash fall Data

Since the whole sample has been exposed to the November 2015 eruption, our empirical analysis does not rely on the comparison of an affected group with a non-affected group. Rather, we use the fact that the sampled communities have not received the same quantity of ash, leading to variations in the shock intensity across communities. In fact, while communities situated under the middle of the cloud were highly exposed, those on the edges were much less impacted.

Ash fall data have been collected by the Geophysical Institute and the Institute of Research for Development (IRD) using a network of 55 geo-referenced captors set up in the affected area. The map below (Figure 3) represents the sampled communities as well as their exposure to ash from the November 2015 eruption. It is worth underlying that the sampled communities are roughly at the same distance from the volcano and that the variation in their ash exposure is therefore only due to their relative position to the ash cloud.

Figure 3: Sampled communities

Note: Sampled communities with ash thickness of the November 2015 eruption reported in parentheses. Source: Author's elaboration.

4.3 Descriptive Statistics

Table 1 provides summary statistics on sampled household characteristics. Households are, on average, made of 3.6 people, and 86% of them are headed by male. Wealth per capita is a wealth index computed using a principal component analysis (see Appendix A for details) which we express in per capita terms. Household heads are 55 years old and received, on average, primary education. They reported an average risk aversion score of 5.5 on a 1 to 10 scale where 1 stands for disliking risk and 10 for liking risk. Depending on their communities of living, households were affected differently by the 2015 eruption. Some of them received very few ashes (0.5 mm) while others received 10 times more. On average, people receive 3.2 mm of ash, a quantity sufficient to incur serious damages to crops (Wilson et al. 2007).[2] Regarding social capital, the level of trust toward relatives is above average, meaning that households think that they can be trusted. This is not the case for neighbors whose trust felt below average. Looking at institutions, scientists of the Geophysical Institute and local authority tend to be pretty well trusted, while the score for national authority is lower. Turning to measures of cooperation, the willingness of people to participate with time or money to a collective good is extremely high.

[2]In the remaining of the paper, we employ the logarithm of ash thickness where the minimum is normalized to zero to ease the interpretation of interactive terms in the empirical analysis.

Finally, the number of people ready to help in case of a small problem (Network1) is 3.3, and, as expected, it is higher than the number of people ready to help in case of a severe problem (Network2).

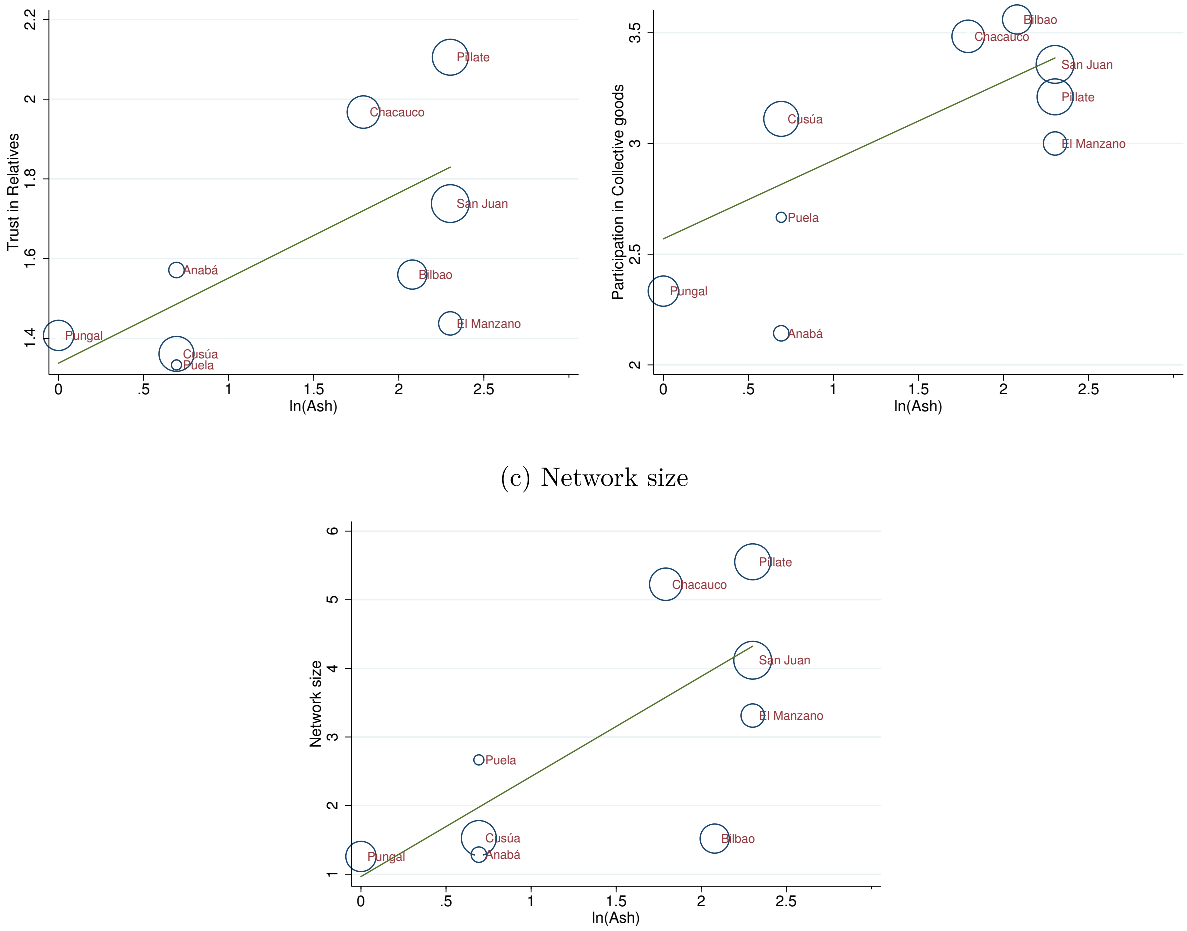
Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Household characteristics					
HHsize	3.64	2.048	1	12	225
Wealth per capita	-0.15	0.652	-2.321	3.876	225
Male (head)	0.858	0.35	0	1	225
Age (head)	55.48	17.091	22	96	225
Education (head)	1.084	0.595	0	3	225
Risk aversion (head)	5.551	2.554	1	10	225
Ash fall					
Ash thickness (in mm)	3.256	1.826	0.5	5	225
Social capital: Trust					
Relatives	1.68	1.024	0	3	225
Neighbors	1.151	0.815	0	3	225
Geophysical Institute	1.533	0.945	0	3	225
Local	1.493	0.897	0	3	225
National	1.333	0.916	0	3	225
Social capital: Cooperation					
People are ready to help you	2.502	1.005	0	4	225
People don't trust to lend	2.222	0.961	0	4	225
Coll. goods	3.138	1.071	0	4	225
Help someone in need	2.071	0.873	0	3	225
Social capital: Network Size					
Network1	3.302	10.672	0	100	225
Network2	1.982	4.634	0	50	225

