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THREE ESSAYS ON THE ECONOMIC IMPACT OF NATURAL DISASTERS

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"Je tremble toujours de n'avoir écrit qu'un soupir, quand je crois avoir noté une vérité."

— Stendhal, De l'amour (1822)

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Résumé

Les désastres naturels ont des conséquences particulièrement dévastatrices dans les pays en développement où les individus sont hautement vulnérables et les institutions inefficaces. Néanmoins, leurs impacts sur le bien être des ménages et le rôle des autorités publiques restent encore mal compris. En outre, alors que la plupart des études se focalisent sur le risque climatique, les désastres géologiques, et les éruptions volcaniques en particulier, restent peu étudiés. Pourtant, même si elles représentent une fraction marginale des désastres naturels au niveau mondial, les éruptions volcaniques sont une menace majeure dans certains pays tels que l'Indonésie ou l'Equateur.

La présente thèse tente de contribuer à la littérature en étudiant l'impact du risque volcanique sur l'accumulation de capital des ménages (Chapitre 2), la coopération post-désastre (Chapitre 3), ainsi que le rôle des autorités publiques dans les décisions de migration (Chapitre 4). Le principal défi empirique inhérent à l'étude du risque volcanique étant le manque de données, le Chapitre 2 se base sur des simulations et les Chapitres 3 et 4 utilisent une enquête que nous avons conduite en Juin 2016 en Equateur autour du volcan Tungurahua et dont le questionnaire est reporté dans le Chapitre 6.

Le Chapitre 2 étudie l'impact de long terme de l'exposition au risque volcanique sur l'accumulation de capital des ménages agricoles. Ce travail contribue à la littérature en se concentrant principalement sur l'effet ex-ante du risque volcanique, c'est à dire sur les changements dans les décisions d'investissement dus à l'exposition au risque, plutôt que sur les chocs en eux même. Nos résultats sont de trois ordres. D'abord, l'effet de l'exposition au risque volcanique est négatif sur l'investissement en actif productif. Autrement dit, l'exposition à un volcan induit un changement de comportement dans les décisions d'investissement, de telle sorte que le ménage exposé préfèrera consommer une plus grande partie de son revenu plutôt que de l'investir dans un actif pouvant potentiellement être endommagé ou détruit par de futures éruptions. Aussi, nous montrons que, pour notre ensemble de paramètres estimés, cet effet est quantitativement important. Enfin, nous mettons en évidence que les changements dans la perception du risque tels que mesurés dans la littérature, ayant lieu suite à un désastre naturel ralentissent le processus de reconstruction.

Le Chapitre 3 étudie l'impact de l'éruption de Novembre 2015 du Tungurahua sur le capital social des ménages et apporte une double contribution à la littérature. L'apport principal de ce chapitre réside dans l'analyse empirique de plusieurs mécanismes énoncés dans la littérature comme étant de potentiels canaux de transmission, à savoir le comportement d'aléa moral, la perception du risque,

et les mouvements temporaires de population. Ensuite, en étudiant des mesures de coopération bilatérale, de contribution à un bien public et de confiance dans les institutions, nous étudions un spectre plus large du capital social que ce qui est généralement traité dans la littérature. L'hypothèse d'aléa moral n'étant pas directement testable empiriquement, nous partons d'un modèle théorique simple pour guider l'analyse empirique et nous identifions la variable d'inégalité de richesse au sein d'une communauté comme moyen de tester ce canal de transmission. Nos résultats empiriques corroborent ce mécanisme, à savoir qu'à la suite d'un choc, la coopération entre individus décroit dans les communautés homogènes alors qu'elle croit dans les communautés hétérogènes. Aussi, l'éruption volcanique entraine une hausse inconditionnelle de la propension à contribuer à un bien public et de la confiance envers les autorités.

Enfin, le Chapitre 4 cherche quant à lui à mettre en lumière le rôle des autorités publiques dans les décisions de migration des ménages. La littérature a mis en évidence le rôle de la migration comme outil de diversification spatiale des revenus et souligne que celle-ci peut être utilisée à la fois comme stratégie ex-ante ou ex-post. D'un point de vue théorique, nous soutenons que l'impact des politiques publiques sur les décisions de migration est ambigu et dépend des préférences des membres du ménage et du processus de décision. Empiriquement, nous étudions l'impact de la confiance dans les institutions sur la dispersion spatiale des enfants. Nos résultats montrent qu'une hausse de la confiance du chef de ménage dans les autorités publiques accroit la propension des enfants à vivre dans la même paroisse que lui. Ces résultats sont robustes à la prise en compte de l'aversion au risque, de la perception du risque d'éruptions futures, de la confiance dans les autres membres de la communauté et des décisions de fertilité.

Mots clés : Économie du développement ; Désastres naturels ; Investissement ; Perception du risque ; Capital social ; Coopération ; Aléa moral ; Confiance ; Migrations ; Institutions.
Codes JEL : D15 ; D81 ; O12 ; O15 ; O17 ; Q54 ; R23.

Summary

Natural disasters have particularly devastating consequences in developing countries where people are highly vulnerable and institutions remain inefficient. Nevertheless, their impacts on households' well being and the role of public interventions are, yet, not fully understood. In addition, while most studies focus on climatic risk, geological disasters, and volcanic eruptions in particular, are clearly understudied. However, despite representing a marginal share of natural disasters at the global level, volcanic eruptions are a major threat in some countries, such as Indonesia or Ecuador.

The present dissertation tries to contribute to the literature by investigating the impact of volcanic hazard on farmers' capital accumulation (Chapter 2), and on post-disaster cooperation (Chapter 3), as well as the potential mitigating role of public authorities on migration decisions (Chapter 4). The main empirical challenge arising when studying the microeconomic impact of volcanic risk is the lack of data. To tackle this issue, Chapter 2 relies on simulations, and Chapters 3 and 4 are based on a survey whose questionnaire is reported in Chapter 6 that we conducted in June 2016 in Ecuador, around Mt. Tungurahua.

Chapter 2 studies the long-term impact of volcanic risk exposure on farmers' capital accumulation. This work contributes to the literature by focusing on the ex-ante effect, that is, on the changes in investment behavior induced by risk exposure, rather than on the shocks themselves. In this aim, we set up a stochastic growth model for which we estimate the parameters using data on Indonesian farm households not exposed to volcanoes. Volcanic risk is then simulated under different scenarios. Our results are as follows. First, we find that the ex-ante effect of volcanic hazard on investment is negative. In other words, exposed farmers change their investment behavior so that they prefer to increase their levels of consumption rather than to invest in productive assets that could be damaged or even destroyed by future eruptions. In addition, we show that, for our set of estimated parameters, this effect is quantitatively large. Finally, we show that changes in risk perception after a shock, such as estimated in the literature, slow down the recovery process.

Chapter 3 investigates the impact of the November 2015 eruption of Mt. Tungurahua, Ecuador, on social capital, and brings a twofold contribution to the literature. The main contribution lies in the empirical test of several mechanisms highlighted in the literature as potential transmission channels, namely moral hazard, risk perception, and temporary movements of population. Secondly, by investigating measures of bilateral cooperation, public good contribution, and trust in public authorities, we study a wider spectrum of social capital than what has been

done so far in the literature. Since the moral hazard mechanism is not directly testable empirically, we build a simple theoretical model to guide the empirical analysis, and we identify wealth inequality as a mean to test for it. Our empirical results are in line with the theoretical predictions. Following a shock, bilateral cooperation tends to increase in the most unequal communities, and decreases in the most homogeneous communities, supporting the hypothesis of moral hazard behavior. In addition, the eruption unconditionally promotes the willingness to contribute to collective goods and the levels of trust toward public authorities.

Finally, Chapter 4 highlights the potential mitigating role of public authorities on migration decisions. The literature already provides evidence that migration serves as a mean for spatial income diversification, and shows that it can happen either as an ex-ante or as an ex-post strategy. While post-disaster programs have been shown to mitigate this latter, it remained to be shown whether public authorities could also affect the former. Then, we contribute to the literature by investigating the role of institutions' trustworthiness on ex-ante migration decisions. From a theoretical perspective, we argue that the impact of public policy on migration decisions is ambiguous as it depends on household members' preferences and the decision process within the household. Empirically, we investigate the impact of trust in institutions on children spatial dispersion, and we show that a higher level of trust toward public authorities increases the likelihood of children to live in the same parish as their parents. This result is robust to the introduction of control variables accounting for risk aversion, risk perception about future eruptions, trust in other community members, and fertility decision.

Keywords: Development economics, Natural disasters, Investment behavior, Risk perception, Social capital, Cooperation, Moral hazard, Trust, Institutions, Migration.
JEL codes: D15; D81; O12; O15; O17; Q54; R23

List of acronyms

CERDI:	Centre d'Études et de Recherches sur le Développement International
ClerVolc:	Clermont-Ferrand centre for research on Volcanism
CRED:	Centre for Research on the Epidemiology of Disasters
EM-DAT:	Emergency Events Database
Fct:	Function
FE:	Fixed Effects
FONDEN:	Fondo Nacional para el Desarrollo Nacional
Freq:	Frequency
GFDRR:	Global Facility for Disaster Reduction and Recovery
GDP:	Gross Domestic Product
IDGM:	Initiative pour le Développement de la Gouvernance Mondiale
IDMC:	Internal Displacement Monitoring Center
IFLS:	Indonesian Family Life Survey
IG:	Institute of Geophysics
IRD:	Institut de Recherche pour le Développement
IV:	Instrumental Variable
Km:	Kilometers
LSMS:	Living Standards Measurement Study
Mt:	Mount
NELM:	New Economics of Labor Migration
OECD:	Organization for Economic Cooperation and Development
OLS:	Ordinary Least Squares
VEI:	Volcanic Explosivity Index
2SLS:	Two-Stage Least Squares

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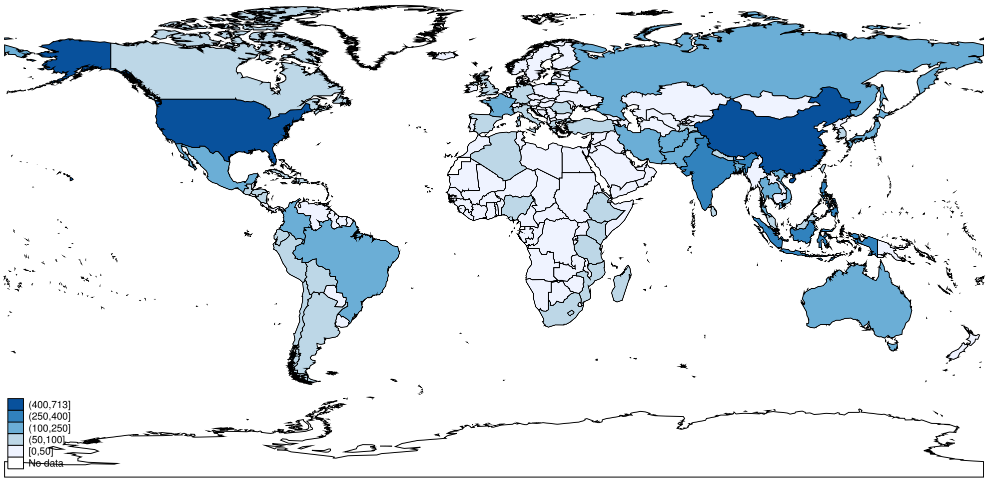
Chapter 1
Introduction

While the macroeconomic literature was initially inconclusive on the impact of natural disasters on GDP growth, showing positive, negative, or no effect, recent studies, addressing the endogeneity problem of economic losses (Felbermayr and Gröschl, 2014) and the "partial-out" problem (Strobl, 2011), unambiguously show their adverse consequences. Whether these losses are temporary (Elliott et al., 2015), or long lasting (Hsiang and Jina, 2014) remains debated but the adverse economic effect of natural disasters is now unquestionable. In the words of Felbermayr and Gröschl (2014), "[...] natural disasters harm development, period."

Contrary to what one may think, developing countries are not more exposed to natural disasters than developed ones. In fact, using panel data on 73 nations over the 1980-2002 period, Kahn (2005) shows that GDP per capita has no effect on the probability that a natural disaster takes place. On the contrary, geography does matter in determining the distribution of natural disasters as Americas, Asia, and Europe are exposed to more shocks than Africa. Figure 1.1 plots the number of natural disasters per country using a more recent version of the EM-DAT dataset, covering the 1990-2017 period. Similar findings seem to emerge, namely that despite observing less natural disasters in Africa than in others continents, no visible pattern appears between natural disaster frequency and development level.

However, despite not suffering from more frequent or stronger natural disasters than the developed world, developing countries still bear the greatest human cost. The figure presented in Kahn (2005) speaks for itself: "Between 1980 and 2002, India experienced fourteen major earthquakes that killed a total of 32,117 people while the United States experienced eighteen major earthquakes that killed only 143 people." His empirical analysis confirms this idea as richer nations are less likely to experience a death when shocks occur. In addition to experiencing more deaths, developing countries also bear the highest economic cost. Using the EM-DAT database over the 1990-2017 period, Figure 1.2 plots the economic losses induced by natural disasters. While damages expressed in dollars are clearly positively related to the level of income per capita, this pattern is reversed when losses are expressed as a percentage of GDP, reaching an average of 2.5% of the GDP for the least developed countries. This latter correlation might be explained by both low quality infrastructures and inefficient institutions (Athey and Stern, 2002; Besley and Burgess, 2002).

Figure 1.1: Number of disasters reported per country (1990-2017)

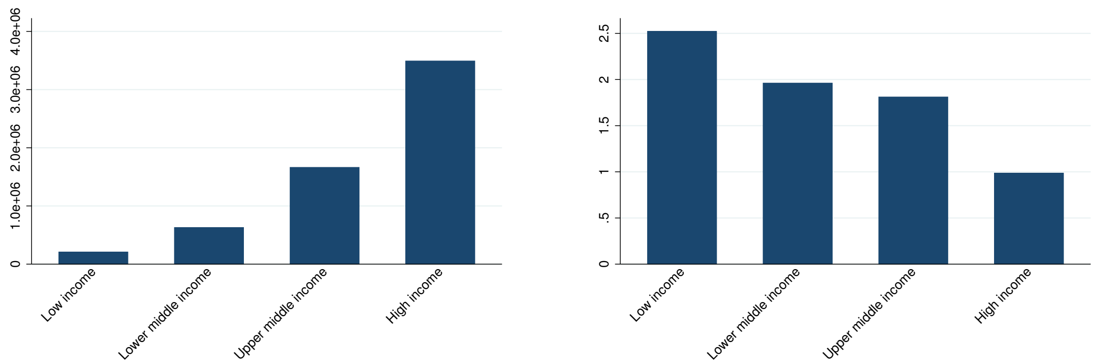


Source: Author's elaboration on EM-DAT database.

Figure 1.2: Economic losses of natural disasters (1990-2017)

(a) Economic losses in US dollars

(b) Economic losses as % of GDP



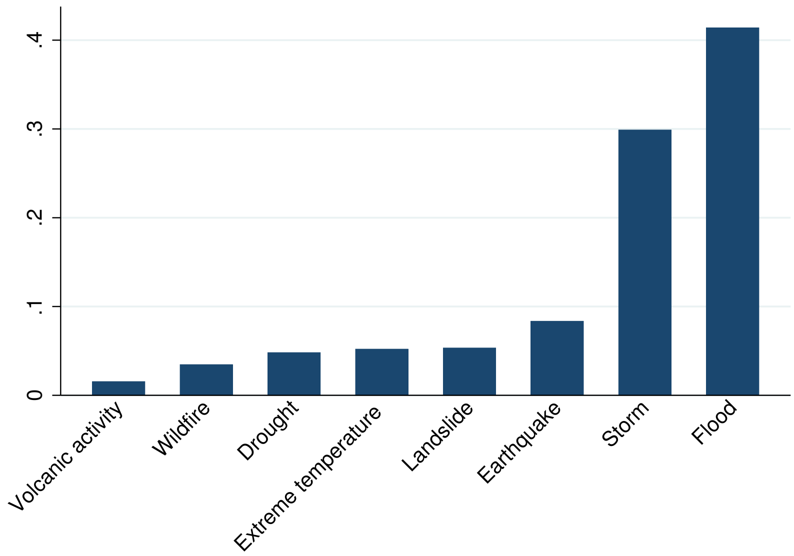
Source: Author's elaboration on EM-DAT database.

These devastating consequences have triggered the attention of major actors of development. As Jim Kim, the World Bank's president, said: "Severe climate shocks threaten to roll back decades of progress against poverty. Storms, floods, and droughts have dire human and economic consequences, with poor people often paying the heaviest price. Building resilience to disasters not only makes economic sense, it is a moral imperative."[1]

[1]Source: http://www.worldbank.org/en/news/press-release/2016/11/14/natural-disasters-force-26-million-people-into-poverty-and-cost-520bn-in-losses-every-year-new-world-bank-analysis-finds

Despite this urgent need, the impacts of natural disasters on households' well being and the role of public interventions are, yet, not fully understood. The main reason lies in the fact that, while there is a large literature on the economics of risk, most of the results are derived under conditions that do not fit for the study of natural hazards. In fact, natural disasters differ from 'traditional risk' on, at least, two dimensions: their distribution which rather follows extreme type distributions, and their spatial correlation. Consequently, a flourishing literature has emerged over the last years investigating the impacts of natural disasters on poverty (Carter et al., 2007; Dercon, 2004), migration (Alem et al., 2016; Gröger and Zylberberg, 2016), risk and time preferences (Cassar et al., 2017), as well as the impacts of post-disaster programs on growth (De Janvry et al., 2016), education decisions (De Janvry et al., 2006) or migration decisions (Chort and De La Rupelle, 2017). A common trait of these papers is their focus on climatic shocks, while geological disasters, and volcanic eruptions in particular, remain clearly understudied. This pattern is, nevertheless, not unfounded. Figure 1.3 represents the distribution of natural disasters according to their type over the 1990-2017 period using the EM-DAT database, and the conclusion is clear: at the global scale, climatic disasters drastically overweight geological shocks. Quantitatively, floods and storms account for more than 70% of total disasters, while earthquakes and volcanic eruptions represent together less than 10%.

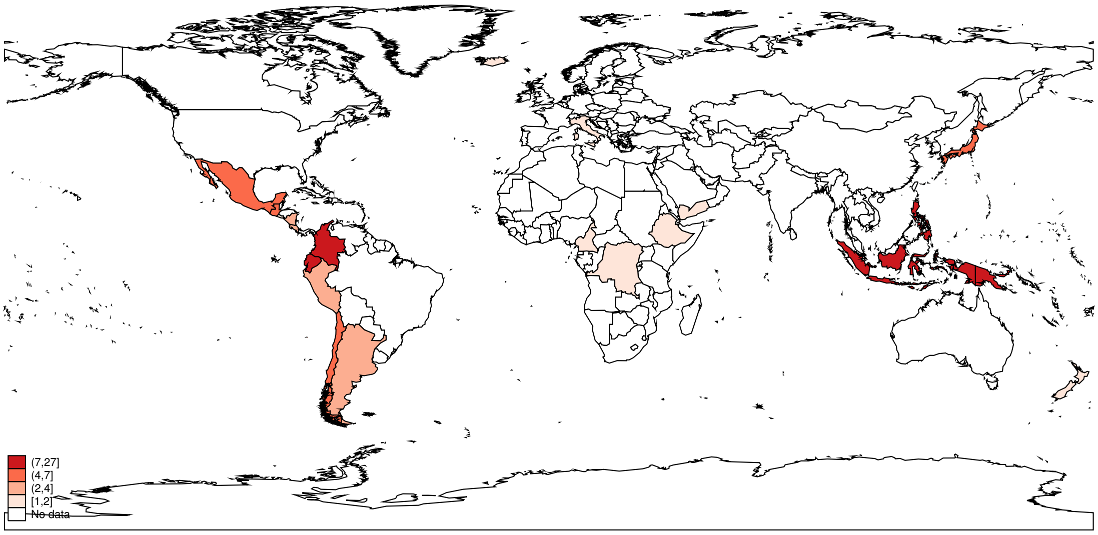
Figure 1.3: Share of occurrence of natural disasters by type (1990-2017)



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

In this context, one may fairly questioned the relevance of studying the impact of volcanic eruptions. Figure 1.4 provides a first piece of answer by representing the spatial distribution of volcanic activity at the global level over the 1990-2017 period. A striking feature lies in the high concentration of volcanic events in two regions of the world, namely Latin America and Asia.

Figure 1.4: Spatial distribution of volcanic risk (1990-2017)



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

Therefore, while volcanic risk is marginal at the world scale, it may still represent a serious threat in these countries. As a matter of illustration, we discuss the case of two countries, namely Indonesia and Ecuador.

Indonesia regularly experiences devastating disasters. In fact, according to the National Disaster Management Agency (BNBP), over the last 30 years, there were on average 289 significant natural disasters per year in Indonesia, with an average annual death toll of approximately 8,000 (WorldBank, 2016). While it experiences different types of disasters, its location on the Pacific Ring of Fire, an area with a high degree of tectonic activity, highly exposed the country to geological disasters and volcanic eruptions in particular. With around 140 volcanoes, Indonesia is, in fact, the world's most exposed country to volcanic risk. In addition, due to the high number of inhabitants living around volcanoes, Indonesia is also considered to be one of the most vulnerable (Brown et al., 2015). In this context, volcanic eruptions inevitably represent a serious threat for the country. As a matter of fact, the 2010 eruption of Merapi volcano in Indonesia caused the evacuation of approximately 400,000 people, 386 deaths and an estimated loss of $300 million.

Similarly, Ecuador experiences a wide range of natural disasters but is home to the greater part of the northern volcanic zone of the Andes range. Then, with 35 volcanoes and more than 4 million people living in a perimeter of 30km from a volcano, accounting for about one-third of the population, the country is also highly exposed to volcanic risk.[2] In particular, the volcanoes Tungurahua, Pichincha, and El Reventador have all been active within the past decade, inducing very important economic losses, mainly in the agricultural and livestock sectors (WorldBank, 2012). According to the EM-DAT database, over the 1990-2016 period, half of the people affected by a natural disaster in Ecuador were threatened by a volcanic eruption. What is more, Quito, the capital city, is directly under the threat of an eruption of the Cotopaxi volcano.