Source: Author's elaboration.

Finally, Figure 4 presents the correlations between ash thickness and three measures of social capital namely trust toward relatives, participation to collective goods, and network size for small problems (Network1). We find a positive correlation between ash thickness and the three measures of social capital.

Figure 4: Ash and Social Capital



(a) Trust in relatives

(b) Collective good

(c) Network size

Note: Correlations at the community level weighted by the number of individuals sampled in each community. Source: Author's elaboration.

5 Empirical Analysis

This section presents our empirical analysis. The baseline specification is presented in Section 5.1 where we test for the unconditional effect of ash thickness on social capital. Then, Sections 5.2, 5.3 and 5.4 test for the effect of ash thickness conditionally on the level of wealth inequality, risk perception about future shocks, and the public policy of relocation, respectively.

5.1 Baseline Specification

Model Our empirical strategy is simple. We regress the social capital variables on the shock intensity, proxied by ash thickness, while controlling for household characteristics and parish fixed effects. We cluster all specifications at the community level. More specifically, we estimate the following model using OLS estimator.

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{7}$$

where $Scapital_{hcp}$ is a measure of social capital of household h, living in community c, situated in parish p. Ash_{cp} is the thickness of ash fall received in community c during the November 2015 eruption. $\boldsymbol{X}$ is a vector of control variables including household head characteristics such as age, gender, education and risk aversion; as well as household characteristics such as household size and wealth per capita. ν_p is a parish fixed effect.

Identification strategy Our identification strategy relies on the fact that ash dissemination is highly influenced by climatic conditions, especially wind and rain, at the time of eruption, which are highly seasonal dependent (Le Pennec et al. 2012), and can therefore be considered as exogenous. Still, we may worry that our sample suffers from a selection bias if the least connected people in the most affected communities migrated out of the affected area, leading to an upward bias of our estimates. This threat is ruled out the fact that, as stated above, migration of the full households out of the affected area is actually extremely unlikely due to the dramatic cost it would incurred and the lack of business opportunities in the neighboring urban areas. Finally, to the best of our knowledge, deaths induced by volcanic eruptions were extremely rare since the beginning of the eruptive phase, ruling out any death selectivity bias.

Results Table 2 presents the output of the regressions of Equation 7. Results for trust toward relatives, neighbors, the Geophysical Institute (GI), local authority, and national authority are reported in columns 1 to 5. The impact of ash thickness on cooperation is presented in columns 6 to 9. Last, the impact of ash on network size is presented in column 10 for network used in case of minor problems (Network1), and column 11 for network used in case of severe problems (Network2).

First, we find no significant effect of the shock intensity on trust toward people living in the community such as relatives (col. 1) and neighbors (col. 2). There is, however, a positive and highly significant impact of the shock intensity on trust toward the Geophysical Institute, and local authority. The impact on trust toward national authority is positive but weakly significant. Regarding cooperation, we find that the shock intensity has a positive and significant effect on the willingness of people to help others in the community (cols. 6 and 7), as well as a positive effect on the willingness to contribute with time or money to collective goods (col. 9).[3] However, we find no effect on the willingness to lend money (col. 8). Last, we find a positive and highly significant impact of ash thickness on Network1, the number of people ready to help in case of small problems (col. 10) as well as a positive and significant effect on Network2, the number of people ready to help in case of severe problems (col. 11).

[3] Since the number of possible answers is not the same for the two questions, coefficients in columns 6 and 7 are not directly comparable.

Table 2: OLS Regressions

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
$\ln(Ash)$	0.165	0.123	0.196***	0.196***	0.139*	
	(0.117)	(0.073)	(0.053)	(0.053)	(0.074)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	225	225	225	225	225	
R-Squared	0.077	0.090	0.147	0.138	0.093	
	Cooperation				Network size	
	(6) Help you	(7) Help someone	(8) Credit	(9) Coll. goods	(10) Network1	(11) Network2
$\ln(Ash)$	0.362**	0.170*	-0.005	0.187**	1.628**	0.949***
	(0.120)	(0.082)	(0.055)	(0.059)	(0.561)	(0.271)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.168	0.118	0.021	0.148	0.036	0.054

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capital, and risk aversion, age, gender, and education of household head. Source: Author's estimations.

5.2 The Role of Inequalities

We showed, in our theoretical model (Section 3), that if a natural disaster induces both an increase in the benefits of cooperation and an asymmetry of information on post-disaster income, the impact of the shock on cooperation in a community could be either positive or negative, and that the key variable determining whether one effect dominates the other is the level of inequality in the community. The aim of this section is to empirically test this hypothesis.

Model Starting from the baseline specification presented in Section 5.1, we introduce an interactive term between ash thickness and wealth inequality in the community. We follow McKenzie (2005) and we measure inequality by taking the standard deviation, at the community level, of the wealth per capita variable. We also include the average wealth level per community in the regressions, so that we interpret an increase of wealth inequality as a mean preserving spread. We estimate the following model using OLS estimator:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times sdWealth_{cp} + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{8}$$

where $Scapital_{hcp}$ is a measure of social capital of household h, living in community c, situated in parish p. Ash_{cp} is the thickness of ash fall received in community c during the November 2015 eruption. $sdWealth_{cp}$ is the level of wealth inequality in community c. $\boldsymbol{X}$ is a vector of control variables including household head characteristics such as age, gender, education and risk aversion; as well as household characteristics such as household size and wealth per capita. ν_p is a parish fixed effect.

Identification strategy We may worry that wealth inequality suffers from a reverse causality bias. In fact, one may argue that social capital, by improving risk-sharing, helps households to recover from idiosyncratic shocks and therefore restrains the level of inequality in the community. To tackle this issue, we use the standard deviation, at the community level, of the surface of inherited land of each household as an instrument for current wealth inequality. Our argument is that the level of inequality of inherited land in a community is likely to affect the current level of wealth inequality, but we see no particular reason of how inequality in inherited land could affect the current levels of trust and cooperation apart from its effect on current wealth. We also use the square of our instrument, so that our model is over identified which allows to test for the exogeneity condition through the Hansen statistics.

Results Results of the OLS regressions are reported in Table 3 and a graphical representation of the marginal effects for the least and the most heterogeneous communities is reported in Appendix C. Our estimates suggest a positive and highly significant impact of the interactive term between ash thickness and wealth inequality for trust toward relatives (col. 1) and neighbors (col. 2). In sum, an increase of the shock intensity in the least unequal communities leads to a decrease of the level of trust toward local people; while an increase of the shock intensity in the most unequal communities tends to foster it. A similar mechanism applies for the willingness to help (col. 8 & 9), as well as network size (col. 12 & 13). These findings are completely consistent with our theoretical model. As expected, we find no significant effect on trust toward institutions like the Geophysical Institute, local authority, and national authority ($pvalue = 0.99$ for this latter). We also find no significant effect on the willingness to lend money. Finally, we find no evidence of a conditional effect of the shock intensity on the willingness to contribute to collective goods.

Turning to the IV estimates, first stage regressions are presented in Table A2. Since, our instruments are not specific to each of the two endogenous variables, we estimate the IV regressions using the GMM estimator. Results are reported in Table 4 below. We note that the estimated coefficients across the two estimation methods (OLS and IV) are highly similar, meaning that, the reverse causality bias, if any, is weak. Estimates only differ across the two specification regarding the effect on network size in case of small problems (Network1) which are not significant, although their magnitudes is similar to the ones obtained by OLS regressions.

Table 3: OLS Regressions

	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National
ln(Ash) × sdWealth	2.339***	2.423***	0.899	0.973	1.794*
	(0.352)	(0.268)	(0.676)	(0.633)	(0.963)
ln(Ash)	-1.380***	-1.359***	-0.333	-0.475	-0.969
	(0.206)	(0.159)	(0.400)	(0.378)	(0.574)
sdWealth	-2.721***	-1.386**	-0.917	-0.166	-1.404
	(0.234)	(0.493)	(0.673)	(0.460)	(0.770)
Control variables	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225
R-Squared	0.104	0.135	0.150	0.151	0.109

	Cooperation				Network size	
	(6) Help you	(7) Help someone	(8) Credit	(9) Coll. goods	(10) Network1	(11) Network2
ln(Ash) × sdWealth	5.446***	2.561***	0.306	-0.994	8.628**	10.068***
	(0.544)	(0.330)	(0.996)	(0.639)	(3.014)	(1.129)
ln(Ash)	-2.845***	-1.389***	-0.127	0.809*	-4.302**	-5.081***
	(0.323)	(0.193)	(0.589)	(0.387)	(1.851)	(0.665)
sdWealth	-5.521***	-1.362	-2.278**	2.103***	-10.636***	-9.781***
	(0.566)	(0.794)	(0.866)	(0.622)	(2.796)	(1.408)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.269	0.164	0.038	0.154	0.041	0.070

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Source: Author's estimations.

Table 4: IV Regressions

	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
$\ln(Ash) \times$ sdWealth	2.522**	2.243**	-0.048	0.266	0.536	
	(1.260)	(0.934)	(1.214)	(1.096)	(1.228)	
$\ln(Ash)$	-1.494*	-1.252**	0.231	-0.052	-0.222	
	(0.783)	(0.569)	(0.737)	(0.665)	(0.739)	
sdWealth	-2.983*	-1.092	0.359	0.773	0.364	
	(1.751)	(1.331)	(1.831)	(1.566)	(1.906)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	225	225	225	225	225	
R-Squared	0.104	0.134	0.147	0.149	0.103	
p-value Hansen	0.855	0.312	0.650	0.932	0.498	
	Cooperation				Network size	
	(6) Help you	(7) Help someone	(8) Credit	(9) Coll. goods	(10) Network1	(11) Network2
$\ln(Ash) \times$ sdWealth	6.089***	2.455**	1.221	-0.015	8.292	10.917*
	(1.116)	(1.084)	(1.258)	(1.297)	(13.946)	(5.753)
$\ln(Ash)$	-3.238***	-1.322**	-0.692	0.221	-3.993	-5.608
	(0.700)	(0.655)	(0.761)	(0.783)	(8.398)	(3.669)
sdWealth	-6.512***	-1.070	-3.610**	0.887	-11.025	-10.354
	(1.654)	(1.671)	(1.817)	(2.165)	(13.153)	(7.761)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.268	0.163	0.033	0.151	0.040	0.068
p-value Hansen	0.368	0.072	0.059	0.285	0.582	0.391