As volcanic risk clearly represents a major concern in both countries, the present dissertation tries to contribute to the economic literature by investigating the impact of volcanic hazard on farmers' capital accumulation (Chapter 2), and on post-disaster cooperation (Chapter 3), as well as the potential mitigating role of public authorities on migration decisions (Chapter 4). The main empirical challenge arising when studying the microeconomic impact of volcanic risk is the lack of data. In fact, while a growing number of surveys, such as the LSMS, are undertaken and made publicly available, we were unable to find data on households affected by volcanic eruptions. The Indonesian case is highly representative of this difficulty. As stated above, Indonesia is the world's most exposed country to volcanic risk. In addition, from 1993 to 2007, four waves of a national comprehensive survey, the Indonesian Family Life Survey (IFLS), have been undertaken leading to a panel dataset covering more than 7,000 households. Then, at first sight, Indonesia seems to be an ideal case study. Nevertheless, while a number of eruptions occurred during the sampled period, those were of moderate intensity and only had a localized impact. What is more, by geolocalizing the sampled villages and by measuring their distances to the volcanoes, we found out that the sampled households were simply too far (usually more than 20 kms) to be affected by the eruptions.[3] A similar issue emerged in Ecuador where a national survey was implemented in 2016 but did not cover the areas affected by volcanic eruptions. To tackle this issue, Chapter 2 relies on simulations, and Chapters 3 and 4 are based on a survey that we conducted in June 2016 in Ecuador, around Mt. Tungurahua, one of the most active volcano of the country. We sampled 229 households living in 11 communities in the affected area, and we administered the questionnaire provided in Chapter 6.

In what follows, we present a brief overview of the three chapters developed in this dissertation by briefly discussing the motivation of the research question, the

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

[3]We are not even mentioning that, since ash clouds are driven by wind direction at the time of eruption, being close to the volcano is not even a sufficient condition for a community to be impacted.

results, and how it applies to public policies.

How Do Natural Disasters Affect Farmers' Investment Behavior?

Motivation

As illustrated above, understanding the impact of natural disasters on poverty is probably the topic that creates the highest expectations from outside academia. The reason is simple: by pushing back people into poverty, natural disasters are one reason for which eradicating poverty is so difficult. As a matter of fact, Dang et al. (2014) show that, between 2006 and 2011, while 45 percent of poor households in Senegal escaped poverty, 40 percent of nonpoor households fell into it, and households affected by a natural disaster were 25 percent more likely to fall in poverty during the period. Similarly, among Guatemalan households hit by tropical storm Agatha in 2010, per capita consumption fell 5.5 percent, increasing poverty by 14 percent (Baez et al., 2017). What is more, natural disasters may also keep people into poverty for several years. For instance, Dercon (2004) show that after Ethiopia's 1984–85 famine, it took a decade for most asset-poor households to restore livestock holdings to pre-famine levels .

The existing literature

Understanding the mechanisms behind the impact of natural hazards on capital accumulation calls on three strands of literature. First, the theoretical literature has long highlighted that being exposed to a risk affects the consumption/investment decisions of an individual. Nevertheless, the sign of the effect remains ambiguous (Gunning, 2010) and, apart from the noticeable exception of Gollier and Pratt (1996), results are hardly applicable to natural disasters. Second, the empirical literature, focusing on the ex-post consequences of natural disasters, have highlighted the adverse impact of shocks on assets and poverty on the short run, but remains inconclusive on the ability of households to recover on the long run (Carter et al., 2007; Gignoux and Menéndez, 2016). Finally, a literature drawing on experimental economics has shown that people hit by natural disasters tend to change their perception about future shocks in the wake of natural disasters (Cameron and Shah, 2015). However, evidence lack on how these changes in beliefs affect the recovery process.

Contribution to the literature

Chapter 2 of this dissertation studies the long-term impact of volcanic risk exposure on farmers' capital accumulation. This work contributes to the literature by focusing on the ex-ante effect, that is, on the changes in investment behavior induced by risk exposure, rather than on the shocks themselves. In this aim, we set up a stochastic growth model for which we estimate the parameters using data on Indonesian farm households not exposed to volcanoes. Volcanic risk is then simulated under different scenarios. Our results are as follows. First, we find that the ex-ante effect of volcanic hazard on investment is negative. In other words, exposed farmers change their investment behavior so that they prefer to increase their levels of consumption rather than to invest in productive assets that could be damaged or even destroyed by future eruptions. In addition, we show that, for our set of estimated parameters, this effect is quantitatively large. Finally, we show that changes in risk perception after a shock, such as estimated in the literature, slow down the recovery process.

Public policy implications

If anything, this chapter sheds additional light on two levers that may be used to improve the ability of exposed individuals to cope with natural hazards. First, by highlighting the strong behavioral response to volcanic risk exposure, our results suggest that insurances against natural disasters might have hidden benefits on growth as the ex-ante effect of risk is rarely taken into account, and should therefore be supported. Second, since individuals tend to reduce their investment in the wake of a shock due to risk perception distortion, increasing post-disaster program duration might improve their efficiency.

Behind the Ash Veil: Natural Disasters and Social Capital

Motivation

Apart from the losses in physical assets mentioned above, natural disasters may also increase the vulnerability of households by affecting their social capital. In fact, social networks, trust, and the propensity to cooperate – all three belonging to the broad concept of social capital – play an important role for the livelihood of communities in the developing world, especially by providing informal insurance and credit when markets are imperfect or absent (Udry, 1990, 1994; Rosenzweig, 1988; Fafchamps and Lund, 2003; Townsend, 1994; Kinnan and Townsend, 2012; Ligon et al., 2002; Anderson and Baland, 2002; Attanasio et al., 2012). While it has long been considered as fixed by economists, recent evidence suggest that social capital can be affected by conflicts (De Luca and Verpoorten, 2015; Rohner et al., 2013; Voors et al., 2012), or natural disasters.

The existing literature

The literature on the effects of natural disasters on social capital is burgeoning and remains highly ambiguous both on the sign of the effect and on the underlying mechanisms. On the one hand, some papers find a positive effect (Cassar et al., 2017), potentially explained by several factors such as the time spent with others during the reconstruction process, a decrease of inequality following the shock, a change in risk perception, or, finally, as a reward toward people providing help during the recovery process. On the other hand, some papers find evidence of a negative effect (Fleming et al., 2014) that might be explained by migration, rivalry generated by disputes to obtain scarce relief and recovery resources, or moral hazard behavior, which consists for individuals to exploit the asymmetry of information on their post-disaster income to pretend to be poorer than they actually are, and escape solidarity mechanisms.

Contribution to the literature

Chapter 3 uses the survey that we conducted in Ecuador in June 2016 around Mount Tungurahua to investigate the impact of the November 2015 eruption on social capital. This chapter brings two contributions to the literature. First, we offer a formal test of several transmission channels highlighted in the literature, namely: risk perception, temporary movement of individuals, and moral hazard behavior. Since this latter is not directly testable empirically, we build a simple theoretical model to guide the empirical analysis, and we highlight the level of wealth inequality as a mean to test for it. Second, by studying measures of bilateral cooperation, contribution to public goods, and trust in public authorities, we investigate a larger spectrum of social capital than what has been done so far in the literature. Our results are threefold. First, bilateral cooperation decreases in homogeneous communities, in line with the moral hazard hypothesis, while it increases in heterogeneous communities. In addition, the willingness to contribute to public goods is positively correlated with the intensity of the shock, but we do not find evidence of moral hazard behavior. Finally, we find that public intervention triggered by the intensity of the eruption tends to increase the levels of trust toward public authorities, confirming the finding in Andrabi and Das (2017).

Public policy implications

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 individuals against idiosyncratic shocks.

Natural Disasters and Migration: The Role of Trust in Institutions

Motivation

In the face of natural disasters, people in developing countries have few available options to mitigate the effects of the shocks since the usual coping strategies such as risk-sharing or activity diversification are notoriously inefficient. Consequently, households exposed to natural hazards may decide to engage in a spatial diversification of their income through migration, a mechanism initially highlighted by Rosenzweig and Stark (1989). According to the Internal Displacement Monitoring Center, since 2008, an average of 26 millions individuals have been displaced by natural disasters each year, equivalently to one person per second (IDMC, 2015). Existing studies show that migration mainly occurs within the boundaries of the country (Beine and Parsons, 2015), and may have adverse effects at destination by increasing unemployment (Strobl and Valfort, 2013), or inducing violences (Morales, 2018). Consequently, public authorities have a central role to play in the management of migration flows.

The existing literature

The existing literature provides abundant evidence of natural disaster-induced migration. Interestingly, these papers highlight that migration may happen either as an ex-ante or as an ex-post strategy (Alem et al., 2016; Dillon et al., 2011). By contrast, the role of public authorities in mitigating the migratory response to natural disasters has, surprisingly, remained largely unexplored in the literature. A noticeable exception is Chort and De La Rupelle (2017) who investigate the effect of two programs implemented in Mexico, namely Fonden and Procampo on post-disaster international migration. Procampo is the largest agricultural program funded by the Mexican federal government and consists in direct payments to agricultural producers, while Fonden is a disaster fund aimed at providing insurance to localities hit by a natural disaster. Interestingly, they find evidence of a mitigating impact of the two programs on undocumented flows only. Then, while post-disaster programs have been shown to mitigate ex-post migration, it remains to be investigated whether public authorities could also affect ex-ante migration decisions.

Contribution to the literature

Chapter 4 contributes to the literature by investigating the role of institutions' trustworthiness on ex-ante migration decisions. From a theoretical perspective, we argue that this effect is ambiguous as it depends both on household members' preferences and on the decision process within the household. This question remains, therefore, mainly empirical. Then, to test this hypothesis, we rely on the survey we conducted around Tungurahua volcano where we collected data on trust in public authorities and on children' place of living. Consequently, our empirical strategy consists in investigating the impact of household heads' trust in institutions on children spatial dispersion. Our results show that a higher level of trust toward public authorities increases the likelihood of children to live in the same parish as their parents. This result is robust to the inclusion of control variables accounting for risk aversion, risk perception about future eruptions, trust in local people, and fertility decisions.

Public policy implications

The idea that institutional quality matters is of course long known. This chapter takes a slightly different perspective by underlying the importance for local population to adopt and trust the tools developed by public authorities to mitigate the effect of the shock. In this vein, the Ecuadorian initiative to associate local people to the monitoring of the volcano certainly goes in the right direction and should be supported.

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Chapter 2

How Do Natural Disasters Affect Farmers' Investment Behavior?

2.1 Introduction

The 2010 eruption of Merapi volcano in Indonesia caused the evacuation of approximately 400,000 people, 386 deaths and an estimated loss of $300 million. Like other natural disasters, volcanic eruptions are a particular concern in developing countries where people are highly vulnerable and remain largely uninsured. This is particularly true in Indonesia where areas surrounding volcanoes are often rural and devoted to agricultural activities. As ash fall often seriously damage or even destroy the productive capital of farmers, including their crops, livestock, buildings and machinery, farm households living close to volcanoes may suffer from recurrent negative wealth shocks during active volcanic phases.

Despite the increasing numbers of natural disasters (CRED, 2015), their long-term effects on individual welfare remain poorly understood. In fact, while the empirical literature suggests an adverse effect on the short run, a debate remains on the ability of households to recover on the long run. On the one hand, natural disasters may push households into poverty traps that can persist in the long run (Carter et al., 2007). These latter occur at the level of the household when returns to assets are locally increasing, so that a decrease in the stock of assets below a certain threshold traps households in a low-income equilibrium (Carter and Barrett, 2006). On the other hand, if no such locally increasing asset returns are observed, or if well-functioning financial markets exist, capital could be reconstituted. This recovery could be further eased if afflicted areas benefit from external transfers for aid and reconstruction (Gignoux and Menéndez, 2016). However, asset destruction or income losses are not the only way through which natural disasters affect households' wealth. In fact, the theoretical literature has long highlighted the ex-ante impact of risk exposure on investment decisions, that is, the changes of investment decisions induced by risk exposure before the shock. However, the sign of this effect remains undetermined as people can either increase their investment for a precautionary motive or, on the contrary, increase their consumption and reduce their investment to avoid buying assets that would be damaged in the future. Also, this literature assumes that the risk at stake is fair, an assumption that does not hold for natural disasters which only incur losses. A noticeable exception is Gollier and Pratt (1996) who show that being exposed to an unfair additive risk makes people more risk averse. Whether this is also the case for a multiplicative risk remains to be investigated as well as the magnitude of this effect. In addition, a burgeoning literature has highlighted that affected people temporarily change their risk perception about future shocks in the wake of natural disasters (Cameron and Shah, 2015; Samphantharak and Chantarat, 2014). In fact, following a shock, affected people tend to overweight the probability of future disasters, which may in turn affect investment decisions (Rosenzweig and Udry, 2013). Whether the magnitude of these changes in risk perception significantly affects the recovery process remains to be investigated.

Using data on farm households in Indonesia, this paper aims at quantifying these two effects on capital accumulation, namely the ex-ante effect and the impact of changes in risk perception after a shock. The crucial public policy debate lying behind our research question is whether governments should care about natural disasters only right after the shock or rather at a longer time scale. In fact, if the ex-ante effect of volcanic risk exposure is negative but negligible or even positive, one may argue that long-term public policies are unnecessary. On the contrary, a strong and negative ex-ante effect would advocate for public policies such as relocation programs or insurance subsidies. Similarly, if changes in risk perception after a shock strongly affect investment decisions, adapting post-disaster programs could increase their efficiency.

Our focus on farm households in Indonesia is not without reason. Indeed, as a number of both developed and developing countries such as Iceland, Philippines, Mexico, or Ecuador, Indonesia is highly exposed to volcanic risk. In fact, with 142 active volcanoes, and 179 million inhabitants living in a perimeter of 100 km to a volcano, Indonesia is not only the most exposed country to volcanic risk but also one of the most vulnerable (Brown et al., 2015). Moreover, while very large eruptions remain relatively rare, more localized eruptions are more frequent and may still induced significant damages to households living around. Since those areas are particularly prone to agricultural activities (Annen and Wagner 2003 and Muzayyanah et al. 2013), farm households are the most exposed to volcanic risk.

Identifying the behavioral effect of natural disasters is hardly feasible with reduced form empirical models. In fact, comparing households affected by volcanoes with non-exposed households would allow to quantify the global effect of volcanic risk on wealth but not to disentangle the behavioral effect from the shocks themselves. Doing so would require additional sources of variation that are arguably rarely met in practice. Moreover, we are not aware of any micro data on households exposed to volcanic risk, which requires the use of simulations. To tackle these issues, we adopt a structural approach that allows us to estimate the parameters of a stochastic growth model using data on farm households not affected by volcanoes, and then to simulate the impact of volcanic risk on their capital accumulation. The estimation follows the method proposed by Elbers et al. (2007). In a first step, we estimate the parameter of the production function and the second step estimates the remaining parameter of the model using a nested-fixed point algorithm. Then, we rely on simulations to investigate how households react to the exposure of volcanic risk. Volcanic risk is modeled along two dimensions: its distribution, which is estimated from the actual distribution of active Indonesian volcanoes over the last century; and the damages it incurs on productive assets. Values to characterize changes in risk perception after a shock are drawn from the literature.

This paper makes three contributions to the literature. First, while empirical papers focus on the ex-post consequences of natural disasters on households' welfare, this paper offers an original perspective by quantifying the ex-ante effect. Second, we claim to be the first trying to quantify how changes in risk perception in the wake of natural disasters, such as estimated in the literature, affect the recovery process. Last but not least, despite their importance we are not aware of any microeconomic study focusing on the welfare impact of volcanic risk.

Our results show that the ex-ante effect of volcanic risk on investment is negative meaning that exposed households prefer to increase their consumption rather than to invest in assets than could be potentially damages by future disasters. In addition, changes in risk perception after an eruption worsen this mechanism and incur additional losses in capital by delaying the recovery process. Overall, we find that, on the long run, the behavioral response to risk exposure (i.e. the sum of the ex-ante effect and of the impact of changes in risk perception) accounts for a significant share of total losses incurred by volcanic risk.

The remainder of the paper is as follows. Next, we discuss the related literature. Section 2.3 describes the data and the sample characteristics. Section 2.4 exposes the model. Section 2.5 discusses the estimation method. Section 2.6 is devoted to the characterization of volcanic hazard, the simulations and a discussion of the results. Finally, Section 2.7 concludes.

2.2 Related Literature

Being exposed to risk, whether it is a natural disaster or not, has two main effects on capital accumulation. The first one, which is referred to the ex-ante effect, stands for the changes in behavior that risk exposure induces before the occurrence of the shock. The second one is the ex-post effect which corresponds to what happens once the shock is realized.

Several theoretical papers investigate the ex-ante effect of risk on investment but their conclusions remain ambiguous as they offer justifications for both increase and decrease in investment. Whether the impact is positive or negative depends on several factors. In a 2-period model, Gunning (2010) shows that the nature of risk (whether it affects labor income, asset, capital income or wealth) as well as the preferences of the decision taker toward risk determine the outcome. The theoretical framework is also at stake. In fact, in the expected utility framework, an increase in background risk can lead a decision maker to become more risk averse (Eeckhoudt et al., 1996). Conversely, Quiggin (2003) has shown that within a framework of generalized expected utility theory, such as Yaari's (Yaari, 1987) dual theory, background risk may have the opposite effect and increase the propensity of a decision maker to opt for a given risky option. Most of the results derived from the comparative statics analysis of risk rely on the assumption that the risk at stake is fair. Obviously, this framework does not fit for the study of environmental hazards which only incur losses and are thus commonly considered to be unfair risks. An exception in the literature is Gollier and Pratt (1996) who introduce the notion of risk vulnerability. In their framework, adding an unfair background risk to wealth raises the aversion to any other independent risk and reduces the demand for the risky asset. Whether the ex-ante effect is strong or not is an empirical question that has, to our knowledge, only been investigated by Elbers et al. (2007). Based on micro data, they estimate a structural growth model and rely on simulations to quantify the ex-ante and the ex-post effects of risk. They show that, for a fair risk affecting wealth, the ex-ante effect clearly induces a larger cost in terms of growth than the realization of the shock it self.

Turning to the ex-post consequences of natural disasters, numerous articles empirically investigate the impact of natural disasters on households' welfare. For instance, Rodriguez-Oreggia et al. (2013) study, at the municipal level, in Mexico, the effects of floods and droughts and find a significant negative impact on human development and poverty levels. Carter et al. (2007) reach similar conclusions on Honduras and Ethiopia and suggest that households may fall into a poverty trap. Similarly, the long lasting effect of shocks on consumption growth has also been shown by Dercon (2004) in rural Ethiopia. On the other hand, some papers highlight the households' ability to recover. For instance, Arouri et al. (2015) conclude to adverse effects of natural disasters on welfare and poverty of rural households in Vietnam and underline the role of credit and remittances in the resilience process. Gignoux and Menéndez (2016) study the impact of Indonesian earthquakes on individual outcomes. They find that households affected by earthquakes report losses on the short run but are able to recover on the medium run and even exhibit welfare gains in the long run thanks to public infrastructure improvements.

Apart from economic losses, a number of studies show that people tend to change their behavior toward risk after a natural disaster. More precisely, studies on developing countries suggest that, after a shock, affected people tend to behave in a more risk averse way than others. This conclusion is supported by van den Berg et al. (2009) studying the impact of climatic disasters in Nicaragua and Peru, Cameron and Shah (2015) who focus on the impact of floods and earthquakes in Indonesia, Reynaud and Aubert (2013) who investigate the impact of floods in Vietnam, and Chantarat et al. (2015) investigating floods in Cambodia. Interestingly, Cameron and Shah (2015) identify risk perception as the transmission channel. In fact, they find that affected individuals overweight the probability of future disasters, making people more worried and fearful, and that worry leads to more risk-averse behavior. Similarly, Samphantharak and Chantarat (2014) find that affected individuals overweight the probability of future floods. These papers also suggest that, as time goes by, differences in behavior are likely to vanish. This is confirmed by Becchetti et al. (2012) who do not find any significant differences in observed risk preferences seven years after the 2004 tsunami. These results seem however specific to developing countries since studies on developed countries such as Eckel et al. (2009), Hanaoka et al. (2015) and Page et al. (2014) find evidence of a decrease in observed risk aversion among the affected population.

2.3 Data and Sample Characteristics

The Indonesian Family Life Survey (IFLS) is an on-going longitudinal survey in Indonesia. The sample contains over 7,000 households living in 13 of the 26 provinces in the country. This dataset is particularly appealing for its ability to track individuals over time and its wide time dimension as four waves have been undertaken, in 1993, 1997, 2000 and 2007. In addition, useful information is provided regarding farm activities. Indeed, the household head is asked about the value of the different types of capital used in the production process as well as the farm revenue. Individual occupations are also reported which allows to assess the number of household farm workers.

Despite the volcanic activity in Indonesia during this period, none of the interviewed households reported economic damages due to eruptions. This can be explained both by the distance between sampled villages and volcanoes, and the relatively weak magnitude of eruptions during this period. This shortcoming requires to work with a sample of non-affected households on whom we simulate the impact of volcanic risk. Since areas around volcanoes are usually rural and devoted to agricultural activities (Annen and Wagner 2003 and Muzayyanah et al. 2013), we restrict our sample to self-employed farmers living in rural areas, leading to 2520 households. In addition, as our estimation strategy relies on the evolution of capital over time of each household, we only keep households that have been observed over the four waves of the survey. Doing so drastically reduces the sample size since 1677 households are observed over at least two waves over the survey, 831 households over at least three waves, but only 90 households over the four waves. Nevertheless, we opt for the latter option since it maximizes the information per household and restrains the computational burden of the estimation.[1] Then, we are left with a balanced dataset of 90 households for which we provide descriptive statistics in Table 2.1.

We note that 90% of households are headed by male and that 70% of household heads received, at least, basic education. On average, two persons per household are devoted to farming. Most of households own their land and small tools, and half of them owns livestock. However, very few invested in agricultural assets such as tractors. In addition to farm activity, around 15% of the sample reports to have at least one non-farm-business.

Table 2.1: Summary statistics

Variable	**1993**	**1997**	**2000**	**2007**
Male headed household	0.89 (0.32)	0.89 (0.32)	0.89 (0.31)	0.89 (0.31)
Educated household head	0.63 (0.48)	0.70 (0.46)	0.71 (0.46)	0.73 (0.45)
Farm-income (*ln*)	13.02 (1.04)	13.20 (1.16)	14.20 (1.25)	15.35 (1.26)
Nb. of farm workers	1.58 (0.90)	2.09 (0.94)	2.24 (1.19)	2.19 (0.96)
Owning land	0.90 (0.30)	0.88 (0.32)	0.94 (0.23)	0.90 (0.30)
Owning livestock	0.49 (0.50)	0.50 (0.50)	0.48 (0.50)	0.42 (0.50)
Owning tools	0.96 (0.21)	1 (0)	0.98 (0.15)	0.99 (0.11)
Owning tractor	0.03 (0.18)	0.06 (0.23)	0.06 (0.23)	0.09 (0.29)
Value of land (*ln*)	14.28 (1.29)	14.82 (1.53)	15.47 (1.77)	16.69 (1.12)
Value of livestock (*ln*)	13.09 (1.69)	13.47 (1.50)	13.76 (1.84)	15.22 (1.28)
Value of tools (*ln*)	9.87 (1.16)	10.32 (0.90)	11.14 (0.99)	11.80 (0.81)
Value of tractor (*ln*)	14.91 (0)	15.51 (0.27)	15.67 (0.35)	15.95 (0.45)
Non-farm-business	0.16 (0.36)	0.11 (0.32)	0.16 (0.36)	0.17 (0.37)

Notes: Mean values of variables. Standard deviations are in parentheses. Household size is the number of people by household; Male headed household is a dummy variable taking the value one if the household is headed by a male and zero otherwise; Educated household head is a dummy variable taking the value one if the household head received at least elementary education and zero otherwise; Farm income is the logarithmic value of the annual farm income of the household; Nb. of farm workers is the number of household members working in the farm business; Owning land, livestock, tools, and tractors are dummy variables taking the value one if the household owns such asset and zero otherwise; Value of land, livestock, tools, and tractors are the logarithm of the value of the asset (in Indonesian rupiahs) owned by the household conditional on having this asset. Non-farm business is a dummy variable taking the value one if the household reports having at least one non-farm business and zero otherwise. *Source:* Author's elaboration on IFLS panel data.

[1]Increasing the number of households in the sample also increases the computational burden of the estimation which would become intractable with 800 households.

2.4 The Model

Farmers are considered to generate their income through an agricultural production process which involves capital and labor. Capital is modeled as a single bundle of productive assets including land, livestock, tools and tractor. Despite not being exposed to volcanoes, farm households' income is likely to be affected by several other shocks. Since we have no particular information on these non-volcanic income shocks, we assume that they are *i.i.d* and drawn from a centered Gaussian distribution for which we estimate the parameter. We also assume that farmers have no access to credit, saving, or insurance facilities. Therefore, income is either consumed or invested in productive capital. In addition, studying the impact of a natural disaster conveniently allows to abstract from modeling risk coping strategies such as risk sharing or income diversification. In fact, despite evidence that a small fraction of the sample also have a non-farm business, and that informal risk sharing may happen in developing countries (Townsend, 1994), these mechanisms are considered to be vain against covariate shocks like natural disasters. Abstracting from them in our analysis is, therefore, unlikely to affect our conclusions.[2] In sum, consumption smoothing is the only risk coping strategy available to households. Finally, households are considered to be rational and perfectly informed. In other words, when the household decides on current consumption and on the next period level of capital, both the current level of capital and the state of nature are known. In addition, despite its ignorance about future shocks, the household knows the distribution from which they are drawn. Then, each household maximizes its expected lifetime utility over an infinite horizon:

$$\max_{c_{ht}, k_{ht+1}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t u_h(c_{ht}) \tag{2.1}$$

subject to:

$$c_{ht} + i_{ht} = s_{ht} y_{ht} \tag{2.2}$$

$$k_{ht+1} = (1-\delta) k_{ht} + i_{ht} \tag{2.3}$$

$$y_{ht} = a_h f(k_{ht}, l_{ht}) \tag{2.4}$$

[2]To check that this non-farm activity does not influence investment in farm-business assets we regress the value of farm assets on a dummy variable taking the value one if the household reports at least one non-farm-business and zero otherwise. Results are reported in Table A1. We show that having at least one non-farm-business is not significantly correlated with the level of capital in farm assets, except for tractors which are positively correlated with non-farm activity but only at the 10% level.

where u is the utility function, β is the discount factor, c denotes consumption of a single perishable good, i is the level of investment, y denotes income, s is an income shock, k is the capital stock, δ is its depreciation rate, l is the quantity of labor, a is the parameter of total factor productivity and f is the production function. Households and time are indexed by h and t, respectively.

2.5 Estimations

Following Elbers et al. (2007), we rely on a two-step method to estimate the parameters of the model. First, we estimate the parameters related to the production function, that is, the elasticity of capital and the total factor productivity parameter. In a second step we run a nested fixed point algorithm, in the language of Rust (1987), to estimate the remaining parameters.

2.5.1 Production Function Parameters

A standard Cobb-Douglas production function is assumed such that:

$$y_{ht} = a_h l_{ht}^{\gamma} \prod_{i=1}^{I} k_{iht}^{\alpha_i} \tag{2.5}$$

where y denotes farm income, a is the time-invariant total factor productivity parameter, l is the number of farm workers, k_i denotes the different types of capital, h and t index household and time respectively. The form of the Cobb-Douglas production function allows for log-linearization, making estimations convenient. Expressing farm income and productive assets in per-worker terms, indexed with the superscript pw, we are left with Equation 2.6, which we estimate using the fixed-effect estimator.[3]

$$\ln(y_{ht}^{pw}) = \sum_{i=1}^{I} \alpha_i \ln(k_{iht}^{pw}) + \nu_h + \varepsilon_{ht} \tag{2.6}$$

where ν_h is an household fixed effect and ε_{ht} is an *i.i.d* error term. As often in agricultural economics, all households do not use all types of capital in their production process, leading to zero-values of some input variables. Despite violating a fundamental assumption of the Cobb Douglas function (if the value of one input is null, then no output is produced), the zeros make the log-linearization problem-

[3]Testing for the constant returns to scale hypothesis, we could not reject this hypothesis at the 10% level.

atic. We follow the procedure proposed by Battese (1997) to estimate unbiased coefficients.[4] Results are reported in Table 2.2.

Table 2.2: Production function estimation

	(1) $\ln(y_{ht}^{pw})$	(2) $\ln(y_{ht}^{pw})$	(3) $\ln(y_{ht}^{pw})$	(4) $\ln(y_{ht}^{pw})$
$\ln(land_{ht}^{pw})$	0.54***	0.39***	0.37***	0.36***
	(8.30)	(5.89)	(5.71)	(5.54)
$\ln(tools_{ht}^{pw})$		0.39***	0.36***	0.37***
		(5.91)	(5.83)	(5.90)
$\ln(livestock_{ht}^{pw})$			0.17***	0.16***
			(3.03)	(2.91)
$\ln(tractor_{ht}^{pw})$				0.03***
				(2.67)
Households Fixed Effects	Yes	Yes	Yes	Yes
Nb. of Observations	360	360	360	360
Nb. of Households	90	90	90	90
R-Squared	0.34	0.45	0.46	0.47

Notes: Standard errors clustered at the household level. t statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Dependent variable: logarithmic value of annual farm income per worker. Independent variables: logarithmic value of assets per worker. Dummy variables, D_{iht}, taking the value one if the value of asset i of household h at time t is null and zero otherwise are included in the regression but not reported, and asset variables are transformed such that: $k_{iht} = \max(k_{iht}, 1)$. Hausman test based on the full specification gives chi2(9) = 28.90 and p-value = 0.001 which leads to reject the random-effects model. *Source:* Author's estimation on IFLS panel data.

The production function estimates are similar to those found in previous studies (Bardhan 1973 and Randrianarisoa and Minten 2001). Based on the estimated elasticities, we aggregate the different types of asset into a single bundle of capital per worker, denoted k_{ht}^{ag}, and we derive its elasticity α, that are both used in

[4]We include dummy variables, D_{iht}, in the regression that take the value one if the value of asset i of household h at time t is null and zero otherwise, and we transform asset variables such that: $k_{iht} = \max(k_{iht}, 1)$.

the following estimations and simulations.[5] Table 2.3 reports summary statistics about the aggregate variable of capital, k_{ht}^{ag}, its elasticity parameter, α, and the household specific total factor productivity parameter, a_h.

Table 2.3: Summary statistics of production function estimates

Variable	Mean	Std. Dev.
$\hat{k}_{ht}^{ag}$	$5.17*10^5$	$7.45*10^5$
$\hat{\alpha}$	0.76	0.14
$\widehat{a}_h$	11.24	8.85

Notes: $\hat{k}_{ht}^{ag}$ is the aggregate variable of capital per worker. $\hat{\alpha}$ is the estimated elasticity of the aggregate capital variable $\hat{k}_{ht}^{ag}$. The household specific productivity parameter is computed as: $\widehat{a}_h = \exp(\hat{\nu}_h)$. *Source:* Author's elaboration on IFLS panel data.

2.5.2 Accumulation Parameters

Based on the previously estimated values of k^{ag}, α, and a this section aims at estimating the remaining parameters. Back to the model, we assume that households have a Stone-Geary utility function such that:

$$u(c) = \begin{cases} \dfrac{(c - c_{min})^{1-\sigma}}{1-\sigma} & \text{if } \sigma \neq 1 \\ \log(c - c_{min}) & \text{if } \sigma = 1 \end{cases} \tag{2.7}$$

We are left with five parameters to estimate: the parameter of the utility function, σ, the discount factor, β, the depreciation rate of capital, δ, the parameter μ characterizing the centered Gaussian distribution from which the income shock, s, is drawn, and the parameter of consumption subsistence, c_{min}.

Following Elbers et al. (2007), these parameters are estimated by simulated maximum likelihood. First, an arbitrary set of parameter values, is chosen. Given these parameters, the optimization problem is solved for each household.[6] This

[5] $k_{ht}^{ag} = \left(\prod_{i=1}^{I} k_{iht}^{\hat{\alpha}_i}\right)^{\frac{1}{\sum_i \mathbb{1}_{(k_{iht})}\hat{\alpha}_i}}$, where $\mathbb{1}_{(k_{iht})}$ is an indicator variable that takes the value one if the household h uses the asset i in its production process at time t, and zero otherwise; and $\hat{\alpha}_i$ is the estimated elasticity of asset i.

[6] See Appendix for details.

gives an household and state of nature specific policy function, ψ_{hs}, which indicates optimal investment as a function of wealth on hand determined by the capital stock and the shock in the current period. This function links the current level of capital with the next period level of capital. Unfortunately, observations on capital are only available for the years 1993, 1997, 2000 and 2007. Thus, we need to fill missing values in order to be able to run the estimation. This is done by simulation. For instance, for a given value of the accumulation parameters, we can simulate the conditional distribution of $k^{ag}_{h,1994}$, $k^{ag}_{h,1995}$, and $k^{ag}_{h,1996}$, given $k^{ag}_{h,1993}$.[7] We replicate the procedure for the following periods. Taking the mean of the simulated values for each household and each increment gives a complete data set that allows us writing the following log-likelihood function:

$$\log L = -\frac{n}{2}\log(2\pi) - \frac{n}{2}\log\left(\zeta^2\right) - \frac{1}{2\zeta^2}\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{j=1}^{J}\{\left(k^{ag}_{h,t+1} - \psi_{hs}(k^{ag}_{h,t})\right) * (Pr(s_{h,t} = j))\}^2 \tag{2.8}$$

where ψ_{hs} is the policy function, $Pr(s_{h,t} = j)$ denotes the probability of being in state j, n is the sample size, ζ is arbitrarily fixed to 1, H is the number of households, T is the number of periods and J is the number of discretized states of nature.

The parameter vector is then changed using simulated annealing algorithm to maximize the likelihood with respect to the accumulation parameters. Results are reported in Table 2.4. In general, whether estimated coefficients correspond to the global maximum or simply to a local one greatly depends on starting values. While this threat is minimized by using global optimization method, we run the estimation with different starting values to test the robustness of our result.

The estimation method follows a two-step procedure where the parameters of the production function are used to estimate the parameters of the model. Thus, as shown by Murphy and Topel (2002), the standard errors in the second step should be adjusted with the asymptotic variance of the first step parameters. We use bootstrap method to get correct standard errors. For each sample drawn we run the first regression and we introduce the estimated coefficients in the second regression that we run on the same sample. We repeat this procedure several times and we derive the standard errors of the second regression parameters. Results are reported in Table 2.4.

[7]Each increment is simulated 500 times.

Table 2.4: Estimated accumulation parameters

Parameters	Coefficients	Standard Errors
σ	0.68	0.16
δ	0.09	0.03
β	0.49	0.06
μ	0.11	0.02
c_{min}	362	1530

Notes: Standard errors based on bootstrap method to take into account variance of production function estimates. σ: risk aversion parameter; β: discount factor; δ: depreciation rate of capital, μ: parameter of the income shock distribution; c_{min}: parameter of consumption subsistence. *Source:* Author's estimation on IFLS panel data.

The coefficient of risk aversion is 0.68, meaning that agents are risk averse. This value is comparable to the ones obtained by Harrison et al. (2010) in India, Ethiopia and Uganda using experimental games. The depreciation rate is nine percents. The estimate of β is 0.49, suggesting a high degree of impatience. This finding is however not surprising in light of the hypothetical time preference games that have been administered in the fourth IFLS wave in 2007. In fact, most households head reported a discount factor smaller than 0.64 (see Table A2 in Appendix). The standard deviation, μ, of the distribution from which the income shocks are drawn is small compared to Elbers et al. (2007). This is not surprising as we expect households to have risk sharing agreements that we do not take into account in the model. Then, μ should be interpreted as the share of shocks that are not informally insured. Finally, the minimum consumption parameter is equal to 362 but suffers from low precision.

2.6 Simulations of Volcanic Risk

This section is devoted to the simulations of the model based on the previously estimated parameters. Simulations aim at quantifying the ex-ante effect of volcanic risk and the impact of changes in risk perception, after an eruption, on the recovery process. Doing so requires to characterize volcanic risk, which is done is Section 2.6.1. Section 2.6.2 formally exposes how volcanic risk and changes in risk perception enter the model. Results and a discussion are provided in Section 2.6.3.

2.6.1 Characterization of Volcanic Risk

We characterize volcanic hazard through two dimensions: the distribution of eruptions and the economic damages they incur. These two dimensions are respectively treated in the next two sections.

Distribution of Volcanic Eruptions

To recover the distribution of Indonesian volcanic eruptions we use data from the Global Volcanism Program of the Smithsonian Institution which inventories the date of eruptions and their explosiveness measured through the Volcanic Explosivity Index (VEI thereafter). The VEI is a widely used index, ranging on a zero (small eruption) to eight (large eruption) discrete scale, to measure the size of explosive eruptions. As we use year as time reference, we can only deal with one observation per year and per volcano. Then, only the strongest eruption is kept when several ones occur within a year. We are left with 32 volcanoes, listed in Table 2.5, and 507 eruptions for which summary statistics are reported in Table 2.6.[8]

Table 2.5: List of active Indonesian volcanoes (1900-2015)

Awu (5)	Batur (19)	Dempo (13)
Dieng (13)	Gamalama (17)	Gamkonora (10)
Gede-Pangrango (5)	Ijen (6)	Iliboleng (14)
Iliwerung (10)	Kaba (6)	Karangetang (34)
Kelut (8)	Kerinci (21)	Krakatau (37)
Lewotobi (16)	Lokon-Empung (20)	Marapi (32)
Merapi (23)	Paluweh (8)	Perbakti-Gagak (6)
Peuet Sague (7)	Raung (43)	Rinjani (10)
Sangeang Api (13)	Semeru (16)	Sirung (6)
Slamet (25)	Soputan (29)	Talang (5)
Tangkubanparahu (8)	Tengger Caldera (22)	

Notes: Number of eruptions in parentheses. *Source:* Author's elaboration on data from Global Volcanism Program, Smithsonian Institution.

[8] To avoid a large concentration of non eruption, the sample is restricted to volcanoes with at least five eruptions over the period considered.

Table 2.6: Summary statistics of Indonesian eruptions (1900-2015)

VEI	Freq.	Percent
1	131	25.84
2	331	65.29
3	38	7.50
4	7	1.38

Source: Author's elaboration on data from Global Volcanism Program, Smithsonian Institution.

The volcanic shock distribution is discrete and then can be written under the form of a Markov chain. Observing an eruption at a period may influence the probability of observing another at the next period. This hypothesis, known as the Independence of repose times hypothesis in the volcanologic literature, may affect the recovery process and therefore needs to be tested. To do so, we estimate the Markov chain by maximum likelihood and we find no evidence of serial correlation, a finding similar to Mendoza-Rosas and De la Cruz-Reyna (2008) on Mexico and Dzierma and Wehrmann (2010) on Chile. The estimated Markov chain is reported in Table 2.7. In line with the idea that natural disasters are rare, we find that the probability of not experiencing an eruption in a given year is high and equals 0.86. Also, stronger eruptions are less likely to happen since the probability of experiencing a VEI 1 or VEI 2 is 0.036, and 0.09, respectively, while the probability of a VEI 3 equals 0.01, and it falls to 0.002 for a VEI 4.

Table 2.7: Steady-state probability transition matrix (1900-2015)

$$\pi^v = \begin{array}{c} \\ VEI0 \\ VEI1 \\ VEI2 \\ VEI3 \\ VEI4 \end{array} \begin{array}{c} \begin{array}{ccccc} VEI0 & VEI1 & VEI2 & VEI3 & VEI4 \end{array} \\ \begin{pmatrix} 0.862 & 0.036 & 0.090 & 0.010 & 0.002 \\ 0.862 & 0.036 & 0.090 & 0.010 & 0.002 \\ 0.862 & 0.036 & 0.090 & 0.010 & 0.002 \\ 0.862 & 0.036 & 0.090 & 0.010 & 0.002 \\ 0.862 & 0.036 & 0.090 & 0.010 & 0.002 \end{pmatrix} \end{array}$$

Source: Author's elaboration.

Economic Damages of Volcanic Eruptions

To completely characterize volcanic risk we need to specify a loss function, that is, a function that links the strength of an eruption to its economic losses. Existing studies provide evidence that agriculture is particularly vulnerable to volcanic eruptions, which may directly impact crops, soil, animal health, farm infrastructure and machinery (Magill et al., 2013; Wilson et al., 2007, 2010, 2011). However, quantitative information on losses incurred by volcanic eruptions are quite limited. For that reason we remain agnostic about the functional form of the loss function and we propose three specifications. We only fix the upper bound of the loss functions, that is, the percentage of wealth lost due to a VEI 4 eruption, to 60%. This value is consistent with losses reported in fieldwork such as Ilham and Priyanti (2013) investigating the 2010 Merapi eruption (VEI 4) in Indonesia and Chandra et al. (2015) studying the impact of cold lahar (an avalanche of volcanic water and mud) of the 2014 eruption of Mont Kelut (VEI 4) in Indonesia. Regarding the loss function specifications, a first alternative is to assume that economic losses depend exponentially on the VEI. In that case, low quantity of volcanic materials would incur small agricultural losses and only strong eruptions would represent a serious threat. This is an extremely optimistic assumption, and values from this specification can fairly be considered as a lower bound of economic damages. A second alternative, is to assume that economic losses are linearly related to the VEI. A third alternative is to consider a logarithmic relationship between the economic losses and the VEI. This is the most pessimistic case, as few volcanic material cause severe losses, and therefore values from this specification can fairly be considered as an upper bound of economic damages. Values for each specification are reported in Table A4 in appendix. The three loss functions are then used in simulations (Section 2.6.3) to test the sensitivity of our results.

2.6.2 Simulation Method

To investigate how volcanic risk affects investment we augment the model presented in Section 2.4 with volcanic risk. That is, we now consider that farmers live close to a volcano, and that, following the existing literature, volcanic eruptions affect both farm income and agricultural assets. Therefore, households are now affected by two types of risk: the non-volcanic income shock, s, for which we estimated the distribution parameter, and the eruptions. Written in a Bellman equation form, the household maximization problem becomes:

$$V_{ht}(s_{ht}, \Upsilon_t, k_{ht}) = \max_{k_{ht+1}} u(\Upsilon_t s_{ht} y_{ht} + \Upsilon_t (1-\delta) k_{ht} - k_{ht+1}) + \beta\pi V_{ht+1}(s_{ht+1}, \Upsilon_{t+1}, k_{ht+1}) \tag{2.9}$$

where Υ denotes the volcanic shock, and the transition matrix, π, captures the joint distribution of income shock, s, and volcanic eruptions, Υ. [9][10]

The growing literature about natural disasters and risk perception suggests that, being affected by such shocks not only incurs income losses or asset destruction but also change people's beliefs about future shocks. Among them, Cameron and Shah (2015) run a study in Indonesia, based on both self-collected and IFLS data, to investigate the impacts of floods and earthquakes. They find that people update their perception of background risk after experiencing a disaster. More precisely, people report unrealistically high probabilities that another will occur in the next year and that it will be severe. Apart from being appealing for studying Indonesian households, this study also estimates, at different points in time, by how much affected households overestimate the probability of future occurrence of a disaster. These differences in subjective probabilities are reported in Table A3. One year after having experienced a shock, a person reports a probability of occurrence in the next year that is 34 points higher than an individual who was unaffected during the preceding seven years. This difference in subjective probabilities between affected and non affected people remain high for four years until it decreases sharply, and vanishes seven years after the shock. To quantify how changes in risk perception, in the magnitude estimated by Cameron and Shah (2015), affect the recovery process, we model changes in beliefs after an eruption in the following way. For each year after an eruption, the household overweights the probability that an eruption will occur next year by the corresponding value reported in Table A3. To model this persistence of beliefs shocks, we assume that the decision taker is myopic with respect to its own risk perception. In other words, the household knows the current state of nature and has beliefs about the probabilities of what will be the next period state of nature. However, despite the evolution of beliefs that actually occurs over time, the household assumes, at each period, that its current beliefs will last forever, and so makes its investment/consumption decision accordingly. Practically, when doing the simulations, we derive policy functions that are households' states of beliefs specific.