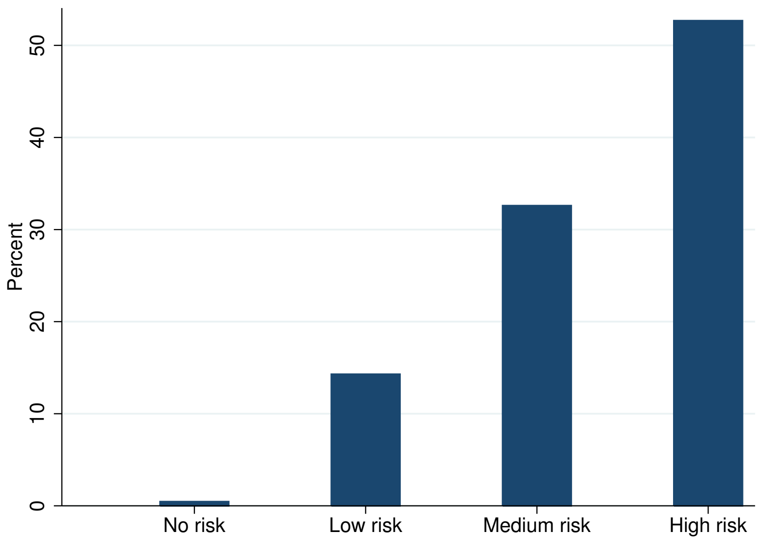
Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: community average wealth, household size, wealth per capita, and risk aversion, age, gender, and education of household head. Kleibergen-Paap F-statistic: 194.107. Source: Author's estimations.

5.3 The Role of Risk Perception

Among the potential transmission channels cited in the literature, Cassar et al. (2017) mention the positive role that may play risk perception. This idea echoes with the burgeoning literature highlighting the changes in beliefs of affected people about future shocks following a natural disaster (Cameron and Shah 2015). More precisely, as suggested by Cassar et al. (2017), an increase in the perceived probability that a future shock will occur is likely to increase the potential for needing help in the future, leading people to strengthen their network.

To test this hypothesis, we measure the perceived likelihood of a future eruption. More precisely, each household head was asked the following question: *"Based on your knowledge and experience, what is the risk that an eruption will occur in the next two months?"*. Respondents could answer: "no risk", "low risk", "moderate risk", or "high risk". Figure 5 shows the repartition of the answers. Half of the respondents consider that the risk is high, around 30% consider that the risk is moderate, and 15% that the risk is low or nul.

Figure 5: Perceived likelihood of future eruptions



Source: Author's elaboration.

Model To test whether risk perception is a transmission channel of the impact of the volcanic eruption on social capital, we estimate the following model using OLS estimator:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times Riskp + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{9}$$

where $Scapital_{hcp}$ is a measure of social capital of household h, living in community c, situated in parish p. Ash_{cp} is the thickness of ash fall received in community c during the November 2015 eruption. $Riskp$ is the perceived likelihood of future eruptions, and the variable lies in 0 (no risk) and 3 (high risk). $\boldsymbol{X}$ is a vector of control variables including household head characteristics such as age, gender, education and risk aversion; as well as household characteristics such as household size and wealth per capita. ν_p is a parish fixed effect.

Results Results are reported in Table 5. We find no significant effect of the interactive term $\ln(Ash_{cp}) \times Riskp$, suggesting that risk perception is not a transmission channel.

Table 5: OLS Regressions

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
$\ln(Ash) \times$ Riskp	-0.006	-0.086	-0.114	-0.040	-0.086	
	(0.063)	(0.048)	(0.086)	(0.067)	(0.079)	
$\ln(Ash)$	0.171	0.315*	0.448**	0.288	0.336	
	(0.169)	(0.137)	(0.168)	(0.171)	(0.189)	
Riskp	0.206**	0.194***	0.289**	0.010	0.083	
	(0.087)	(0.034)	(0.103)	(0.114)	(0.157)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	224	224	224	224	224	
R-Squared	0.094	0.097	0.159	0.139	0.097	
	Cooperation				Network size	
	(6) Help you	(7) Help someone	(8) Credit	(9) Coll. goods	(10) Network1	(11) Network2
$\ln(Ash) \times$ Riskp	-0.099	0.154	0.032	-0.092	0.137	0.111
	(0.090)	(0.099)	(0.085)	(0.100)	(0.515)	(0.319)
$\ln(Ash)$	0.590**	-0.187	-0.074	0.395	1.312	0.692
	(0.215)	(0.206)	(0.197)	(0.229)	(1.407)	(0.816)
Riskp	0.189	-0.258	-0.018	0.247	-0.138	-0.090
	(0.137)	(0.173)	(0.095)	(0.214)	(0.493)	(0.310)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	224	224	224	224	224	224
R-Squared	0.175	0.123	0.021	0.158	0.036	0.053

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Source: Author's estimations.

5.4 The Role of the Relocation Program

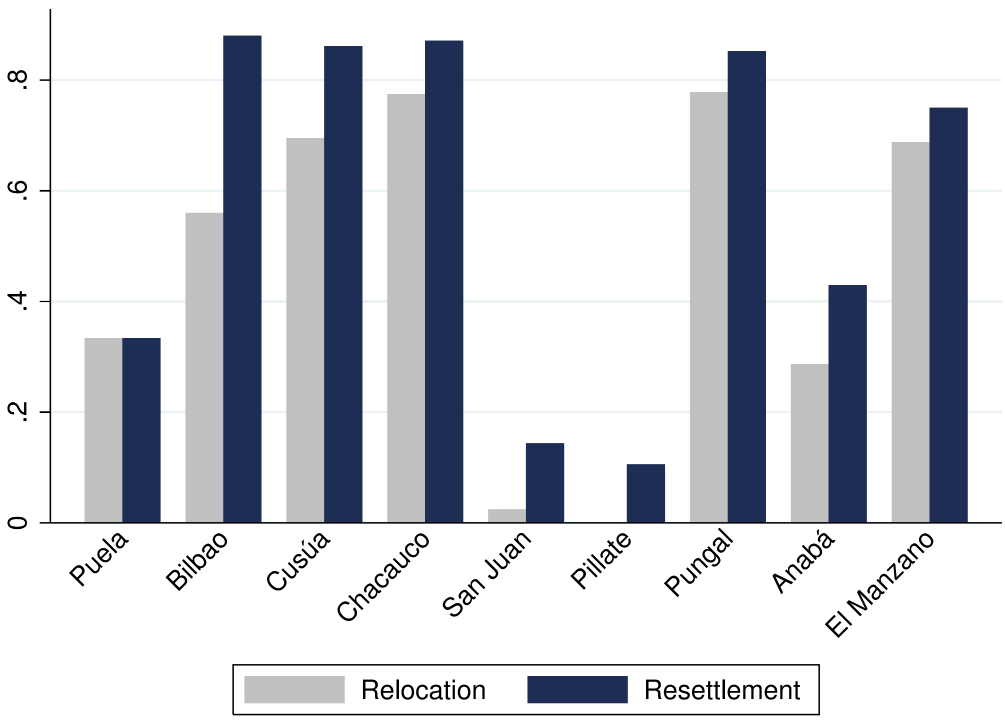
As suggested by Barr (2003) and Fleming et al. (2014), movements of individuals between communities may negatively affect trust. Due to an unsuccessful relocation program, some households of our sample also have a house in the non-affected area. In fact, from 2007 to 2014, in response to the sustained volcanic activity, the Ecuadorian state and some non-profit organizations decided to engage in the relocation of the most exposed households. In total they built more than 750 homes across the different relocation sites. Theses houses were offered to households under some conditions. One of these was for their owners to live permanently in their new homes. However, due to the lack of business opportunities in the resettlement areas, many families have decided to split their residence, with some family members living in the resettlement and others living in their homes close to their agricultural land (Few et al. 2017). Therefore, our sample includes households living permanently in their land as well as households sharing their time between their land and the resettlement area. Table 6 provides summary statistics of the relocation program. In our sample, 57% of households have been offered a house in a resettlement area, but "only" 75% of them accepted it, so that 44% of the sample lives, at least temporarily, in the resettlement area. Figure 6 illustrates the distribution of the program across communities. Interestingly, all of our sampled communities have been treated but in none of them the program was offered to all households.

Table 6: Summary statistics: Relocation program

Variable	Mean	Std. Dev.	Min.	Max.	N
Resettlement	0.573	0.496	0	1	225
Relocation	0.44	0.497	0	1	225

Notes: Resettlement is a dummy variable taking the value one if the household has been offered a house, by the government, in a resettlement area, and zero otherwise; Relocation is a dummy variable taking the value one if the household lives even non exclusively in a house provided by the government, and zero otherwise. Source: Author's elaboration.

Figure 6: Means of Resettlement and Relocation by communities



Source: Author's elaboration.

We exploit this feature of our case study to test whether having a house in the non-affected area, making evacuation easier in case of eruptions, affects the impact of the shock on social capital.

Model To test this hypothesis, we introduce the variable *Relocation*, a dummy variable taking the value one if the household declares to live, even non exclusively, in the relocation area and zero otherwise; and the interactive term $\ln(Ash) \times Relocation$ in our empirical model. More formally, we estimate Equation 10:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times Relocation_{hcp} + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{10}$$

Identification Strategy Using the *Relocation* variable as a predictor in the model might lead to biased estimates due to the reverse causality issue. In fact, while living outside the community may affect the level of social capital of households (Barr 2003), the decision to move out of the community might also be determined by the level of social capital. To tackle this issue, we implement a 2SLS model where *Relocation* is instrumented by *Resettlement*, a variable taking the value one if the household has been offered a house in a resettlement area and zero otherwise. Our identification strategy relies on the fact that the government was unable to supply houses for the whole population living in the risky area. Therefore, houses were only proposed to some households who then decided to accept them or not. To the best of our knowledge, no study has investigated the implementation of this program, and the attribution rule of houses remains unclear. We do not pretend that this allocation was random, but we believe that the most plausible criteria used in the decision rule such as household size, education of the household head, wealth are already included in our empirical model as control variables. Then, we are pretty confident that, conditionally on our set of control variables, our instrument is exogenous. Without loss of generality, the interactive variable ($\ln(Ash) \times Relocation$) is instrumented by the interactive variable ($\ln(Ash) \times Resettlement$).

Results Table A3 presents the first stage regressions. As required, the *Resettlement* variable is a good predictor of *Relocation* but is not correlated with $\ln(Ash) \times Relocation$. Inversely, $\ln(Ash) \times Resettlement$ is a good predictor of $\ln(Ash) \times Relocation$ but is not correlated with *Relocation*. Table 7 reports the 2SLS regressions of Equation 10. We find no significant effect of the interactive variable except for trust toward the Geophysical Institute and Local Authority. In fact, while the impact of the shock remains positive on these two variables, its magnitude is lower for people having a house in the non-affected area.

Table 7: IV Regressions

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
$\ln(Ash) \times Relocation$	-0.211	-0.243	-0.356***	-0.314***	-0.147	
	(0.149)	(0.133)	(0.068)	(0.088)	(0.203)	
$\ln(Ash)$	0.261*	0.240**	0.373***	0.385***	0.234	
	(0.122)	(0.095)	(0.045)	(0.064)	(0.140)	
$Relocation$	0.247	0.316*	0.478**	0.560***	0.290	
	(0.201)	(0.159)	(0.191)	(0.145)	(0.293)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	225	225	225	225	225	
R-Squared	0.080	0.075	0.147	0.140	0.097	
	Cooperation				Network size	
	(6) Help you	(7) Help someone	(8) Credit	(9) Coll. goods	(10) Network1	(11) Network2
$\ln(Ash) \times Relocation$	0.148	-0.206	0.016	-0.074	-0.469	0.128
	(0.233)	(0.179)	(0.271)	(0.254)	(1.133)	(0.752)
$\ln(Ash)$	0.279	0.304**	-0.019	0.329*	1.732*	0.952
	(0.165)	(0.117)	(0.134)	(0.167)	(0.779)	(0.535)
$Relocation$	-0.240	0.411	-0.049	0.540	0.099	0.103
	(0.303)	(0.323)	(0.272)	(0.454)	(1.147)	(0.788)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.168	0.123	0.021	0.161	0.034	0.057

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Cragg-Donald Wald F statistic: 108.122. Source: Author's estimations.