2.6.3 Results and Discussion

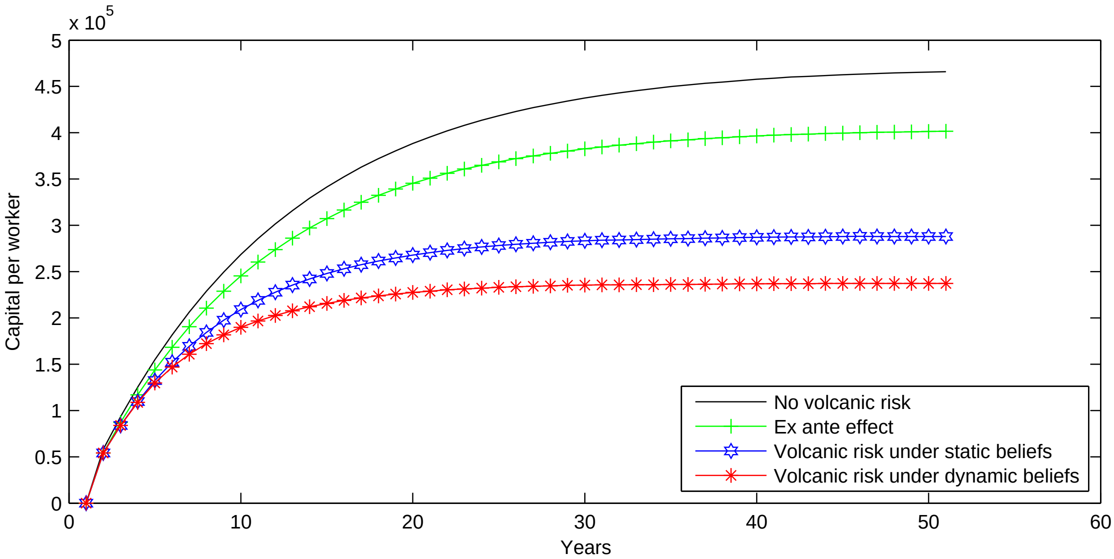
The model is simulated over a 50-year period for a single household under four cases: (a) when the household only suffers from income shock (No volcanic risk), (b) when the household suffers from income shock and is exposed to volcanic risk

[9] Υ_t is a discrete variable describing the five states of nature (from VEI 0 to VEI 4) and to which we assign values such that Υ_t = (1 - *Economic losses*) where *Economic losses* is drawn from Table A4.

[10] In practice, π is the Kronecker product of the transition matrix of income shock and of the transition matrix of volcanic shock, π^v, estimated in Section 2.6.1.

without experiencing eruption (Ex-ante effect), (c) when the household suffers from income shock and is exposed to volcanic risk with eruptions (Volcanic risk under static beliefs) and (d) when the household suffers from income and volcanic shocks and adjusts his beliefs after an eruption (Volcanic risk under dynamic beliefs). To avoid the results to be driven by a particular path we simulate the model 200,000 times and get the average values of capital held by the household. Simulation outcomes are reported below. A graphical illustration of the linear loss function case is provided in Figure 2.1. Table 2.8 proposes a sum-up of the findings for the three loss functions.

Figure 2.1: Capital accumulation for a selected household based on the linear loss function.



Notes: Capital accumulation path based on 200,000 simulations for a selected household under four cases: No volcanic risk: the household only suffers from income shock; Ex-ante effect: the household suffers from income shock and is exposed to volcanic risk without experiencing eruption; Volcanic risk under static beliefs: the household suffers from income shock and is exposed to volcanic risk with eruptions; Volcanic risk under dynamic beliefs: the household suffers from income and volcanic shocks and adjusts his beliefs after an eruption. *Source:* Author's elaboration.

Table 2.8: Average loss of capital stock

	Exponential loss fct	Linear loss fct	Logarithmic loss fct
Ex-ante effect	-7%	-12%	-17%
	(-26,680)	(-44,140)	(-62,350)
Volcanic risk (static beliefs)	-22%	-33%	-42%
	(-82,520)	(-121,730)	(-154,030)
Volcanic risk (dynamic beliefs)	-33%	-43%	-51%
	(-122,740)	(-158,830)	(-187,690)

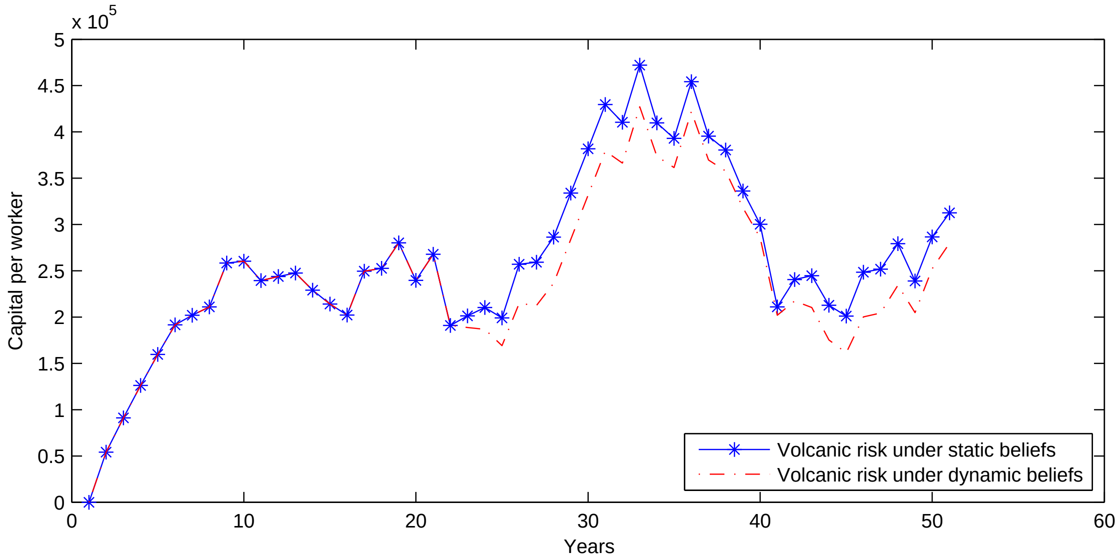
Notes: Average loss of capital, $\hat{k}_{ht}^{ag}$, over the 50-year period for 200,000 simulations under three scenarios and three loss functions. Losses in level are reported in parentheses. Losses in percentage and in level measure the deviation from the "No volcanic risk" scenario. *Source:* Author's calculation.

First, light should be shed on the sign of the ex-ante effect since, as mentioned earlier, the theoretical literature is unclear about the impact of a unfair multiplicative wealth risk on investment. Given our set of estimated parameters, we show that this ex-ante effect is negative. In other words, being exposed to volcanic hazard without experiencing any eruption has a negative impact on capital accumulation. Also, the magnitude of this effect is relatively strong. For instance, based on the linear loss function, exposing an household to volcanic risk would lower its average quantity of capital by 12% over the period. The exponential loss function and the logarithmic loss function result in a difference of 7% and 17%, respectively (Table 2.8). Comparing the impact of the ex-ante effect with the total losses incurred by volcanic risk under static beliefs (which includes the ex-ante effect and the shocks), we show that the behavioral response accounts for around one-third of the total losses (Table 2.8). As a matter of comparison, Elbers et al. (2007) compare a risky environment to the deterministic case and find that the ex-ante effect of risk dominates the ex-post one. Although our results suggest a weaker ex-ante effect on investment behavior, being exposed to volcanic risk still represents an important impediment to households' asset accumulation.

In addition, simulation outcomes (Figure 2.1 and Table 2.8) highlight that the quantity of capital held by an household who adjusts his beliefs after an eruption is significantly lower than an household who would not. Then, it suggests that changes in risk perception, in the magnitude estimated by Cameron and Shah (2015), incurs non-negligible capital losses. To further investigate how changes in beliefs affect post-disaster behavior, the model is simulated over a single path under two cases: (c) Volcanic risk with eruptions under static beliefs, and (d) Volcanic risk with eruptions under dynamic beliefs. Results are presented in Figure 2.2. In this scenario, the household suffers from two eruptions: at t=21 and t=40, that are strong in magnitude since both are VEI 3. Interestingly changes in risk perception after an eruption affect investment behavior on the short run but also have long lasting effects. In fact, Table 2.9 shows that over-weighting the probability of future disasters decreases the level of investment such that, everything else being constant, the quantity of capital is lowered by 18%, five years after an eruption. While, in the standard static-beliefs framework, a negative shock is immediately followed by an increase in investment (the so called "back to the trend" phenomenon), we provide evidence that this is no more the case when we introduce changes in risk perception. In addition, while changes in beliefs are temporary, their detrimental effects on capital are long lasting. Indeed, while net investment decreases during the five years following the eruption (Table 2.9), Figure 2.2 shows that recovering this loss is a long lasting process. In fact, 18 years after the shock, differences in the level of capital still remain. Our results bring therefore a potential additional explanation to the empirical microeconomic literature, such as Dercon (2004) and Carter et al. (2007), which highlights the long lasting effects of natural disasters. Indeed, our findings suggest that these long term effects might be due to the postponement of investment decisions.

Last but not least, Table 2.10 presents the losses repartition for the three loss functions, that is the percentage of wealth losses due to changes in investment decisions and to the eruptions themselves. On the long run, changes in investment behavior (due both to the ex-ante effect of risk and changes in beliefs after a shock) account for half of the total losses of capital incurred by volcanic hazard. This result is particularly robust across the three loss functions. In sum, our results indicate that if we could have compared two identical groups of farm households, one living in a non-affected area, the other living under the threat of a volcano, the latter would be poorer and half of the wealth difference would be imputable to changes in investment behavior.

Figure 2.2: Capital accumulation for a selected household based on the linear loss function



Note: Capital accumulation path based on a single simulation for a selected household under two cases: Volcanic risk under static beliefs: the household is exposed to volcanic risk and suffers from eruptions; Volcanic risk under dynamic beliefs: the household suffers from volcanic shocks and adjusts his beliefs after each eruption. *Source:* Author's elaboration.

Table 2.9: Short-term difference in capital quantity after an eruption

Time from eruption	t+1	t+2	t+3	t+4	t+5	t+6	t+7
Difference in capital	-6%	-11%	-15%	-16%	-18%	-17%	-15%

Notes: Difference in the quantity of capital, $\hat{k}_{ht}^{ag}$, after an eruption between static beliefs (the baseline) and dynamic beliefs based on the linear loss function. *Source:* Author's calculation.

Table 2.10: Loss repartition

% of losses due to	Exponential loss fct	Linear loss fct	Logarithmic loss fct
Investment behavior	54%	51%	51%
Eruption damages	46%	49%	49%

Notes: Percentage of total loss in capital, $\hat{k}_{ht}^{ag}$, due to volcanic risk exposure. Investment behavior accounts for both the ex-ante effect and changes in risk perception. Eruption damages is the direct economic loss incurred by eruptions. *Source:* Author's calculation.

2.7 Conclusions

It is long known that the level of risk is a strong determinant of investment decisions, especially for farm households in developing countries where insurances are particularly missing. Natural disasters are no exception. Quite the contrary, the recent empirical literature has shown that natural disasters could even change people's beliefs about future shocks, making them more pessimistic. Nevertheless, existing studies on the long-term impact of natural disasters on households' welfare have not yet focused on the behavioral response from natural hazards exposure. This is the aim of the paper. Using Indonesian data, we investigate how being exposed to volcanic risk affects farm households' capital accumulation. To do so, we estimate the parameters of a stochastic growth model using data on farm households not exposed to volcanoes, and we simulate the impact of volcanic risk on capital accumulation. This structural approach allows us to partially tackle the lack of data and to disentangle the effect of the shocks themselves from the change in investment behavior. Nevertheless, despite our greatest efforts to overcome the numerous difficulties incurred by data limitation, we acknowledge that a number of shortcomings, such as the sample size or the arbitrary loss functions, remain in our analysis. To that extent, the ultimate goal of the present paper is in no way to provide a very precise estimation of the economic losses induced by volcanic risk. Rather, we remain highly prudent regarding the discussion of our results, and we mainly favor a qualitative interpretation of our simulations. That said, our results converge to the same evidence, namely the adverse impact of changes in investment behavior on wealth. In fact, we find that the ex-ante effect strongly and negatively affects capital accumulation, and that changes in risk perception after an eruption worsen the impact of the shock and delay the recovery process. In sum, our results indicate that households living under the threat of a volcano are poorer than non-exposed households and that a significant share of this wealth difference is imputable to changes in investment behavior.

From a public policy perspective, our results regarding the ex-ante effect suggest that risk management tools against natural disasters should be supported. This policies could take the form of relocation programs, or insurance against natural disasters. Let us recall that offering households an actuarially fair insurance brings them an actual gain equals to the full effect of risk. However, the ex-ante effect is not always taken into account in public policy evaluation. In that sense, disaster insurance may have, in the Indonesian case, important hidden benefits. Second, we confirm the idea that changes in risk perception in the wake of natural disasters distort the income allocation in favor of consumption. Hence, on the short run, any aid provided directly to the household would rather be consumed than invested. Apart from emergency needs that post-disaster aid programs aims at covering on the short run, our results suggest that increasing the duration of aid could make the recovery process more efficient.

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Appendix to Chapter 2

Non Farm Business Activity

Table A1: Farm assets and non-farm-business activity

	(1) $\ln(land_{ht})$	(2) $ln(tools_{ht})$	(3) $ln(livestock_{ht})$	(4) $ln(tractor_{ht})$
Non-Farm Business$_{ht}$	0.277	-0.0780	0.305	0.535*
	(0.66)	(-0.41)	(0.51)	(1.77)
Constant	13.17***	10.79***	5.637***	-0.533
	(11.67)	(21.07)	(3.53)	(-0.65)
Households Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	360	360	360	360
No. of Groups	90	90	90	90
R-Squared	0.002	0.001	0.001	0.017

Notes: Standard errors clustered at the household level. t statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Dependent variables are the values of productive assets. *Non-Farm Business*$_{ht}$ is a binary variable taking the value one if the household declares at least one non farm activity and zero otherwise. *Source:* IFLS panel.

Solving the Stochastic Ramsey Model

Estimating the deep parameters of the model requires to solve the stochastic Ramsey model. We explain the procedure below.[11]

The household maximization problem, exposed in the Section 2.4, can be written recursively in Bellman equation form as:

$$V_{ht}(s_{ht}, k_{ht}) = \max_{k_{ht+1}} \{u(s_{ht}a_h f(k_{ht}, l_{ht}) + (1-\delta)k_{ht} - k_{ht+1}) + \beta \mathbb{E} V_{ht+1}(s_{ht+1}, k_{ht+1})\}$$

Obtaining a closed form solution of the policy function happens in very limited cases and a numerical approximation is usually needed. This is the followed approach in this paper. This requires to discretize the capital stock variable and the distribution of shocks. The former is done by defining a grid around the steady

[11] A detailed description of the method is provided in the appendix of Elbers et al. (2007).

state value of capital. The latter is done by applying the Gauss-Legendre quadrature to the normal distribution $\mathcal{N}(0;\mu^2)$ from which the shock variable s is drawn. The problem is then solved using the Value function iteration method. The Blackwell theorem insures that the iteration converges for $\beta < 1$. The discretization of states of nature implies that several policy functions are approximated, one for each state of nature.

Time Preferences

Table A2: Household's head time preferences

Category	Terminal payoff chosen	Terminal payoff foregone	Constant annual discount rate	Discount factor, β	Nb. Obs
4	1,000,000 now	10,000,000 5 years from now	(0.585, ∞)	(0, 0.63)	81
3	10,000,000 5 years from now	1,000,000 now	(0.320, 0.585)	(0.63, 0.75)	6
2	1,000,000 now	2,000,000 5 years from now	(0.149, 0.320)	(0.75, 0.87)	1
1	2,000,000 5 years from now	1,000,000 now	(0, 0.149)	(0.87, ∞)	1

Source: Author's elaboration on IFLS4.

Evolution of Beliefs

Table A3: Difference in perceived probabilities of natural disasters occurrence

Year from disaster	Difference in probabilities
t+1	0.34
t+2	0.34
t+3	0.33
t+4	0.30
t+5	0.23
t+6	0.13
t+7	0

Notes: Values for t+1, t+5 and t+7 are drawn from Cameron and Shah (2015). Remaining values are filled by quadratic interpolation.

Ecenonmic Losses

Table A4: Economic losses

VEI	Exponential loss fct	Linear loss fct	Logarithmic loss fct
0	0	0	0
1	4	15	26
2	19	30	41
3	38	45	52
4	60	60	60

Notes: Economic losses as a percentage of wealth by eruption intensity.
Source: Author's elaboration.

Chapter 3

Behind the Ash Veil: Natural Disasters and Social Capital

3.1 Introduction

Social capital, including trust and social networks, is central for the livelihood of people in developing countries. In fact, it provides informal insurance and credit when markets are imperfect or absent (Anderson and Baland, 2002; Attanasio et al., 2012; Coate and Ravallion, 1993; Fafchamps, 1992; Fafchamps and Lund, 2003; Kinnan and Townsend, 2012; Ligon et al., 2002; Rosenzweig, 1988; Townsend, 1994; Udry, 1990, 1994), facilitates technology diffusion (Bandiera and Rasul, 2006; Cai et al., 2015; Conley and Udry, 2010) and provides opportunities for human capital investment and resource redistribution (Angelucci and De Giorgi, 2009; Angelucci et al., 2010). 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, 2017). 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). Most of 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 were able to measure trust toward different kinds of people like relatives and neighbors, but also toward institutions such as the Geophysical Institute, and local and national authorities. We also measured 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.[1] 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

[1]Le Pennec et al. (2012) have shown that ash falls are particularly harmful during the wet season.

a simple theoretical model that highlights the impact of a natural disaster on social capital in a community when the shock creates an asymmetry of information on the post-disaster income. Given the difficulty of measuring such an "intangible" asset as social capital, our theoretical analysis concentrates on one of its most important components, which is particularly straightforward to measure: cooperation decision. Our baseline framework is as follows. We consider a community populated by several individuals, each of them being 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 invites some other members of the community to financially contribute to her recovery process. Once they have been invited, people can either accept or decline the invitation. In response, she can decide to punish them by refusing any future cooperation. In the baseline framework, we show that punishment is optimal only on non-cooperative individuals whose income is above a certain threshold, leading to the participation of these latter only. In a second step, we investigate the exact same game but in the wake of a natural disaster. We assume that the natural disaster heterogeneously affects individuals within a community and creates, at least temporarily, an asymmetry of information on individuals' post-disaster income. We show that some community members may thus adopt a moral hazard behavior by using this asymmetry of information to pretend to be poorer than they actually are, to deny cooperation and avoid punishment. The most interesting feature for the empirical analysis is that the number of individuals able to adopt such a behavior is a decreasing function of the level of wealth inequality in the community. In other words, our model predicts that cooperation should decrease in the most homogeneous communities in the wake of a natural disaster. 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 may help to sustain cooperation 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 3.2 presents the related literature. Section 3.3 presents the theoretical framework. Data and descriptive statistics are presented in Section 3.4. Sections 3.5 and 3.6 discuss the empirical method and the results. Finally, Section 3.7 concludes.

3.2 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, the 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, the authors 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 (2017) 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 increase 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.

3.3 The Model

The aftermath moral hazard hypothesis is not directly testable empirically. The aim of this section is therefore to setup a simple 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 concentrates on one of its components which is particularly straightforward to measure: cooperation decision. We consider a community in which one individual is affected by a negative idiosyncratic shock and needs help to recover. In this aim, she invites some members of the community to participate. In what follows, we investigate cooperation before and after a natural disaster. We show that by inducing an asymmetry of information on post-disaster income, a natural disaster offers the possibility to some community members to pretend to be poorer than they actually are, to deny cooperation and avoid punishment, and that the number of individuals adopting such a behavior negatively depends on the level of wealth inequality in the community.

3.3.1 Setup

We consider a community formed by N individuals, indexed by z. 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:

$$y_z = w_z \tag{3.1}$$

We assume that one individual, to whom we refer as "she" thereafter, suffered from a negative idiosyncratic shock and needs help from the community to recover. Then, she invites some members of the community to financially contribute to her recovery process. Once they have been invited, people can either accept to cooperate by paying a fixed contribution g, or decline the invitation. In turn, she may decide to punish them by refusing any future cooperation. In fact, we consider that people are aware that each of them may also need help in the future, and that they value the discounted value of future cooperation. In sum, the timing of the game is as follows:

1. The individual in need decides whether to ask one individual for help.
2. The invited individual decides to participate or not.
3. The individual in need decides to punish him or not.

Invited individuals having accepted to participate and who are not punished are characterized by the following utility function:

$$U_z = u(y_z - g) + \alpha \tag{3.2}$$

where $u(y_z - g)$ represents the utility derived by the individual from the consumption of his income y net of the payment of the contribution g, and α represents the discounted benefits of future cooperation which is dropped in case of punishment.

The individual in need, indexed i, who receives help and does not punish is characterized by the following utility function:

$$U_i = g + \gamma \tag{3.3}$$

where g is the fixed contribution received from the participant, and γ represents her discounted value of future cooperation, which is dropped in case of punishment. We consider that γ takes two values depending on the behavior of the invited individual. We assume that the discounted value of future cooperation with a cooperative individual, denoted $\bar{\gamma}$, is positive such that $\gamma = \bar{\gamma} > 0$, while we consider that sustaining cooperation with a non-cooperative individual is costly such that $\gamma = \underline{\gamma} < 0$. Last, we consider that punishing an individual who denies cooperation for economic reasons (because he is too poor) is socially unacceptable and is severely punished by the rest of the community by incurring a cost θ to the punisher. Then, an individual in need banned from the rest of the community for having punished a poor non-cooperative individual, is characterized by the following utility function:

$$U_i = \theta \tag{3.4}$$

3.3.2 Cooperation under Perfect Information

Assumption 1. $u(.)$ is strictly increasing and concave and it satisfies the two following conditions: $u(g) - u(0) \geq \alpha$ and $\lim\limits_{y \to +\infty} u^{'} = 0$.

An invited individual decides to cooperate if the utility drawn from cooperation is higher than the utility drawn from non-cooperation. More formally, an individual cooperates if:

$$u(y_z - g) + \alpha \geq u(y_z) \tag{3.5}$$

We define $y^\star$ the minimum income level which insures the cooperation of the invited individual. This income level solves the following equation:

$$u(y^\star - g) + \alpha = u(y^\star) \tag{3.6}$$

It exists and is unique under Assumption 1. Then, any invited individual whose income is below $y^\star$ prefers to deny cooperation and suffers from punishment rather than to transfer g. Alternatively, any individual whose income is above $y^\star$ prefers to cooperate and avoid punishment.