5.5 Robustness

We may worry that not including the double residence status in the set of control variables in our empirical models induces an omitted variable bias. To check the robustness of our results we run the empirical models presented in Sections 5.1, 5.2, and 5.3 including the double residence status as a control variable. We apply the instrumental strategy presented in Section 5.4, and results are reported in Tables 8, 9, and 10. Empirical estimates are highly consistent with previous ones, except for the impact of the shock on the willingness to contribute to collective goods which appears to be conditional on the level of wealth inequality in the community. Indeed, once the relocation variable is included in the set of control variables, the magnitude of the effect decreases, but remain positive, as inequality increases (Table 9).

Table 8: OLS Regressions

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash)	0.141	0.102	0.170**	0.206***	0.150*	
	(0.123)	(0.070)	(0.064)	(0.057)	(0.072)	
Relocation	-0.100	-0.084	-0.109	0.043	0.048	
	(0.144)	(0.129)	(0.223)	(0.170)	(0.267)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	225	225	225	225	225	
R-Squared	0.079	0.085	0.151	0.138	0.092	
	Cooperation				Network size	
	Help you (8)	Help someone (9)	Credit (10)	Coll. goods (11)	Network1 (12)	Network2 (13)
ln(Ash)	0.363***	0.187*	-0.010	0.287***	1.465**	1.025***
	(0.096)	(0.089)	(0.083)	(0.055)	(0.566)	(0.252)
Relocation	0.005	0.071	-0.023	0.418	-0.674	0.314
	(0.259)	(0.152)	(0.296)	(0.227)	(1.014)	(0.873)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.168	0.126	0.020	0.163	0.034	0.057

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Cragg-Donald Wald F statistic: 212.186. Source: Author's estimations.

Table 9: IV Regressions: Inequality

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash)× sdWealth	2.347***	2.270***	0.780	1.006	1.834	
	(0.307)	(0.345)	(0.659)	(0.755)	(1.155)	
ln(Ash)	-1.383***	-1.301***	-0.287	-0.487	-0.984	
	(0.186)	(0.214)	(0.357)	(0.432)	(0.659)	
sdWealth	-2.751***	-0.812	-0.467	-0.291	-1.553	
	(0.426)	(0.855)	(1.200)	(0.897)	(1.549)	
Relocation	0.009	-0.181	-0.141	0.039	0.047	
	(0.151)	(0.187)	(0.289)	(0.199)	(0.341)	
mWealth	-0.558***	0.150	0.235	-0.502*	0.055	
	(0.157)	(0.211)	(0.280)	(0.237)	(0.182)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	225	225	225	225	225	
R-Squared	0.104	0.126	0.155	0.151	0.107	
	Cooperation				Network size	
	Help you (8)	Help someone (9)	Credit (10)	Coll. goods (11)	Network1 (12)	Network2 (13)
ln(Ash)× sdWealth	5.425***	2.556***	0.400	-0.652**	8.515*	10.378***
	(0.594)	(0.291)	(0.964)	(0.261)	(3.734)	(1.141)
ln(Ash)	-2.837***	-1.387***	-0.162	0.678***	-4.259*	-5.199***
	(0.349)	(0.167)	(0.549)	(0.124)	(2.155)	(0.572)
sdWealth	-5.442***	-1.346	-2.628*	0.819	-10.211*	-10.945***
	(0.691)	(0.946)	(1.300)	(1.039)	(5.356)	(2.698)
Relocation	-0.025	-0.005	0.110	0.404	-0.134	0.366
	(0.142)	(0.229)	(0.328)	(0.282)	(0.858)	(0.654)
mWealth	1.346***	0.190	0.625**	-0.104	-3.586***	1.730**
	(0.111)	(0.303)	(0.231)	(0.139)	(0.618)	(0.600)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	225	225	225	225	225	225
R-Squared	0.268	0.163	0.042	0.164	0.041	0.074

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Cragg-Donald Wald F statistic: 160.887. Source: Author's estimations.

Table 10: IV Regressions: Risk perception

	Trust				
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National
$\ln(Ash)\times$ Riskp	-0.007	-0.088	-0.116	-0.040	-0.086
	(0.061)	(0.048)	(0.084)	(0.069)	(0.080)
$\ln(Ash)$	0.165	0.386*	0.544*	0.333	0.427
	(0.229)	(0.175)	(0.264)	(0.219)	(0.257)
Riskp	0.206**	0.193***	0.288**	0.010	0.083
	(0.085)	(0.032)	(0.105)	(0.113)	(0.156)
Relocation	-0.063	-0.083	-0.100	0.028	0.029
	(0.120)	(0.134)	(0.230)	(0.178)	(0.267)
Control variables	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes
No. of Observations	224	224	224	224	224
R-Squared	0.096	0.092	0.162	0.139	0.096

	Cooperation				Network size	
	Help you (8)	Help someone (9)	Credit (10)	Coll. goods (11)	Network1 (12)	Network2 (13)
$\ln(Ash)\times$ Riskp	-0.099	0.155	0.032	-0.086	0.127	0.116
	(0.090)	(0.099)	(0.083)	(0.102)	(0.512)	(0.308)
$\ln(Ash)$	0.688**	-0.324	-0.109	0.568	1.054	0.645
	(0.284)	(0.299)	(0.314)	(0.352)	(1.931)	(1.196)
Riskp	0.189	-0.256	-0.018	0.253	-0.147	-0.085
	(0.138)	(0.169)	(0.096)	(0.212)	(0.484)	(0.314)
Relocation	-0.002	0.090	-0.016	0.431*	-0.649	0.347
	(0.263)	(0.164)	(0.279)	(0.222)	(0.906)	(0.794)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	224	224	224	224	224	224
R-Squared	0.175	0.133	0.020	0.173	0.034	0.057

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. Cragg-Donald Wald F statistic: 207.912. Source: Author's estimations.