Facing a non-cooperative player, the individual in need may decide either to punish him or not. As stated above, punishment consists in breaking the tie with the other individual. That is, if individual i punishes individual z, she will refuse to help him in the future but she will also refrain herself from asking him for help. Punishing a non-cooperative individual whose income is below $y^\star$ is considered socially unacceptable and it incurs a cost θ to the punisher.

Assumption 2. The cost from being punished by the rest of the community for punishing a poor individual is higher than the cost to sustain cooperation with a non-cooperative individual: $\theta < \underline{\gamma} < 0$.

The individual in need punishes the non-cooperative individuals if the utility derived from punishment is higher than the utility derived from non-punishment. More formally, the punishment of a non-cooperative individual of income y_z occurs if:

$$U_i(p, nc) = \theta > U_i(np, nc) = \underline{\gamma} \quad \text{if} \quad y_z < y^\star \tag{3.7}$$

and,

$$U_i(p, nc) = 0 > U_i(np, nc) = \underline{\gamma} \quad \text{if} \quad y_z > y^\star \tag{3.8}$$

Under Assumption 2, Equation 3.8 is satisfied while Equation 3.7 is not. Then, punishment of non-cooperative individuals only occurs if their income is above $y^\star$.

Consequently, any invited individual whose income is below $y^\star$ denies cooperation, and the optimal behavior for the individual in need is to not punish him. Alternatively, for any invited individual whose income is above $y^\star$, the optimal behavior for the individual in need is to punish non-cooperative individuals and to not punish cooperative individuals. The optimal behavior for the invited individual whose income is above $y^\star$ is thus to cooperate.

Proposition 1. The set of strategies (non-cooperation, non-punishment) when $y_z < y^\star$, and (cooperation, non-punishment) when $y_z > y^\star$ is a subgame perfect Nash equilibrium.

Proof: See Appendix.

3.3.3 Cooperation in the Wake of a Natural Disaster

We now investigate the exact same situation as above, namely cooperation to help one community member to recover from an idiosyncratic shock, but we now assume to be in the wake of a natural disaster. One feature of natural disasters is to negatively and heterogeneously affects individuals' income. In fact, for multiple reasons we discuss later on (Section 3.4.3), individuals can be more or less vulnerable to a shock. Here, we simply assume that community members can either suffer from a large loss, s_1, with probability q, or a moderate loss, s_2, with probability $1-q$, such that $s_1 < s_2 < 0$. Wealth is unaffected by the shock and remains perfectly observable by the whole community but the post-disaster income, denoted $\tilde{y}_z$, is now a private information, and the rest of the community only observes its distribution. More formally,

$$\tilde{y}_z = \begin{cases} w_z + s_1 & \text{with probability } q \\ w_z + s_2 & \text{with probability } 1-q \end{cases} \tag{3.9}$$

There exists a wealth level denoted $w^{'}$ such that any individual whose wealth is below $w^{'}$ will have a post-disaster income below $y^\star$ regardless of the shock intensity. Similarly, there exists a wealth level denoted $w^{''}$ such that any individual whose wealth is above $w^{''}$ will have a post-disaster income above $y^\star$ regardless of the shock intensity. More formally, $w^{'} = y^\star + s_1$ and $w^{''} = y^\star + s_2$.

Then, in the wake of a natural disaster, community members might be divided into three categories. First, invited individuals whose wealth lies in $[w_{min}, w^{'}]$ and for whom the post-disaster income $\tilde{y}$ is thus below $y^\star$ with probability 1, will deny cooperation and the individual in need will not punish them. Second, invited individuals whose wealth lies in $[w^{''}, w_{max}]$ and for whom the post-disaster income $\tilde{y}$ is thus above $y^\star$ with probability 1, will accept cooperation and the individual in need will only punish non-cooperative individuals.

Proposition 2. The only sequentially rational strategies are (non-cooperation, non-punishment) for any $w_z < w^{'}$, and (cooperation, non-punishment) for any $w_z > w^{'}$. This set of strategies is a Nash equilibrium.

Proof: See Proof of Proposition 1 in Appendix.

Last but not least, individuals whose wealth lies in $[w^{'}; w^{''}]$ have a post-disaster income $\tilde{y}$ above $y^\star$ with probability q, and a post-disaster income $\tilde{y}$ below $y^\star$ with probability $1-q$. Recall that the post-disaster income of an invited individual is a private information, and that the individual in need only observes its distribution. Then, in this range, any individual denying cooperation might either be actually too poor to cooperate or might be using the asymmetry of information on his post-disaster income to pretend to be poorer than he is actually to deny cooperation and avoid punishment (the so called moral hazard behavior).

Proposition 3. When $q\theta < \underline{\gamma}$, there is a pooling perfect Bayesian equilibrium in which nobody in $[w^{'}; w^{''}]$ cooperates and no punishment occurs.

Proof: See Appendix.

Proposition 4. No separating perfect Bayesian equilibrium exists in $[w^{'}; w^{''}]$.

Proof: See Appendix.

Consequently, after a natural disaster, the number of individuals adopting a moral hazard behavior (using the asymmetry of information to pretend to be poorer than they actually are to escape cooperation), denoted H, is

$$H = \frac{w^{''} - w^{'}}{w_{max} - w_{min}}(1-q)N \tag{3.10}$$

which simplifies to

$$H = \frac{s_2 - s_1}{w_{max} - w_{min}}(1-q)N \tag{3.11}$$

Then, it positively depends on the heterogeneity of the shock $(s_2 - s_1)$, and it negatively depends on the level of wealth inequality $(w_{max} - w_{min})$ 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. As stated above, this result holds for particular values of parameters q, θ, and $\underline{\gamma}$, namely as long as the expected cost from community punishment is higher than the cost to sustain cooperation with a non-cooperative individual. We argue that this condition is true in our context due to the heterogeneity of economic losses, excluding extreme values of q. Finally, we underline that this effect is only driven by the asymmetry of information on post-disaster income and not by the wealth losses induced by the natural disaster.

Proposition 5. The number of individuals adopting a moral hazard behavior (using the asymmetry of information to pretend to be poorer than they actually are to escape cooperation) is a decreasing function of the level of inequality in the community.

3.4 Data and Descriptive Statistics

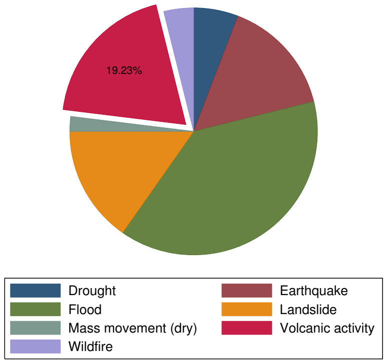
After presenting the context of the study in Section 3.4.1, we expose the data in Section 3.4.2 and we present descriptive statistics in Section 3.4.3.

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 3.1). 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.[2] 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 3.2).

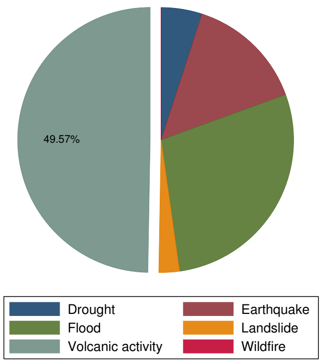
[2]Source: https://www.preventionweb.net/countries/ecu/data/

Figure 3.1: Frequency of natural disasters in Ecuador (1990-2016).



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

Figure 3.2: Affected people by natural disasters in Ecuador (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 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 represents 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 (Parandekar et al., 2002), 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 their diet can be delivered and they may also be transfered 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 collects the ash. The National Secretariat assists the local level authorities by providing bags for ash collection, ash mask, goggles and brooms to assist the clean-up. Groups of the local population, called 'mingas', generally maintain infrastructures and roads within the community, and clear the ash within their neighborhood. However, the provincial level is responsible for the clearance of roads that run between villages. 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 pays 80% of the total cost, with the municipality making up the remaining 20% of the cost.

3.4.2 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). Since, on average, each community is populated by around 50 households our sampling rate equals 48%. The survey was conducted in June 2016, and we investigate the impact of the November 2015 eruption.

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 measured 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 asked 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.

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 3.3) 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 (8 km) and that the variation in their ash exposure is therefore only due to their relative position to the ash cloud.

Figure 3.3: Sampled communities

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

3.4.3 Descriptive Statistics

Table 3.1 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 3.7 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 differently affected by the 2015 eruption. Some of them received very few ashes (0.5 mm) while others received 10 times more. On average, people received 3.2 mm of ash, a quantity sufficient to incur serious damages to crops (Wilson et al., 2007).[3] A central assumption of our theoretical model is that, within communities, households were heterogeneously affected by the shock. In our context, several arguments can be put forward to support this hypothesis. First, since there is no agricultural season,

[3]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. The standard deviation of this variable equals 0.85.

households can have crops at different stages of maturity at the time of eruption.[4] Second, within communities, households have different crop mixes, leading to various degrees of vulnerability. During the interviews, people were asked to report the monetary losses on crops and animals from the last eruption. For each of these two variables, Table B14 in appendix provides summary statistics where we decompose their variances between the within and the between component. These figures clearly highlight that the variance of damages across households is mostly driven by its within component, confirming the hypothesis of heterogeneous damages within communities.

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. 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).

[4]The vulnerability of a plant depends on its stage of maturity.

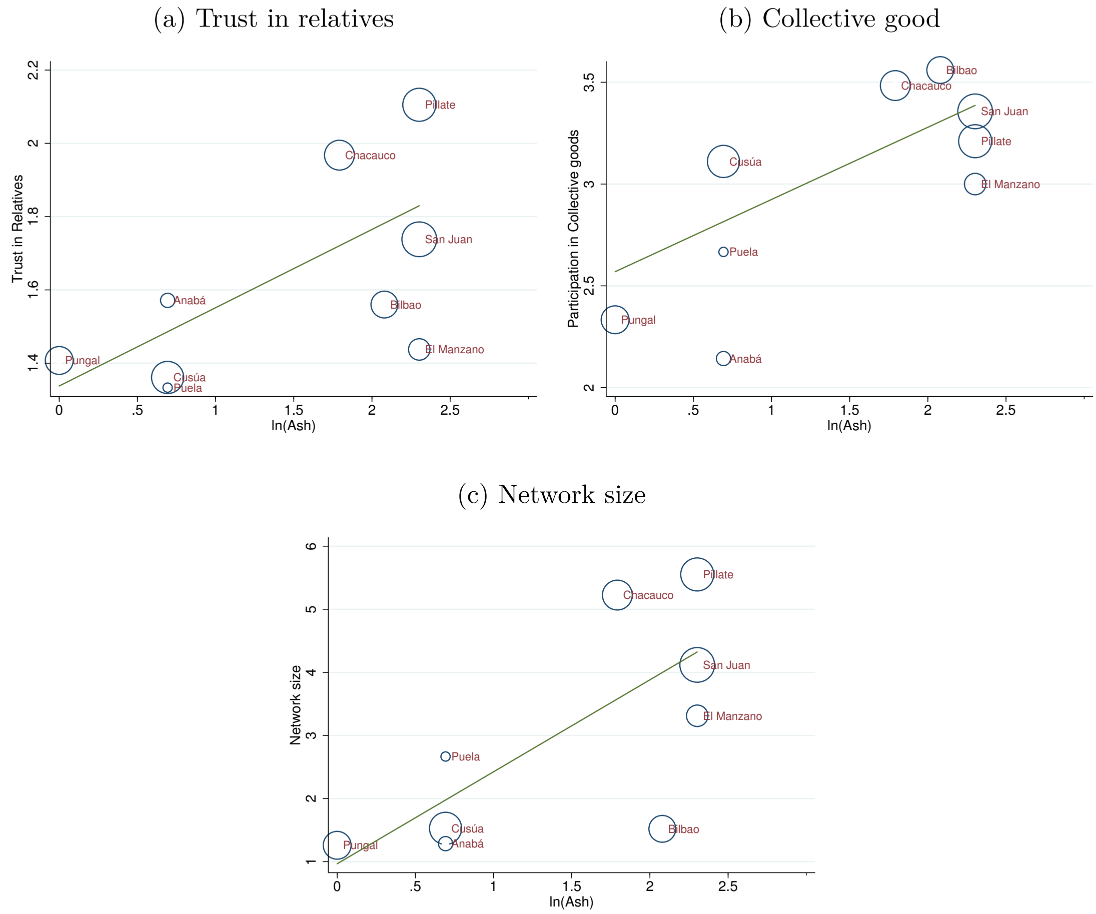
Table 3.1: Summary statistics

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 authority	1.493	0.897	0	3	225
National authority	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

Note: HHsize is the household size; Wealth per capital is wealth index computed using PCA (see appendix); Male (head) is a dummy variable taking the value one if the household head is a male and zero otherwise; Age (head) is the age of the household head; Education (head) is a categorical variable accounting for the household head's level of education taking the values: 0 (no education), 1 (primary), 2 (secondary), or 3 (post-secondary); Risk aversion is measured through the following question: "In a 1 to 10 scale, where 1 stands for disliking risk, and 10 stands for loving risk, how would you evaluate your propensity to take risk?"; Ash thickness is the quantity of ash received at the community level during the November 2015 eruption; Relatives, Neighbors, Geophysical Institute, Local authority, and National authority are measures of trust toward each of these entities, taking values from 0 (low trust) to 3 (high trust). Cooperation measures take values 0 (disagree strongly) to 4 (agree strongly). Network 1 and 2 are the number of people ready to help in case of small or severe problems, respectively. *Source:* Author's elaboration.

Finally, Figure 3.4 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 3.4: 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.

3.5 Empirical Analysis

This section presents our empirical analysis. The baseline specification is presented in Section 3.5.1 where we test for the unconditional effect of ash thickness on social capital. Then, Sections 3.5.2, 3.5.3 and 3.5.4 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.

3.5.1 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.

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{3.12}$$

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 by 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, deaths induced by volcanic eruptions were extremely rare since the beginning of the eruptive phase and, to the best of our knowledge, none were reported due to the November 2015 event, ruling out any death selectivity bias.

Results Table 3.2 presents the output of the regressions of Equation 3.12. Results for trust toward relatives, neighbors, the Geophysical Institute (IG), 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).[5] 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).

Table 3.2: OLS Regressions: Baseline specification

	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.

3.5.2 The Role of Inequalities

We showed in our theoretical model (Section 3.3) that if a natural disaster induces an asymmetry of information on post-disaster income, the key variable determin-

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

ing the number of individuals adopting a moral hazard behavior 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 3.5.1, 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. A graphical representation of the distribution of wealth inequality across communities is provided in Figure B7 in appendix. 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:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times sdWealth_{cp} + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{3.13}$$

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.

Results Results of the OLS regressions are reported in Table 3.3 and a graphical representation of the marginal effects for the least and the most heterogeneous communities is reported in Appendix 3.7. 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 ($pvalue = 0.099$ 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.

Table 3.3: OLS Regressions: Inequality

	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
$\ln(Ash) \times$ 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
$\ln(Ash) \times$ 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

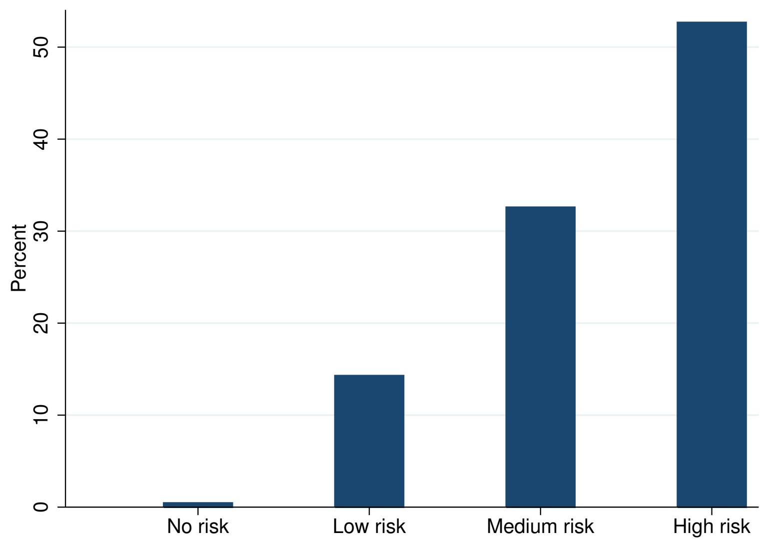
Note: Standard errors clustered at the community level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include: household size, wealth per capita, and risk aversion, age, gender, and education of household head. *Source:* Author's estimations.

3.5.3 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 measured 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 3.5 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 3.5: 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:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times Riskp + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{3.14}$$

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

Table 3.4: OLS Regressions: Risk perception

	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.

3.5.4 The Role of the Relocation Program

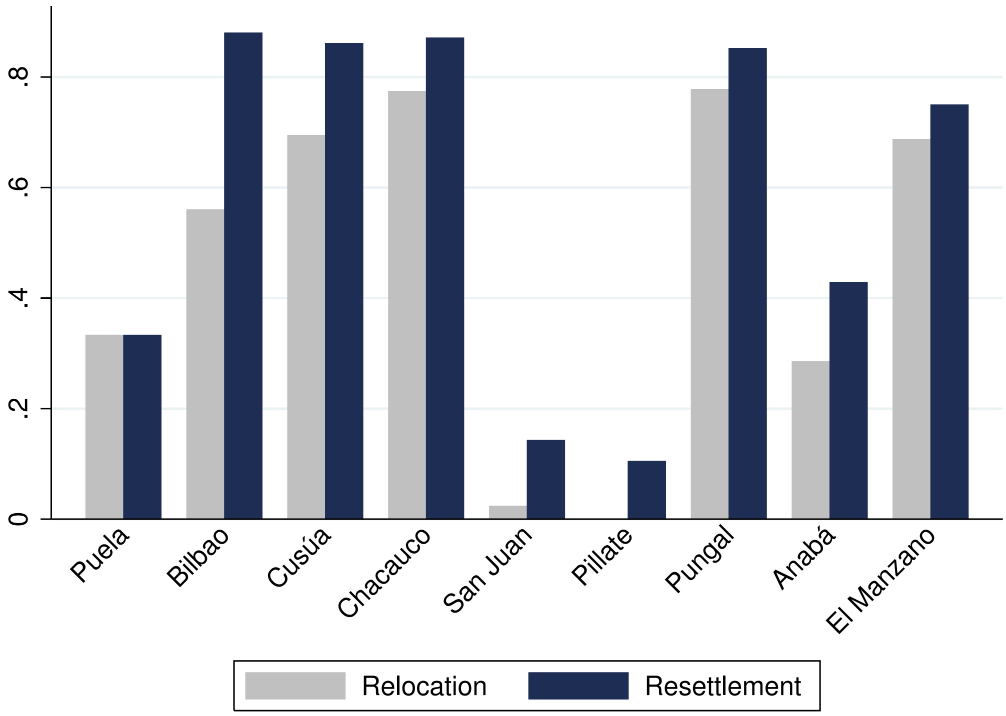
As suggested by Barr (2003) and Fleming et al. (2014), movements of individuals between communities may negatively affect trust. Due to an unsuccessful relocation program, some households of our sample also have a house in the non-affected area. In fact, from 2007 to 2014, in response to the sustained 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 3.5 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 3.6 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 3.5: 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 3.6: Means of Relocation and Resettlement 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 3.15:

$$Scapital_{hcp} = \gamma \ln(Ash_{cp}) \times Relocation_{hcp} + \boldsymbol{X}'\beta + \nu_p + \varepsilon_{hcp} \tag{3.15}$$

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 B16 in appendix 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 3.6 reports the 2SLS regressions of Equation 3.15. 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 3.6: IV Regressions: Relocation program

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash) × *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) × *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.

3.5.5 Robustness

The main result of the paper lies in the identification of an heterogeneous effect of the shock intensity on bilateral cooperation depending on the level of wealth inequality in the community. The section aims at providing several robustness checks to test the validity of this result.

Alternative Measure of Wealth Inequality One may argue that the level of wealth inequality used in Section 3.5.2 might be influenced by the level of social capital in the community, leading to a simultaneous bias of the estimates reported in Table 3.3. To tackle this issue, we use an alternative measure of wealth inequality, namely the level of inequality of inherited land surface. Each household head was asked about the surface of land currently owned that was inherited and we compute the standard deviation of this variable at the community level. Our claim is that this variable is a good proxy for the contemporaneous level of wealth inequality while being free from the reverse causality bias. A graphical illustration of the level of inequality across communities is provided in Figure B9 in appendix. Since Anaba clearly appears as an outlier, we drop it from the regressions. The estimation results are reported in Table 3.7 below. Despite loosing significance, similar results as those presented in Table 3.3 emerge. Regarding bilateral cooperation measures, the interactive term is positive, while the coefficient associated to $\ln(Ash)$ is negative, confirming the heterogeneous impact of the shock intensity depending on the level of inequality. On the contrary, the effect of the interactive term on trust in public authorities is not significant and lower in magnitude, being close to zero.

Table 3.7: OLS Regressions: Robustness Land inequality

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash) × sdSlandI	0.102***	0.085	-0.007	0.028	0.001	
	(0.019)	(0.063)	(0.067)	(0.055)	(0.091)	
ln(Ash)	-0.423***	-0.230	0.206	0.012	0.042	
	(0.050)	(0.188)	(0.212)	(0.176)	(0.280)	
sdSlandI	-0.180	-0.148	0.021	-0.032	0.065	
	(0.096)	(0.250)	(0.259)	(0.218)	(0.365)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	218	218	218	218	218	
R-Squared	0.113	0.133	0.153	0.144	0.089	
	Cooperation				Network size	
	Help you (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
ln(Ash) × sdSlandI	0.101*	0.165**	0.157*	0.040	0.704***	0.361**
	(0.053)	(0.060)	(0.068)	(0.041)	(0.061)	(0.145)
ln(Ash)	-0.230	-0.354*	-0.401*	0.199	-1.587***	-0.519
	(0.151)	(0.176)	(0.206)	(0.119)	(0.227)	(0.413)
sdSlandI	0.068	-0.473	-0.639*	-0.189	-1.854***	-0.731
	(0.222)	(0.251)	(0.277)	(0.176)	(0.236)	(0.625)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	218	218	218	218	218	218
R-Squared	0.269	0.154	0.040	0.147	0.038	0.068

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, household's inherited land surface, and risk aversion, age, gender, and education of household head. *Source:* Author's estimations.