6 Discussion

The present papers investigates the impact of a volcanic eruption on three dimensions of social capital, namely: *a)* bilateral cooperation, measured through the levels of trust toward relatives and neighbors, the willingness to help other members of the community, the willingness to lend money and network sizes; *b)* contribution to collective goods; and *c)* the levels of trust in institutions such as the Geophysical Institute, local authority, and national authority. Apart from investigating the impact of the shock on these distinct measures of social capital, we also propose to empirically test for three mechanisms highlighted in the literature as potential transmission channels. The first mechanism is, in the words of Fleming et al. (2014), the aftermath moral hazard, that is, the ability of individuals to exploit the asymmetry of information generated by the shock on damages and post-disaster income to escape solidarity agreements. The second transmission channel is risk perception, a mechanism highlighted by (Cassar et al. 2017) according to which natural disasters can affect affected households' perception about future shocks who will in turn foster their network against future disasters. Finally, we investigate whether having a house in the non-affected area, making the evacuation easier in case of eruption, plays a role on the impact of the shock on social capital.

Our results are as follows. Regarding the impact of the eruption on bilateral cooperation, we find an heterogeneous effect of the shock conditional on the level of wealth inequality in the community. In the most homogeneous communities, an increase of the shock intensity has an adverse effect on bilateral cooperation, while in the most heterogeneous communities, an increase of the shock intensity tends to promote it. These findings are completely consistent with our theoretical framework suggesting that in the most homogeneous communities people can benefit from the asymmetry of information on their post-disaster income to pretend to be poorer than they actually are and thus to escape from solidarity mechanisms. On the contrary, the noise created by the shock does not allow for such behaviors in the most heterogeneous communities where cooperation is rather fostered by the increasing associated benefits. These findings apply for the whole set of bilateral cooperation measures but the willingness to lend money to other people in the community, for which the associated coefficient is never significant. This is completely consistent with our case study since people living in this area rather rely on labor sharing than money transfers.

Regarding the impact of the shock on the willingness to contribute with time or money to collective goods, or "mingas", we find a positive effect, in line with the idea that an increase in the shock intensity creates more damages and that all members of the community are required to help for the reconstruction. Interestingly, this effect is not conditional on the level of wealth inequality in the community, ruling out any moral hazard behavior. It should be noted, however, that once we control for the double residence status, the interactive term turns significant, and suggests that the magnitude of the effect of the shock intensity is lower, but still positive, even for the most unequal communities. If anything, this result reaches the well established literature suggesting that cooperation for the production of collective goods is harder to enforce in unequal communities (Khwaja 2009).

Finally, we find a positive effect of the shock intensity on the levels of trust toward the Geophysical Institute and local authority. In light of the role played by public authorities, discussed in Section 4.1, the interpretation of this result can be grounded both on the alert system and the post-eruption actions taken. For instance, if people took costly measures to protect their assets, they may reward more public authorities if they were in fact heavily affected than if they were only marginally affected. Second, highly impacted communities are also more likely to trigger the actions of local authorities which may then translates into a higher level of trust as suggested by Andrabi and Das (2010). We note that the magnitude of this effect is lower, but still positive, for households having a house in the non-affected area. We explain this result by the fact that, by partially living in the non-affected area, people might not have fully observed or benefited from the actions taken by public authorities.

7 Conclusions

This paper investigates the impact of a natural disaster, namely a volcanic eruption, on social capital. In this aim, we conducted a survey in June 2016 in rural areas around Tungurahua volcano in Ecuador. We collected information on several measures of social capital that can be summarized in three categories: bilateral cooperation, contribution to collective goods, and trust in institutions. We augment this dataset with data on ash fall thickness received by each community during the November 2015 eruption that we use as a proxy for the shock intensity. Our results show an heterogeneous effect of the shock intensity on bilateral cooperation depending on the level of wealth inequality in the community. In the most homogeneous communities, an increase of the shock intensity tends to decrease bilateral cooperation, a finding consistent with the aftermath moral hazard behavior. On the contrary, the eruption tends to foster bilateral cooperation in the most unequal communities. This heterogeneous effect is however specific to bilateral cooperation since we do not find evidence of this mechanism on the contribution to collective goods. In addition, we find a positive effect of the shock intensity on trust in public authorities which we interpret as a reward for their actions taken to mitigate the effect of the shock.

From a public policy perspective, the main result of the paper is that, in some communities, which we identified to be the most homogeneous in terms of wealth, a natural disaster not only causes economic losses but also breaks informal arrangements. Consequently, affected households are much more vulnerable to idiosyncratic shocks following a natural disaster than in normal times when they would have been supported by their network. If anything, this paper therefore sheds light on an additional role that may play public authorities in the wake of a natural disaster by supporting farm households against idiosyncratic shocks. The natural question arising next is related to the time needed to recover the pre-shock level of cooperation. Answering this question is beyond the possibilities of our study, and is thus left for future research.

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Appendix A Wealth Index

We compute a wealth index using information on house equipment, animals, and farm assets. Regarding house characteristics, we ask each household head how many rooms they have in the house (NRooms), the number of equipment they own such as TV, DVD, radio, Hi-fi, computer, fridge, and washing machine that are functioning. We also include the number of bicycles and motorcycles. We also use farm assets such as land size, the number of animals such as cows, pigs, goats, and horses and llamas, and dummy variables accounting for the owning of plow and sprayer. Summary statistics on the variables used to compute the wealth index are reported in Table A1. This index captures 22% of the variance.

Table A1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
TV	0.804	0.595	0	4	225
Radio	0.72	0.506	0	4	225
Washing machine	0.2	0.401	0	1	225
Fridge	0.502	0.519	0	2	225
Bicycle	0.138	0.37	0	2	225
Motorcycle	0.111	0.367	0	3	225
DVD	0.253	0.502	0	4	225
Hi-fi	0.173	0.444	0	4	225
Computer	0.129	0.349	0	2	225
NRooms	3.067	1.326	1	8	225
Cows	2.511	4.187	0	40	225
Pigs	1.444	3.452	0	30	225
Goats	0.058	0.628	0	8	225
Horses and Llamas	0.236	0.696	0	5	225
Poultries	45.276	149.386	0	2000	225
Land	2.345	8.401	0	120	225
Plow	0.244	0.431	0	1	225
Sprayer	0.453	0.499	0	1	225

Source: Author's elaboration.