Wealth Skewness One may argue that what we are capturing through wealth inequality is the number of "rich people" in the community. Consequently, a higher level of wealth inequality would actually capture a higher number of people able to help the rest of the community after a shock, which would explain the results documented above, especially regarding bilateral cooperation. This argument can be partially ruled out in light of the literature since it is well known that individuals are not connected to their whole community but only to some individuals (Fafchamps and Gubert, 2007) and, apart from altruistic behaviors, the richest individuals have thus few incentives to help the poorest who would probably be unwilling to reciprocate. Nevertheless, to completely rule out this alternative we run our empirical model by replacing the level of wealth inequality by the skewness of wealth at the community level, for which we provide a graphical representation of its distribution in Figure B8 in appendix. Results are reported in Table 3.8 and we find no effect of the interactive term on bilateral cooperation.

Table 3.8: OLS Regressions: Robustness Wealth skewness

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash) × skWealth	0.154*	0.007	0.153**	0.012	0.174*	
	(0.080)	(0.166)	(0.058)	(0.079)	(0.093)	
ln(Ash)	0.055	0.062	0.531***	0.229	0.481**	
	(0.145)	(0.290)	(0.107)	(0.141)	(0.187)	
skWealth	-0.246***	-0.055	-0.025	0.057	-0.032	
	(0.051)	(0.120)	(0.039)	(0.057)	(0.050)	
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	0.096	0.091	0.156	0.144	0.105	
	Cooperation				Network size	
	Help you (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
ln(Ash) × skWealth	0.212	-0.031	0.148	-0.290***	0.441	0.450
	(0.183)	(0.179)	(0.106)	(0.064)	(0.286)	(0.399)
ln(Ash)	0.285	0.027	-0.077	-0.213*	0.460	0.990
	(0.348)	(0.295)	(0.192)	(0.107)	(0.464)	(0.708)
skWealth	-0.487***	-0.057	-0.337***	0.177***	-1.081***	-0.792**
	(0.113)	(0.142)	(0.067)	(0.043)	(0.268)	(0.293)
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	0.217	0.122	0.045	0.159	0.041	0.058

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.

Weak Representativity One may argue that, for some communities, especially Puela and Anaba, where very few individuals were sampled, community level variable such as wealth inequality are not representative. To check the robustness of our result we exclude successively Puela and Anaba from our sample and we report the estimates in Tables 3.9 and 3.10 below. Results remain unchanged with respect to the full sample estimates.

Table 3.9: OLS Regressions: Robustness exclude Puela

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash) × sdWealth	2.315***	2.325***	0.834	0.904	1.729	
	(0.360)	(0.191)	(0.682)	(0.641)	(0.967)	
ln(Ash)	-1.367***	-1.290***	-0.289	-0.428	-0.924	
	(0.210)	(0.114)	(0.403)	(0.383)	(0.577)	
sdWealth	-2.719***	-1.057***	-0.750	0.034	-1.200	
	(0.251)	(0.281)	(0.681)	(0.426)	(0.760)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	222	222	222	222	222	
R-Squared	0.104	0.141	0.157	0.156	0.112	
	Cooperation				Network size	
	Help you (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
ln(Ash) × sdWealth	5.466***	2.438***	0.256	-1.092	8.593**	9.923***
	(0.544)	(0.235)	(1.001)	(0.632)	(2.955)	(1.155)
ln(Ash)	-2.857***	-1.294***	-0.094	0.872*	-4.257*	-4.962***
	(0.323)	(0.132)	(0.592)	(0.381)	(1.807)	(0.680)
sdWealth	-5.554***	-0.776**	-2.163**	2.309***	-10.080***	-8.938***
	(0.582)	(0.303)	(0.880)	(0.594)	(2.470)	(1.040)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	222	222	222	222	222	222
R-Squared	0.266	0.179	0.036	0.152	0.041	0.071

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 3.10: OLS Regressions: Robustness exclude Anaba

	Trust					
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National	
ln(Ash) × sdWealth	2.298***	4.841***	1.315	1.876	2.296	
	(0.551)	(0.518)	(1.682)	(1.336)	(2.150)	
ln(Ash)	-1.354***	-2.590***	-0.552	-0.937	-1.230	
	(0.308)	(0.288)	(0.916)	(0.739)	(1.175)	
sdWealth	-2.764**	-7.661***	-1.881	-2.454	-2.688	
	(1.046)	(0.984)	(3.703)	(2.528)	(4.443)	
Control variables	Yes	Yes	Yes	Yes	Yes	
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	
No. of Observations	218	218	218	218	218	
R-Squared	0.107	0.147	0.154	0.152	0.103	
	Cooperation				Network size	
	Help you (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
ln(Ash) × sdWealth	6.134***	7.629***	2.477	1.131	16.469**	18.029***
	(1.280)	(0.258)	(2.054)	(1.308)	(6.942)	(2.065)
ln(Ash)	-3.200***	-3.976***	-1.239	-0.269	-8.291*	-9.143***
	(0.693)	(0.144)	(1.115)	(0.714)	(3.828)	(1.147)
sdWealth	-7.255**	-14.291***	-7.761	-3.511	-30.965*	-30.254***
	(2.789)	(0.657)	(4.442)	(2.858)	(13.539)	(4.129)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Parish fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	218	218	218	218	218	218
R-Squared	0.270	0.178	0.035	0.137	0.041	0.071

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.

Migration One may argue that the level of wealth inequality is actually capturing a wider dispersion of the households' network. In fact, if land is highly concentrated on a few number of households in the community, it might foster migration of the other households' children to destinations where land is easier to acquire. In turn, spatial dispersion of children is likely to affect the measures of social capital. During the interviews, we gathered information on household heads' children place of living. Then, we create a dummy variable, denoted $migrant_{hcp}$, taking the value one if the household has at least one child leaving in a different parish and zero otherwise. The share of households having a child leaving in another parish is illustrated in Figure B10 in appendix for each community. We include the interactive term between ln(Ash), and the dummy variable $migrant_{hcp}$ in the empirical model. Results are reported in Table 3.11 below, and we find no significant effect of the interactive term.

Table 3.11: OLS Regressions: Robustness Migration

	Trust				
	(1) Relatives	(2) Neighbors	(3) IG	(4) Local	(5) National
ln(Ash) × migrant	0.182*	-0.085	-0.083	-0.002	-0.011
	(0.095)	(0.080)	(0.099)	(0.089)	(0.086)
ln(Ash)	-0.079	0.152**	0.244***	0.118**	0.116*
	(0.066)	(0.060)	(0.054)	(0.039)	(0.057)
migrant	-0.373*	0.005	0.026	-0.087	-0.095
	(0.167)	(0.126)	(0.105)	(0.071)	(0.173)
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	0.094	0.095	0.150	0.143	0.096

	Cooperation				Network size	
	Help you (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
ln(Ash) × migrant	0.057	0.071	0.084	-0.181	-1.166	-0.993
	(0.103)	(0.159)	(0.230)	(0.223)	(0.932)	(0.606)
ln(Ash)	0.411***	0.143	0.017	0.317	1.374**	1.422***
	(0.108)	(0.104)	(0.163)	(0.177)	(0.479)	(0.321)
migrant	-0.043	-0.032	0.286	0.220	0.551	0.438
	(0.161)	(0.187)	(0.413)	(0.402)	(1.556)	(0.680)
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	0.172	0.120	0.052	0.153	0.043	0.068

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.

Relocation Program 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 3.5.1 and 3.5.2 including the double residence status as a control variable. We apply the instrumental strategy presented in Section 3.5.4, and results are reported in Tables 3.12 and 3.13. 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 3.13).

Table 3.12: IV Regressions: Robustness Relocation program

	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 (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
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 3.13: IV Regressions: Robustness Relocation program

	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)	
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 (6)	Help someone (7)	Credit (8)	Coll. goods (9)	Network1 (10)	Network2 (11)
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)
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.

3.6 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)* the 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. In that sense, our results are close in spirit to Baland et al. (2011) and Di Falco et al. (2018) who show that individuals are willing to incur into costs in order to get rid of obligations to redistribute resources towards other members of their network. 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. In light of our theoretical model, this may happen if, due to an increase of vulnerability, the individual in need is willing to reciprocate more in the future following a natural disaster, increasing the incentive of other people to cooperate. 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. In terms of magnitude, an increase of one standard deviation of the shock intensity increases network size by 2 additional connections in the most heterogeneous community of the sample, and decreases network size by 1.6 connections in the most homogeneous community.

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 3.4.1, 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 (2017). 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.

3.7 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 to chapter 3

Proofs

Proof of Proposition 1: We first investigate players' optimal strategies if the invited individual has an income y_z below $y^\star$. Since the game is solved by backward induction, let us first focus on the behavior of the individual in need. If she faces a cooperative individual, she may decide either to punish him a gets a utility equal to $U_i(p; c) = g + \theta$, or not punish him and gets a utility equal to $U_i(np; c) = g + \bar{\gamma}$. Alternatively, if she faces a non-cooperative individual, she may decide either to punish him a gets a utility equal to $U_i(p; nc) = \theta < 0$, or not punish him and gets a utility $U_i(np; nc) = \underline{\gamma} < 0$. Since her optimal strategy is to not punish, regardless of the invited participant's behavior, no-punishment is a dominant strategy. Knowing that, the invited individual may either cooperate and gets a utility $U_z(c; np) = u(y_z - g) + \alpha$ or deny cooperation and gets a utility $U_z(nc; np) = u(y_z) + \alpha$. Therefore, the best response of the invited participant is to not cooperate. Note that even in case of punishment, the invited individual would be better off by not cooperating. In fact, $U(nc, p) = u(y_z) > U(c, p) = u(y_z - g)$. Then, no-cooperation is a dominant strategy for the invited individual. In sum, for any $y_z < y^\star$, the set of strategies: (no-cooperation; no-punishment) is a Nash equilibrium.

We now investigate players' optimal strategies if the invited individual has an income y_z above $y^\star$. Without loss of generality, let us focus on the behavior of the individual in need. If she faces a cooperative individual, she may decide either to punish him a gets a utility equal to $U_i(p; c) = g$, or not punish him and gets a utility equal to $U_i(np; c) = g + \bar{\gamma}$. Alternatively, if she faces a non-cooperative individual, she may decide either to punish him a gets a utility equal to $U_i(p; nc) = 0$, or not punish him and gets a utility $U_i(np; nc) = \underline{\gamma}$. Then, the optimal behavior of the individual in need depends on the behavior of the invited participant. In fact, her best response to a non-cooperative behavior is to punish, while her best response to a cooperative behavior is to not punish. Knowing that, the invited individual may decide either to cooperate and gets a utility equal to $U_z(c; br_i(c)) = u(y_z - g) + \alpha$, or not to cooperate and gets a payoff equal to $U_z(nc; br_i(nc)) = u(y_z)$. Since $u(y - g) + \alpha > u(y)$ is true by definition for any $y_z > y^\star$ (See Equation 3.6) then the invited participant chooses to cooperate. In sum, for any $y_z > y^\star$, the set of strategies: (cooperation; no-punishment) is a Nash equilibrium.

Proof of Proposition 3: Depending on the shock intensity they were exposed to, individuals whose wealth lies in $[w^{'}, w^{''}]$ can be of two types $t = \{R; P\}$ where

R stands for 'rich' and denotes individuals whose post-disaster income is above $y^\star$, and P stands for 'poor' and denotes individuals whose post-disaster income is below $y^\star$.

Because for poor individuals, non-cooperation strictly dominates cooperation (see Proof of Proposition 1), if there exists a pooling perfect Bayesian equilibrium, both types (rich and poor) must play non-cooperation.

We now define the beliefs for the individual in need. Let $\mu(t|A)$ be the probability that the individual in need assigns to one type (R or P) after observing action A (cooperation or non-cooperation). Applying Bayes' rule, we get:

$$\mu(R|nc) = \frac{P(nc|R)P(R)}{P(nc)} = \frac{P(nc|R)P(R)}{P(nc|R)P(R) + P(nc|P)P(P)} \tag{3.16}$$

By construction we know that $P(nc|R) = 1$, $P(nc|P) = 1$, $P(R) = 1 - q$, and $P(P) = q$. Plugging in and solving, we get:

$$\begin{cases} \mu(R|nc) = 1 - q \\ \mu(P|nc) = q \end{cases} \tag{3.17}$$

We now define the best response for the individual in need. Her expected utility from playing no-punishment is:

$$\begin{aligned} \mathbb{E}U_i(np, nc) =& \mu(R|nc)U_i(np, nc; R) + \mu(P|nc)U_i(np, nc; P) \\ =& (1-q)\underline{\gamma} + q\underline{\gamma} = \underline{\gamma} < 0 \end{aligned} \tag{3.18}$$

Similarly, her expected utility from punishing is:

$$\begin{aligned} \mathbb{E}U_i(p; nc) =& \mu(R|nc)U_i(p; nc; R) + \mu(P|nc)U_i(p; nc; P) \\ =& (1-q)0 + q\theta = q\theta < 0 \end{aligned} \tag{3.19}$$

Therefore, non-punishment dominates punishment if $q\theta < \underline{\gamma}$. Then, for values of q, θ, and $\underline{\gamma}$ satisfying this condition, the individual in need will always respond to non cooperation with no-punishment.

We now investigate whether this set of strategy is an equilibrium. Since the individual in need's beliefs are Bayesian, and her strategy is a best response given those beliefs, this is an equilibrium if and only if neither type of invited individual (R or P) has an incentive to deviate. We already know that the poor individual will not deviate because no-cooperation strictly dominates cooperation for him. The rich individual's payoff is $U_z(nc, np; R) = u(y_z) + \alpha$. If he deviates and decides to cooperate, he gets $U_z(c, np; R) = u(y_z - g) + \alpha$, which is lower. Then, since the rich invited individual has no incentive to deviate, it is therefore an equilibrium.

Alternatively, if $\underline{\gamma} < q\theta$, $\mathbb{E}U_i(p, nc) > \mathbb{E}U_i(np, nc)$ and then punishment dominates non-punishment. Thus, the individual in need will always respond to non cooperation with punishment. In that case, the poor individual will not deviate because no-cooperation strictly dominates cooperation for him. The rich individual's payoff is $U_z(nc, p; R) = u(y_z)$. If he deviates, he gets $U_z(c, np; R) = u(y_z - g) + \alpha$. Since, $U_z(c, np; R) > U_z(nc, p; R)$ is true, by definition (see Equation 3.6), for the rich individual ($y_z > y^\star$), he has an incentive to deviate. Then, if $\underline{\gamma} < q\theta$, this is not an equilibrium.

Proof of Proposition 4: Since non-cooperation is a dominant strategy for the poor individual, if there exists a separating perfect Bayesian equilibrium, it must be that the poor individual does not cooperate, and the rich individual cooperates.

We now define the beliefs for the individual in need. If the individual in need sees that the invited individual cooperates, she will assign the probability 1 to the type R, $\mu(R|c) = 1$. If she sees that the invited individual does not cooperate, she will assign the probability 1 to the type P, $\mu(P|nc) = 1$.

We now define the best response for the individual in need. Her expected utility from playing punishment or non-punishment, respectively, against cooperation is:

$$\mathbb{E}U_i(p, c) = \mu(R|c)U_i(p, c; R) + \mu(P|c)U_i(p, c; P) = g \tag{3.20}$$

and

$$\mathbb{E}U_i(np, c) = \mu(R|c)U_i(np, c; R) + \mu(P|c)U_i(np, c; P) = g + \bar{\gamma} \tag{3.21}$$

Since $\mathbb{E}U_i(np, c) > \mathbb{E}U_i(p, c)$, her best response to cooperation is non-punishment. Against non-cooperation, her expected utility from playing punishment or non-punishment is, respectively:

$$\mathbb{E}U_i(p, nc) = \mu(R|nc)U_i(p, nc; R) + \mu(P|nc)U_i(p, nc; P) = \theta < 0 \tag{3.22}$$

and

$$\mathbb{E}U_i(np, nc) = \mu(R|nc)U_i(np, nc; R) + \mu(P|c)U_i(np, nc; P) = \underline{\gamma} < 0 \tag{3.23}$$

Since $\mathbb{E}U_i(np, nc) > \mathbb{E}U_i(p, nc)$ by Assumption 2, her best response to cooperation is non-punishment.

We now investigate whether this set of strategy is an equilibrium. Once again, since the individual in need's beliefs are Bayesian, and her strategy is a best response given those beliefs, this is an equilibrium if and only if neither type of invited individual (R or P) has an incentive to deviate. We already know that the poor individual will not deviate because no-cooperation strictly dominates cooperation for him (See Proof of Proposition 1). The rich individual's payoff is $U_z(c, np; R) = u(y_z - g) + \alpha$. If he deviates, the individual in need will believe, upon seeing no-cooperation played, that the invited individual is of type P with probability 1, and would therefore play no-punishment. The invited individual's payoff from deviating would therefore be $U_z(nc, np; R) = u(y_z) + \alpha$. Since this payoff is higher than what he would get by cooperating, the rich individual has an incentive to deviate. It is therefore not an equilibrium.

Damages Heterogeneity

Table B14: Summary statistics economic losses

Variable	**Panel**	**Std. Dev.**	**N**
Crop losses	Overall	3316.758	N = 191
	Between	1467.53	communities = 9
	Within	2964.89	households = 21.22
Animal losses	Overall	816.3741	N = 190
	Between	147.54	communities = 9
	Within	806.43	households = 21.11

Source: Author's elaboration.

Wealth Index

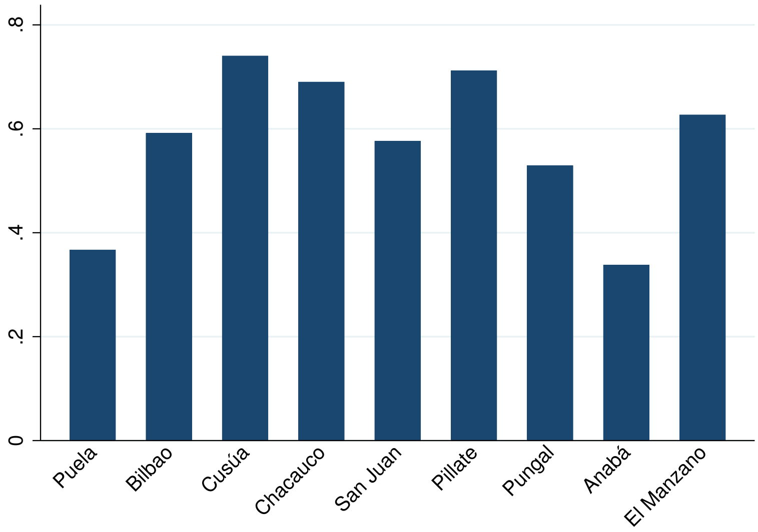
We compute a wealth index using information on house equipment, animals, and farm assets. Regarding house characteristics, we ask each household head how many rooms they have in the house (NRooms), the number of equipment they own such as TV, DVD, radio, Hi-fi, computer, fridge, and washing machine that 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 B15. This index captures 22% of the variance.

Table B15: Summary statistics wealth index variables

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

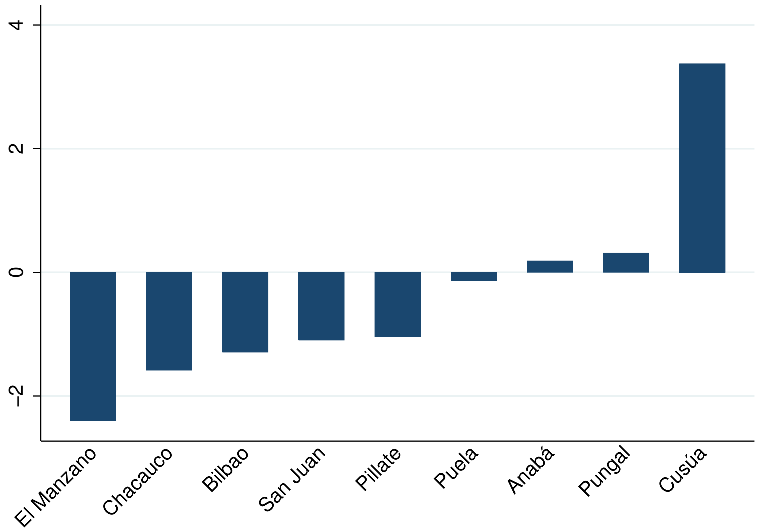
Source: Author's elaboration.

Figure B7: Wealth inequality across communities



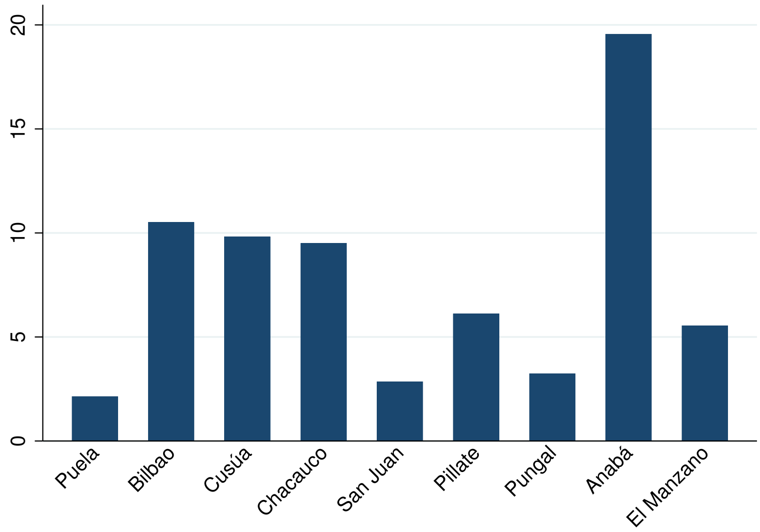
Source: Author's elaboration.

Figure B8: Wealth skewness across communities



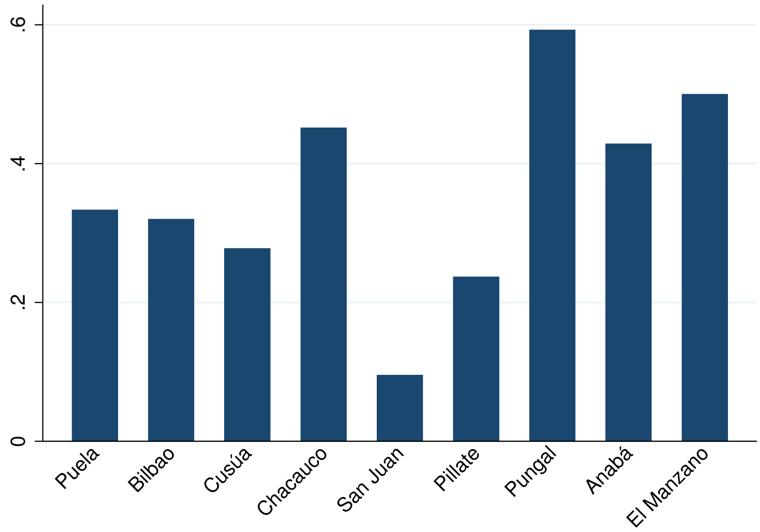
Source: Author's elaboration.

Figure B9: Inherited land inequality across communities



Source: Author's elaboration.

Figure B10: Share of households with a migrant across communities



Source: Author's elaboration.

Table B16: First stage regressions

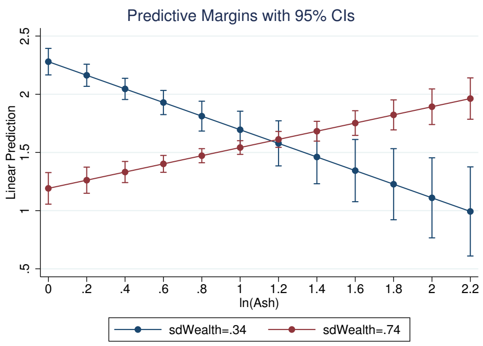
	(1) *Relocation*	(2) $\ln(Ash) \times Relocation$
Resettlement	0.922***	0.127
	(0.063)	(0.129)
$\ln(Ash) \times Resettlement$	-0.107	0.624**
	(0.083)	(0.190)
Control variables	Yes	Yes
Parish fixed effects	Yes	Yes
No. of Observations	225	225
R-Squared	0.659	0.601

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.

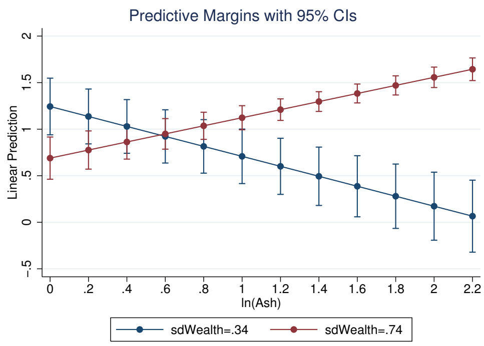
Marginal Effects

Figure B11: Marginal effects of ash on social capital

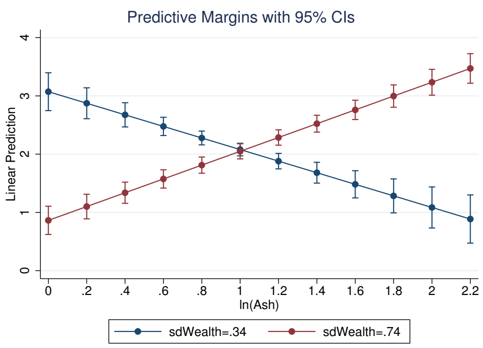
(a) Trust in relatives



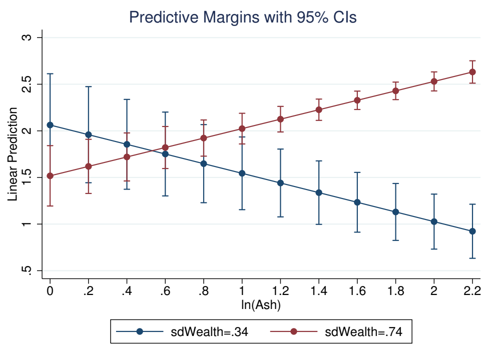
(b) Trust in neighbors



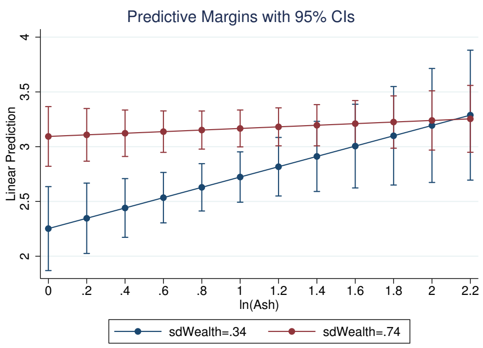
(c) Help you



(d) Help someone



(e) Collective goods



(f) Credit

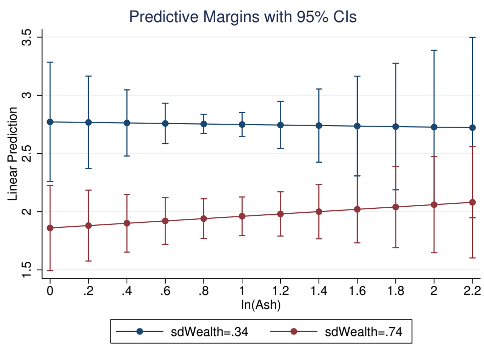
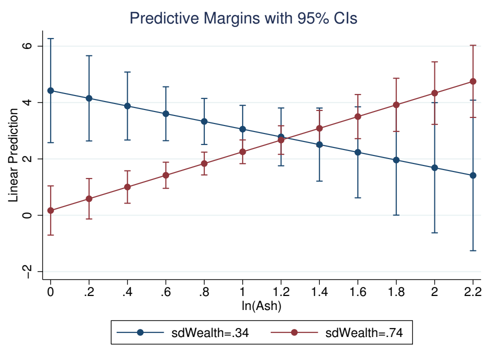
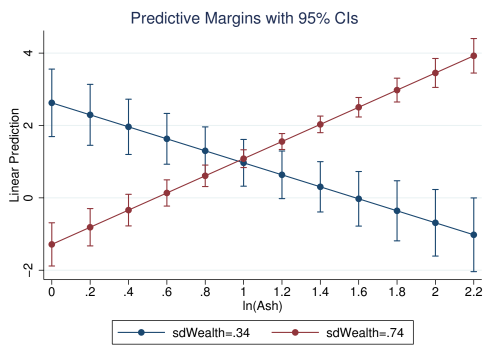


Figure B11: Marginal effects of ash on social capital

(g) Network1



(h) Network2



Chapter 4

Natural Disasters and Migration: The Role of Trust in Institutions

4.1 Introduction

Risk-sharing or activity diversification are notoriously inefficient against covariate shocks. Therefore, households exposed to natural hazards are left with few viable options to mitigate the effect of natural disasters. One of them consists in income spatial diversification through migration, a mechanism highlighted in the seminal paper of Rosenzweig and Stark (1989). Since then, several papers investigated the impact of natural disasters on migration and reach similar conclusions, namely that natural hazards foster migration, either as an ex-ante or an ex-post strategy, allowing households at origin to receive remittances after a shock (Alem et al., 2016; Gröger and Zylberberg, 2016, among others). According to the Internal Displacement Monitoring Centre (IDMC, 2015), since 2008, an average of 27 million people have been displaced annually by disasters brought on by natural hazards, leading to potential adverse effects at destination by raising unemployment (Strobl and Valfort, 2013) or inducing violences (Morales, 2018). The risk of such displacement is estimated to have doubled in the past 40 years. However, the mitigating role of public policies, though critical, has remained largely unexplored in the literature. To the best of our knowledge, the only exception is Chort and De La Rupelle (2017) who investigate the impact of two programs in Mexico, namely Fonden and Procampo, on disaster-induced international migrations.

The present paper aims to contribute to this literature by investigating the role of public authorities on ex-ante migration decisions of households living in a natural hazard prone area. More precisely, we study how the perceived ability of institutions to mitigate the effects of natural disasters, empirically proxied by the level of trust, affects households' migration decisions. To do so, we focus on farm households living around Mount Tungurahua, an active volcano in Ecuador. Our choice to study volcanic risk in Ecuador is not without reason. In fact, this country suffers from extreme vulnerability and high exposure to natural hazards, as approximately 96% of the urban population lives in coastal and mountainous regions that are exposed to seismic, volcanic, flood, landslide and El Niño hazards. In addition, with 35 volcanoes, and more than four millions people living within

30km from a volcano, volcanic risk is particularly prominent in Ecuador.

Mount Tungurahua, whose volcanic activity started in 1999, after 80 years of quiescence, is one of the most active volcano of the country. Since then, eruptions have frequently deposited ash on the neighboring communities, populated by farmers, affecting crops, livestock, machinery, infrastructure, and individuals health (Le Pennec et al., 2012). Due to their farm activity, most of households' assets are anchored to location. Therefore, unless they could sell them, migration of the full household would represent a dramatic wealth loss and is then rarely possible. In addition, temporary post-eruption migration is neither an optimal solution for these households due to the concomitant national economic crisis (Parandekar et al., 2002), making job search in urban areas difficult. Income spatial diversification, as an ex-ante strategy, remains however possible through the choice of children's place of living when, around their 20's, they leave their parents to form their own household. In fact, while children may decide to stay close to their parents, they can also choose to settle out of the affected area at a negligible moving cost. Apart from this mechanism, public authorities also play an important role to help people to cope with volcanic risk. For instance, scientists of the Geophysical Institute permanently monitor the volcano and warn political leaders in case of unrest. In turn, these latter send alerts to local populations, allowing farmers to protect their assets, such as livestock, and to evacuate before the eruption. Moreover, local and national authorities may also provide resources in kind, such as food for animals, or tools to mitigate the effect of the shock.

From a theoretical perspective, an increase of households' trust in public authorities can have two opposite effects on children migration, depending on the theoretical framework. On the one hand, one may investigate this question through the lens of the New Economics of Labor Migration (Stark and Bloom, 1985). The main feature of this approach is that migration serves as a diversification tool, allowing households at origin to receive remittances in case of a shock (Gubert, 2002). Consequently, the decision to migrate results from a trade-off between the costs and the benefits of diversification. In that case, public intervention can be seen as a tentative to correct market failures, namely the absence of formal insurance. Hence, an increase of institutional quality, by reducing the need to receive remittances in the wake of a natural disaster, reduces the benefits from migration, and should therefore decrease children spatial dispersion. An important and somewhat controversial assumption of this model is that migration decision is considered to be taken at the household level, as in a unitary model of household decisions. In other words, household members are assumed to agree on a common objective and act to maximize a social welfare function. This assumption has however been challenged in a number of studies providing evidence that household decisions result from a bargaining process between household members (Fiala and

He, 2017). Then, on the other hand, one may argue that the pertinent framework to investigate the impact of public policies on migration decisions is a non-unitary model of household decision (Nobles and McKelvey, 2015), where household members have their own, and potentially conflicting, preferences. For instance, one may argue that the parents would like the child to stay, while he or she prefers to go. Then, in that case, an increase of institutional quality may relax the moral obligation of children to support their parents, allowing them to move out of the affected area. In this vein, several studies have already highlighted the crowding-out effect of public policies on informal arrangements (Attanasio and Rıos-Rull, 2000; Dercon and Krishnan, 2003; Strupat and Klohn, 2018, among others).

To empirically test this hypothesis, we conducted a survey of 229 farm households living in 11 communities frequently affected by volcanic eruptions of Mount Tungurahua. We collected information on household members and on the household heads' extended family living in other households allowing us to map the spatial distribution of children. In addition, each household head was asked about his level of trust toward the Geophysical Institute, local authority, and national authority. We use these levels of trust as a proxy for the perceived ability of public authorities to efficiently mitigate the effects of volcanic eruptions. Our empirical analysis consists therefore in investigating the impact of trust toward these institutions on the spatial distribution of children. An empirical challenge arising from this specification is that trust can be updated over time, either positively or negatively, depending on the ability of public authorities to manage eruptions. Consequently, the levels of trust measured at the time of the survey could be different from the actual levels of trust that determined migration decisions. To overcome this problem, we rely on the fact that public interventions are taken at the community level or above but rarely target specific individuals inside a community. Therefore, we include community fixed-effects in our empirical model to drop the community specific component of trust, which includes the part imputed to public policies.

Our results show that the levels of trust toward the Geophysical Institute, local authority, and national authority are negatively correlated with children migration. In other words, the higher the levels of trust of the household head toward these institutions, the higher the likelihood that children live in the same parish as their parents. We check the robustness of our results to the inclusion of risk aversion, risk perception about future eruptions, and trust toward other persons living in the community as control variables and by considering the potential endogeneity of fertility decisions. The magnitude of the coefficients of interest is highly stable across specifications, and we find that one standard deviation increase of trust increases the ratio of children living in the same parish by roughly 5%. However, we could not highlight a predominant effect of one institution over the other two.

This is not surprising though as their actions are strongly interrelated leading to high correlations of the three levels of trust.

The closest paper to ours is Chort and De La Rupelle (2017) but we complement their approach in two aspects. Our main contribution lies in the investigation of the impact of public authorities on migration as an ex-ante strategy, while Chort and De La Rupelle (2017) investigate the effects of Fonden and Procampo programs on post-disaster migration. Second, we consider both internal and international migrations while Chort and De La Rupelle (2017) focus exclusively on international migrations (from Mexico to the US). To that extent, we address the argument that the vast majority of people who flee disasters remain within their country of residence (IDMC, 2015).

The remainder of the paper is as follows. Next, we highlight the related literature. Section 4.3 presents the context of our study and the conceptual framework. Section 4.4 describes the data and the sample characteristics. Section 4.5 presents the empirical analysis. Finally, Section 4.6 concludes.

4.2 Related Literature

The present paper is related to two strands of literature. The first one is on the impact of natural disasters on migration. In this vein, the idea that migration serves as a coping strategy against natural disasters in developing countries is now widely documented (Millock, 2015). While migration can be multifaceted, there is now a consensus that disaster-induced migrations mainly remain within the borders of the country. For instance, Beine and Parsons (2015) find no statistically significant effect of neither climate factors nor natural disasters on international migration flows, but provide evidence of internal migration flows, proxied by the rate of urbanization. In the same vein, Barrios et al. (2006) look at 78 developing countries over the 1960–1990 period and find that a reduction in rainfall is associated with an increase in national urban share. Apart from the destination choice, the literature has also focused on the timing of migration decisions. Interestingly, existing studies suggest that migration decisions can be taken either as an ex-ante or as an ex-post strategy. In fact, on the one hand, focusing on Nigeria, Dillon et al. (2011) show that internal migration increases in response to both ex-ante and ex-post risk of adverse weather events. They also point out that this effect is mainly driven by male. In the same vein, Alem et al. (2016) investigate both the ex-ante and ex-post impacts of climate variables on the decision to engage in migration by smallholder farm households in Ethiopia. They find that smallholder farm households that live in places with higher rainfall variability are more likely to send a household member as a migrant. However, contrary to Dillon et al. (2011), they do not find significant evidence of an ex-post response to risk. Similarly, using data from Ecuador, Gray (2009) finds that mean annual rainfall did not affect local migration and had a negative impact on internal and international migration while harvest fluctuations, on the contrary, increased local and regional migration, consistently with the ex-ante effect. On the other hand, several studies provide evidence of migration in the wake of natural disasters. For instance, Chort and De La Rupelle (2017) focus on post-disaster consequences and find that shocks increase undocumented migration from the Mexico to the US. In the same vein, Gröger and Zylberberg (2016) show that rural households in Vietnam managed to cope with the effect of floods through internal labor migration to urban areas. In El Salvador, Halliday (2006) finds that agricultural shocks motivate ex-post migration, while households tend to retain labor for recovery after a major earthquake.

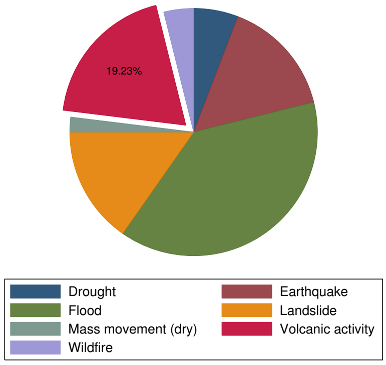
Our paper is also related to the burgeoning literature on public interventions aiming at mitigating the effects of natural disasters. In this vein, De Janvry et al. (2006) investigate the impact of natural disasters on school enrollment in Mexico and show that the Mexican program Progresa helped to keep children at school, although not preventing an increase of child work in response to the shocks. De Janvry et al. (2016) investigate the impact of a post-disaster program in Mexico, namely Fonden, on economic activity after a shock. They show that having access to disaster funding boosts local economic activity between 2 and 4 percent in the year following the shock. To the best of our knowledge, the impact of post-disaster programs on migration has only been investigated by Chort and De La Rupelle (2017). They study the effect of two programs implemented in Mexico, namely Fonden and Procampo. Procampo is the largest agricultural program funded by the Mexican federal government and consists in direct payments to agricultural producers on a per-hectare basis made twice a year, while Fonden is a disaster fund aimed at providing insurance to localities hit by a natural disaster. They find evidence of a mitigating impact of both programs on undocumented flows only.

4.3 Context and Conceptual Framework

4.3.1 Volcanic Risk in Ecuador

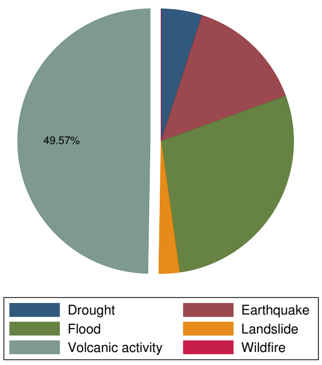
Ecuador suffers from extreme vulnerability and high exposure to natural hazards. In fact, approximately 96% of the urban population lives in coastal and mountainous regions that are exposed to seismic, volcanic, flood, landslide and El Niño hazards (WorldBank, 2012). According to the EM-DAT database, over the 1990-2016 period, volcanic eruptions appear as the second most frequent event in Ecuador behind floods (Figure 4.1). 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 drought has 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 4.2).

Figure 4.1: Frequency of natural disasters in Ecuador (1990-2016).



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

Figure 4.2: Affected people by natural disasters in Ecuador (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

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

entered a new phase of activity in the fall of 1999 (Hall et al., 1999). The volcano has remained active throughout this period 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 represents a permanent threat regardless of the time of eruption. Animals are also vulnerable to eruptions which can cause stress or even deaths. Finally, ashfall has also affected individuals' health, causing a variety of skin, abdominal, digestive, psychological and respiratory problems (Sword-Daniels et al., 2011).

Contrary to what one would expect, despite the recurrent negative shocks most 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 (Parandekar et al., 2002), 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, abandoning it would represent a dramatic wealth loss. Finally, as we noticed during the interviews, people still hope for the volcano to stop.

4.3.2 Role of Public Authorities

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 seismic stations and 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 government. Finally, it is the decision of the local government 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 the population with 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 their diet can be delivered and they may also be transfered 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 collects the ash. The National Secretariat assists the local level authorities by providing bags for ash collection, ash mask, goggles and brooms to assist the clean-up. Groups of the local population called 'mingas' generally maintain infrastructures and roads within the community, and clear the 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 pays 80% of the total cost, with the municipality making up the remaining 20% of the cost.

In sum, public authorities provide alerts before the eruptions and equipments to mitigate the effect of the shock. Local people are left to clean and repair their own assets as well as assets of the community.

4.3.3 Conceptual Framework

This section aims at presenting how the levels of trust in public authorities could affect children migration. Since this topic can be investigated both in light of the New Economics of Labor Migration framework and of non-unitary models of household decisions, we briefly present both approaches.

The New Economics of Labor Migration (NELM thereafter) initiated by Stark and Levhari (1982) and Stark and Bloom (1985) has been extensively used to justify natural disaster-induced migration in developing countries. In this framework, migration is seen as a strategy that seeks not only to maximize expected earnings, but also to diversify income sources, reduce income risks and overcome market failures. In fact, as recalled by Gubert (2002), the starting point of this approach is the recognition that income risks have a strong spatial dimension in rural areas of developing countries. In addition, the lack of formal insurance mechanisms to manage such risks gives farm households the incentive to self-insure through the geographical dispersion of their members. In case of a temporary income shock due to unforeseen bad local conditions (e.g weather variation, incidence of disease, etc.) families can rely on the migrants for financial support. Thus, what motivates migration is the prospect of receiving remittances rather than the wage differential between two locations. Then, once the migrants have successfully established themselves in a distant location, they play the role of financial intermediaries and substitute for missing or imperfect markets. A central assumption of this model is that migration decisions are taken at the household level following a unitary model of household decisions. More precisely, household members are assumed to agree on a common objective, for instance income diversification, and then act as if they were maximizing a social welfare function. Thus, the decision to migrate results from a trade-off between the costs and the benefits of diversification. On the benefits' side, the idea that migrants serve as an insurance in the wake of a natural disasters is now well documented. For instance, Gröger and Zylberberg (2016) show that remittances from internal labor migrants helped to alleviate income losses induced by floods in Vietnam. On the other side, leaving the affected area may incur important costs. One may think about moving costs per se but we believe that they are negligible in our context since settling out of the affected area is not necessarily more costly than settling close to his parents (land might actually even be cheaper in a distant location). However, leaving the affected area means to forgo the multiple benefits drawn from quasi-coresidence (Fafchamps and Quisumbing, 2007). These benefits are threefold. First, many consumption goods are non-rival in the sense that consumption by one does not reduce (by much) consumption by others. Thus, living close to each others allows family members to pool consumption expenditures, and to reduce duplication of public goods and then to achieve a higher utility. Second, as illustrated by Fafchamps and Quisumbing (2003), many household production activities such as cooking, collecting water, or visiting the market, have fixed costs or local increasing returns. Therefore, the amount of time spent on these chores does not vary with household size, or increases less than proportionally with household size. The mechanism naturally extends to the quasi-coresidence case (when people live in a separate but close household). Last but not least, quasi-coresidence also helps risk-sharing against idiosyncratic shocks (Fafchamps and Gubert, 2007) and intergenerational support (Kochar, 2000).

In this framework, any action taken by public authorities aiming at mitigating the impact of natural disasters will therefore reduce the need for households at origin to receive remittances after a shock, decreasing de facto the benefits drawn from migration. Consequently, an increase of the level of trust in public authorities should decrease the propensity to migrate.