Appendix B First Stage Regressions

Table A2: First Stage Regressions

	(1) $\ln(Ash) \times$ sdWealth	(2) sdWealth
$\ln(Ash) \times ln(sdSlandI)$	0.113***	-0.043***
	(0.007)	(0.004)
$\ln(sdSlandI)$	3.435***	4.878***
	(0.199)	(0.135)
$\ln(sdSlandI)^2$	-0.202***	-0.275***
	(0.011)	(0.008)
$\ln(Ash)$	-0.351***	0.338***
	(0.062)	(0.034)
Control variables	Yes	Yes
Parish fixed effects	Yes	Yes
No. of Observations	225	225
R-Squared	0.997	0.992

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculations.

Table A3: First Stage Regressions

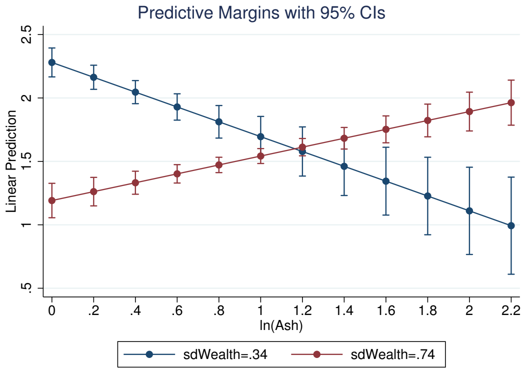
	(1) *Relocation*	(2) $\ln(Ash) \times$ *Relocation*
Resettlement	0.922***	0.127
	(0.063)	(0.129)
$\ln(Ash) \times$ *Resettlement*	-0.107	0.624**
	(0.083)	(0.190)
Control variables	Yes	Yes
Parish fixed effects	Yes	Yes
No. of Observations	225	225
R-Squared	0.659	0.601

Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculations.

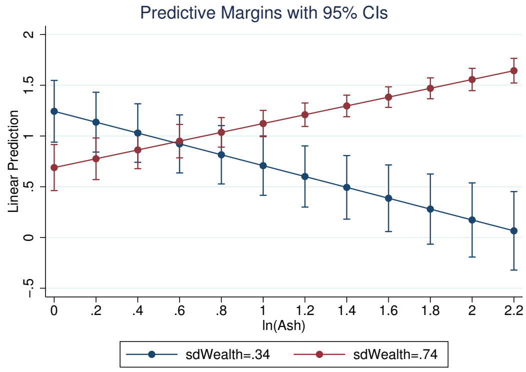
Appendix C Marginal Effects

Figure A1: Marginal effects of Ash on Social Capital

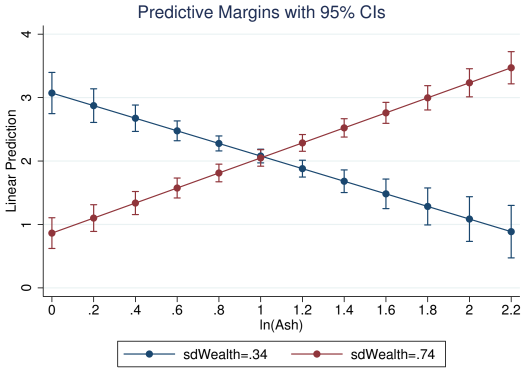
(a) Trust in relatives



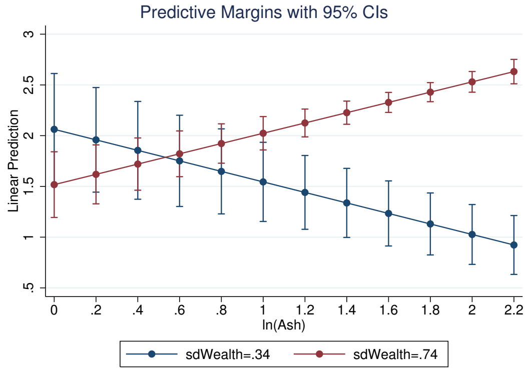
(b) Trust in neighbors



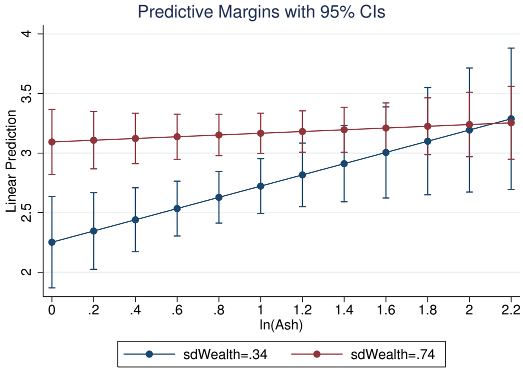
(c) Help you



(d) Help someone



(e) collective goods



(f) credit

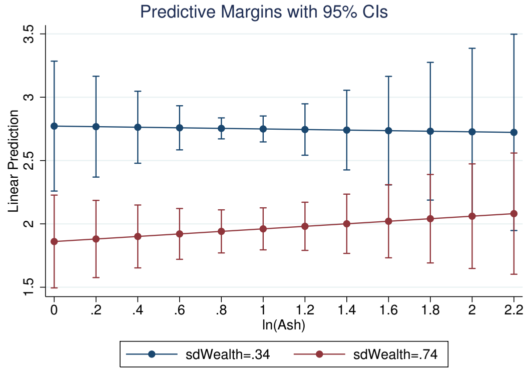
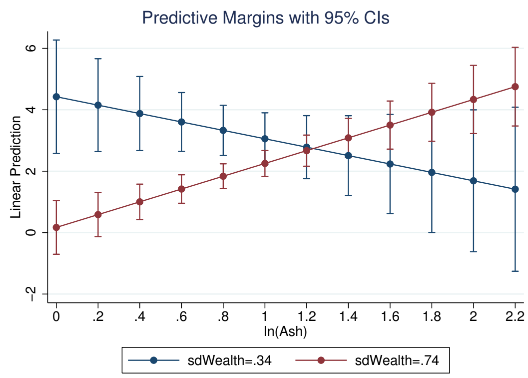


Figure A1: Marginal effects of Ash on Social Capital

(g) Network1



(h) Network2