As stated above, a central feature of the New Economics of Labor Migration framework is that household members act as a single entity when making migration decisions. It is worth underlying that this assumption of unitary model of household decisions has been challenged in various domains. In fact, as recalled by Fiala and He (2017), there is growing evidence that the unitary household model fails to describe intrahousehold decision making, and that bargaining process plays an important role in household decision making. For instance, evidence now exists that bargaining power affects household expenditures (Doss, 2013; Hashemi et al., 1996), consumption of specific goods (De Brauw et al., 2014; Duflo and Udry, 2004), schooling decision (Bobonis, 2009; Rubalcava et al., 2009), and labor supply (Heath and Tan, 2014). Quite surprisingly, to the best of our knowledge, the role of bargaining power in migration decisions is much less documented although, as underlined by Nobles and McKelvey (2015), Stark (1984) already proposed the addition of bargaining power to the NELM model. Nevertheless, ethnographic studies directly asking migrants and their spouses about household decision-making confirm that women have little say over their husbands' migration behavior (Broughton, 2008; Cohen et al., 2008). Arguing that the costs and risks of male migration are disproportionately borne by women, King (2007) concluded that many Mexican women likely oppose male migration but lack the authority to prevent it. Nobles and McKelvey (2015) use data from a policy experiment in Mexico, namely Progresa, to demonstrate that an exogenous increase in a woman's control over household resources decreases the probability that her spouse migrates to the United States.

In light of this framework, one may consider an household where parents and children have diverging preferences. For instance, one may argue that parents would like the child to stay, while he or she prefers to move out of the affected area to escape volcanic risk exposure. In this case, public intervention aiming at reducing the impact of natural disasters may relax the moral obligation of children toward their parents, allowing them to settle out of the affected area. In fact, several studies have shown that public policies could crowd-out informal arrangements. Instances of such a mechanism have been provided in Mexico by Attanasio and Rıos-Rull (2000) with Progresa, in rural Ethiopia by Dercon and Krishnan (2003) with public transfers in the form of food aid, and more recently in Ghana by Strupat and Klohn (2018) with the national health insurance.

In sum, depending on the analytical framework considered, an increase of institutions' ability to mitigate the consequences of natural disasters may have ambiguous effects on migration and thus remains an empirical question. In what follows, we investigate the relationship between trust in public authorities and migration decisions. We must stress, however, that we are unable to formally test one approach over the other. Then, our empirical results must not be interpreted as evidence against one of the two approaches presented above.[2]

[2]Note for instance that parents and children might have opposite preferences to the ones we mentioned.

4.4 Data

4.4.1 Survey

We conducted a survey in June-August 2016 around Tungurahua volcano, Ecuador. 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 229 households, living in 11 communities, situated in three parishes, namely Puela, Bilbao and Cotalo.

We measured the levels of trust toward the three institutions in charge of mitigating the effects of the eruptions, namely the Geophysical Institute, local authority, and national authority. These measures were gathered through survey questions following Grootaert (2004). More precisely, each of the household heads was asked: "*In general, how much do you trust [name]?*", where [name] was replaced by: "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".

To measure the spatial dispersion of children, each of the household heads was asked to list household members and also members of his extended family that do not live in his household and to report their place of living. From these data we construct, for each household, a variable, denoted $SPchild$, equals to the ratio of the number of children living in the same household or in the same parish as the household head, over the total number of children of the household head.

4.4.2 Descriptive Statistics

Summary statistics on household heads and household characteristics are reported in Table 4.1. Over the 229 households sampled, 196 report to have at least one child.[3] Those households are mainly headed by male, aged of 55 years old who received a primary level of eduction. 32% of household heads report to have lived in a different place before, and half of them declare to live exclusively in the affected area (the $Finca$ variable). 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

[3]We discuss this attrition problem in the robustness section.

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.

Regarding the levels of trust toward the Geophysical Institute, local authority, and national authority, household heads have a medium level of trust although it is slightly higher for the former two than for the latter.

Finally, each household has on average 3.5 children, aged of 23 years old, and 73% of them live either in the same household or in the same parish as the household head.

Table 4.1: Summary statistics

Variable	**Definition and survey question**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Age (head)	Age of the household head.	54.923	17.485	22	96	196
Male (head)	Dummy variable taking the value one if the household head is a male.	0.852	0.356	0	1	196
Education (head)	Categorical variable accounting for the level of education of the household head: 0 (none), 1 (primary or less), 2 (secondary or more).	1.082	0.434	0	2	196
Migr (head)	Dummy variable taking the value one if the household head has lived in a different place before, and zero otherwise.	0.321	0.468	0	1	196
Finca	Dummy variable taking the value one if the household only has a house in the affected area, and zero otherwise.	0.5	0.501	0	1	196
IG	Survey question: "How much do you trust the Geophysical Institute?". Values: 0 (to a very small extent), 1 (to a small extent), 2 (to a great extent), 3 (to a very great extent).	1.556	0.907	0	3	196
Local authority	Survey question: "How much do you trust local authority?". Values: 0 (to a very small extent), 1 (to a small extent), 2 (to a great extent), 3 (to a very great extent).	1.505	0.886	0	3	196
National authority	Survey question: "How much do you trust national authority?". Values: 0 (to a very small extent), 1 (to a small extent), 2 (to a great extent), 3 (to a very great extent).	1.327	0.892	0	3	196
Nchildren	Number of children of the household head.	3.474	2.067	1	13	196
SPchild	Ratio of children living either in the same household or in the same parish as the household head $SPchild = \frac{\text{Household head's children living in the same parish}}{\text{Total number of children}}$.	0.732	0.384	0	1	196
Age (children)	Age of household head's children.	23.403	13.978	0	71	196
Male (children)	Share of male among household head's children.	0.479	0.317	0	1	196

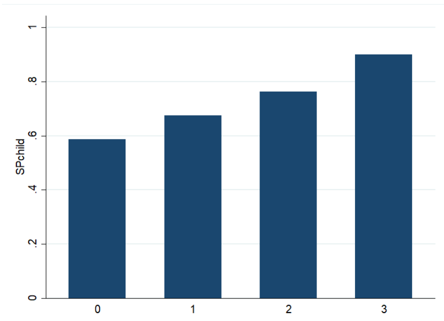
Source: Author's elaboration.

Summary statistics for children having left their parents' household are reported in Table C8 in appendix. This subsample includes both children living in the same parish as their parents (but not in the same household) and children who migrated. We note that 43% of them are male, and unsurprisingly, the average age is higher than for the full sample. On average, they left their parents 15 years ago, when they were around 20 years old. Note that this distribution is highly concentrated around its mean (Figure C7 in appendix), in line with the idea that children leave their parents' house at the time of marriage. Regarding their spatial distribution, 32% of them are living in the same parish as their parents, 51% in another parish but in the same province, 12% in an other province in Ecuador, and 4% are living abroad. To investigate whether they were selected on their age or their gender, we perform a t-test on children characteristics between those who live in the same parish as their parents and those who migrated. Results are reported in Table C9 in appendix, and we observe no difference regarding their age or the time they left. These latter statistics bring additional support to the hypothesis that migration in our context occurs as an ex-ante strategy. Last, children living in the same parish as their parents are slightly more likely to be men.

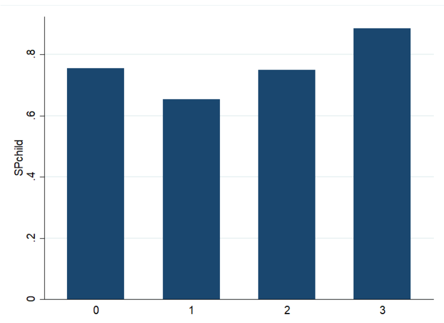
Finally, Figures 4.2a to 4.2c present correlations between our variables of interest, namely the *SPchild* variable and trust toward the Geophysical Institute, local authority, and national authority, respectively. For the three measures of trust, we observe a positive correlation with the SPchild variable, meaning that a higher level of trust toward any of these institutions is associated with a larger share of children living in the same parish as the household head.

Figure 4.3: Children spatial dispersion and trust

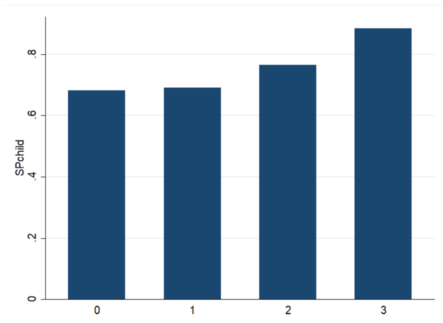
(a) IG



(b) Local authority



(c) National authority



Source: Author's elaboration.

4.5 Empirical Analysis

4.5.1 Baseline Specification

Model The hypothesis to be tested in this paper is whether trust toward institutions affects children spatial dispersion. In this aim, we estimate the following empirical model:

$$SPchild_{hc} = \beta Trust_{hc} + \gamma^{'} \boldsymbol{X} + \nu_c + \varepsilon_{hc} \tag{4.1}$$

where $SPchild$ is the ratio of children of household h living in community c living in the same parish as their parents. $Trust$ stands for the three distinct measures of trust toward the Geophysical Institute, local authority, and national authority. $\boldsymbol{X}$ is a vector of control variables including age, education, gender and migration of the household head, and the double residence status. We also include the surface of land, and the number of animals to account for wealth. ν_c is a community fixed-effect which allows to control for community-specific factors which could affect migration such as the difficulty to acquire land.

Identification Strategy Our empirical model raises several threats to identification. First, in Chapter 3 , we showed that the levels of trust toward the Geophysical Institute and local authority could be updated following an eruption depending on their ability to efficiently mitigate the shock, a finding that echoes the results of Andrabi and Das (2017) in Pakistan. This creates an issue in the current model since the levels of trust measured at the time of the survey toward these institutions can be determined by actions taken in response to eruptions that occurred after children migration. For instance, if children migration occurred at the beginning of the eruptive phase while trust has increased over years due to an improvement of eruptions management, this would cause an upward bias of our estimates. To overcome this problem, we rely on the fact that public interventions are taken at the community level or above but rarely target specific individuals inside a community (the only one we are aware of is the relocation program which is already taken into account in the control variables). Therefore, we include community fixed-effects in our empirical model to drop the community-specific component of trust, which includes the part imputed to public policies.

Another threat to identification may arise if migration of the full household occurred, leading to a sample selection bias of our estimates. While we lack quantitative evidence to show that this is not the case, we argue that this is unlikely for the reasons mentioned above, namely the anchorage of farmers' assets to location, and the job search difficulty due to the concomitant economic crisis.[4]

[4]The difficulty to move out of the affected area is illustrated by the unsuccessfulness of the relocation program.

Finally, one may refer to the norm transfer literature (Batista and Vicente, 2011; Docquier et al., 2016; Spilimbergo, 2009) to warn against a reverse causality bias. In fact, if migrants settle in a place with a higher institutional quality they may influence those stayed behind, leading these latter to increase their requirement regarding their own public authorities. Nevertheless, we argue that this is unlikely to occur in the present context since the literature only provide evidence of this effect when migrants move to developed countries while, as shown in the descriptive statistics, 96% of children having left their parents' household remain in Ecuador.

Results Equation 4.1 is estimated separately for each of the three measures of trust using OLS estimator. Results are reported in Table 4.2. Column 1 reports regressions where no control variable nor community fixed-effects are included. In column 2, we only include community fixed-effects in the regressions. Column 3 presents regressions including only control variables. Finally, column 4, our preferred specification, reports regressions including both control variables and community fixed-effects. Regardless of the specification, we find a positive and significant effect of trust toward the Geophysical Institute, local authority, and national authority. In terms of magnitude, from the full specification (col. 4), an increase of one standard deviation of the level of trust increases the ratio of children living in the same parish by 5.4%. Regarding the full range of the variables, increasing the level of trust from 0 (the lowest level) to 3 (the highest level) toward one of the three institutions, would increase the ratio of children living in the same parish by roughly 18%.

To investigate whether one institution dominates the others, we run the same empirical model by including simultaneously the three measures of trust. Results are reported in Table C10 in appendix. While the level of trust toward the Geophysical Institute appears significant in the first and second columns (when no control variable is introduced), this is no more the case in columns 3 and 4 where control variables are included. This finding is however not surprising as the roles of the three institutions are strongly tied in the emergency process, leading to a strong correlation of their levels of trust.

Table 4.2: OLS Regressions: Baseline specification

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
IG	0.103***	0.091***	0.062***	0.056**
	(0.027)	(0.028)	(0.024)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.059	0.198	0.331	0.464
Local authority	0.058**	0.062**	0.061**	0.063***
	(0.029)	(0.029)	(0.024)	(0.023)
No. of Observations	196	196	196	196
R-Squared	0.018	0.175	0.330	0.467
National authority	0.063**	0.068**	0.060**	0.063**
	(0.029)	(0.029)	(0.025)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.022	0.179	0.329	0.466
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

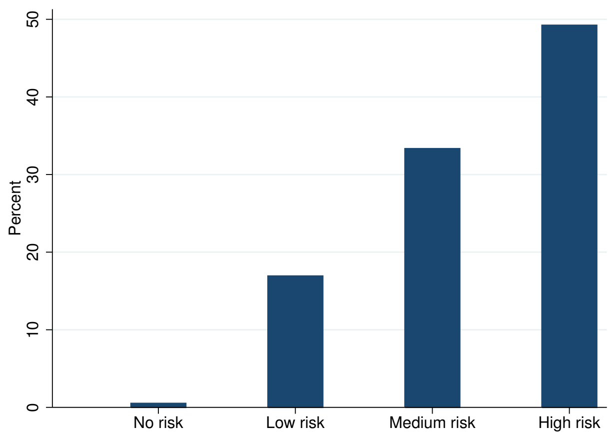
4.5.2 Robustness

Risk aversion and Risk perception

One may argue that risk perception about future shocks should also play a role in migration decision. In fact, there is evidence in the empirical literature that risk perception about future disasters affects the level of observed risk aversion (Cameron and Shah, 2015), and that risk aversion is related to both trust (Karlan, 2005) and migration decisions (Dustmann et al., 2017). Therefore, one may object that the results documented above are driven by an omitted variable bias. In fact, if risk averse households are more likely to favor children migration, and less likely to trust institutions, the omission of risk aversion in the empirical model would lead to an upward bias of the trust estimates. To check the robustness of our results to this alternative, we introduce separately a measure of risk perception and a measure of risk aversion in our empirical model.

We measured risk perception through the following question: "*Based on your experience and information, what is the risk that Tungurahua volcano erupt in the* *next two months?*". Respondent could answer one of the following proposition: "high risk"; "medium risk"; "low risk"; "no risk". The distribution of the answers is illustrated in Figure 4.4. We introduce this variable in Equation 4.1 which we estimate using OLS estimator. We then successively add each measure of trust toward public authorities. Results are reported in Table 4.3. As before, we estimate each specification without control variables or fixed-effects (column 1), by adding community fixed-effects only (column 2), by adding control variables only (column 3), and by adding both control variables and community fixed-effects (column 4). We find a positive correlation between the level of risk perception and the $SPchild$ variable when no trust measure is included. That is, the more people worry about future shocks, the less children migrate. This finding is however not robust to the introduction of the level of trust toward the Geophysical Institute, or to the introduction of our set of control variables. By contrast, coefficients associated to the trust variables remain significant and highly stable compared to the baseline estimation (Table 4.2). Nevertheless, the positive coefficient associated to risk perception is unexpected since we would expect that an increase of the perceived probability of future eruption should favor migration. One hypothesis that may explain this result is that risk perception also influences fertility decisions. Indeed, if the most fearful households delayed their fertility decisions, their children would be younger and therefore not yet ready to leave the household, which would inflate the $SPchild$ variable. We discuss this hypothesis below.

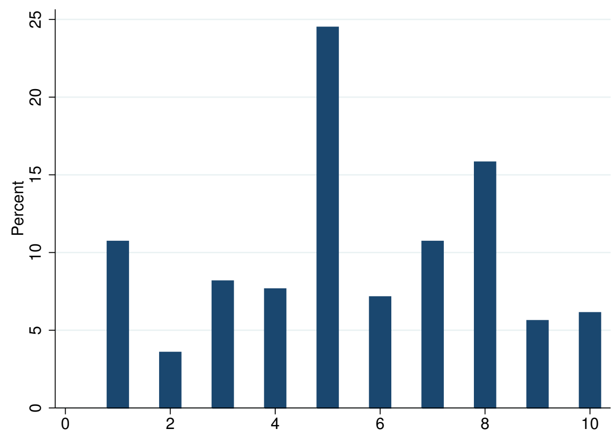
Figure 4.4: Risk perception



Source: Author's elaboration.

Risk aversion can be measured either through experimental games such as lotteries, or through survey questions. We opt for this latter alternative for two reasons. First, experimental games are not easy to implement in rural areas in developing countries, leading to a potentially high non-response rate. Second, evidence has been provided that survey questions accurately predict actual risk taking behavior in lottery experiments (Dohmen et al., 2011). Then, each household head was asked the following question: "*In a 1 to 10 scale, where 1 stands for disliking risk, and 10 stands for loving risk, how would you evaluate your propensity to take risk?*". The distribution of answers is illustrated in Figure 4.5. We introduce this variable in Equation 4.1 which we estimate using OLS estimator. We then successively add each measure of trust toward public authorities. Results are reported in Table 4.4. As before, we estimate each specification without control variables or fixed-effects (column 1), by adding community fixed-effects only (column 2), by adding control variables only (column 3), and by adding both control variables and community fixed-effects (column 4). Surprisingly, we find no significant effect of risk aversion on spatial dispersion of children, regardless of the specification (columns 1-4). Indeed, not only the coefficient is not significant, but it is also close to zero. Nevertheless, the coefficients associated to the trust variables remain significant and of very similar magnitude than in the baseline specification (Table 4.2).

Figure 4.5: Risk aversion



Source: Author's elaboration.

Table 4.3: OLS Regressions: Robustness Risk perception

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
Risk Perception	0.077**	0.072*	0.043	0.026
	(0.038)	(0.037)	(0.035)	(0.034)
No. of Observations	195	195	195	195
R-Squared	0.024	0.174	0.321	0.450
Risk Perception	0.057	0.052	0.032	0.014
	(0.038)	(0.038)	(0.035)	(0.034)
IG	0.094***	0.082***	0.057**	0.054**
	(0.027)	(0.029)	(0.024)	(0.024)
No. of Observations	195	195	195	195
R-Squared	0.071	0.206	0.337	0.464
Risk Perception	0.074*	0.069*	0.040	0.024
	(0.038)	(0.037)	(0.035)	(0.033)
Local authority	0.054*	0.061**	0.059**	0.062***
	(0.029)	(0.030)	(0.024)	(0.023)
No. of Observations	195	195	195	195
R-Squared	0.039	0.191	0.339	0.468
Risk Perception	0.073*	0.070*	0.040	0.024
	(0.038)	(0.037)	(0.035)	(0.033)
National authority	0.059**	0.066**	0.057**	0.062**
	(0.028)	(0.029)	(0.025)	(0.024)
No. of Observations	195	195	195	195
R-Squared	0.043	0.194	0.338	0.468
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4: OLS Regressions: Robustness Risk aversion

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
Risk Aversion	0.003	0.002	0.003	0.007
	(0.011)	(0.011)	(0.009)	(0.009)
No. of Observations	196	196	196	196
R-Squared	0.000	0.157	0.311	0.450
Risk Aversion	-0.008	-0.007	-0.004	0.001
	(0.011)	(0.011)	(0.009)	(0.009)
IG	0.109***	0.096***	0.066***	0.056**
	(0.028)	(0.029)	(0.024)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.062	0.200	0.332	0.464
Risk Aversion	-0.003	-0.005	-0.004	-0.001
	(0.012)	(0.012)	(0.010)	(0.010)
Local authority	0.061*	0.067**	0.065**	0.063**
	(0.032)	(0.033)	(0.026)	(0.025)
No. of Observations	196	196	196	196
R-Squared	0.018	0.176	0.331	0.467
Risk Aversion	-0.003	-0.004	-0.003	0.001
	(0.011)	(0.011)	(0.009)	(0.009)
National authority	0.065**	0.071**	0.062**	0.062**
	(0.031)	(0.031)	(0.025)	(0.025)
No. of Observations	196	196	196	196
R-Squared	0.022	0.179	0.329	0.466
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Fertility decisions

One may also argue that fertility decisions could be related to both the level of trust in public authorities and our dependent variable. In fact, as documented by Alam and Pörtner (2018) in the Tanzanian context, natural disasters can negatively affect fertility decisions for several reasons. First, children are costly in the short run. Indeed, although they can contribute to the household's production in the medium run, their short-term impact on availability of resources is negative, which can be particularly hard to manage following a shock. Secondly, as suggested by Kochar (1999), reallocating time from productive activity to child care will be even more costly if households need to respond to the shock by working more. Finally, household might realize that natural disasters may severely affect children health and might decide to postpone having the next child.

Observing such behavior in our data could bias our estimates. In fact, if people anticipate future eruptions and believe that they will not be helped by public authorities, they might delay their fertility decisions leading to two situations: *(i)* people having a low level of trust toward institutions would have younger children who would be too young to move out of the household, leading to an increase of the $SPchild$ variable; *(ii)* people delaying their fertility decisions can have no child at the time of the survey and would be dropped from the sample. Both cases would induce a downward bias of our estimates. To tackle the former issue, we re-run our regressions (Equation 4.1) including the average age of household head's children as a control variable. We then successively add each measure of trust toward public authorities. Results are reported in Table 4.5 below. Without loss of generality, we estimate each specification without control variables or fixed-effects (column 1), by adding community fixed-effects only (column 2), by including control variables only (column 3), and by adding both control variables and community fixed-effects (column 4). As expected, the coefficient associated to the average age of children is negative and significant regardless of the specification. An increase of the average age of children is then associated with a lower ratio of children living in the same parish as their parents. Regarding the coefficients associated to the levels of trust toward public authorities, they remain positive and significant with the same magnitude as those estimated in the baseline equation (Table 4.2).

Regarding the attrition problem due to childless households, we propose to compare the characteristics of these latter with the rest of the sample to insure that they do not differ from the others. In this aim, we perform a t-test on the household heads' characteristics, farm assets, double residence status, risk aversion, risk perception and trust in institutions. Results of the t-test are reported in Table C11 in appendix. We observe no difference between the two groups but for the level of risk perception toward future eruptions as childless households are more fearful about future eruptions. This result validates our previous interpretation of the estimated coefficient associated to risk perception in Table 4.3. What is more, no difference exists regarding the levels of trust between the two groups.

Table 4.5: OLS Regressions: Robustness Fertility decisions

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
Age children (mean)	-0.015***	-0.014***	-0.014***	-0.012**
	(0.002)	(0.002)	(0.005)	(0.005)
No. of Observations	196	196	196	196
R-Squared	0.315	0.397	0.366	0.486
Age children (mean)	-0.015***	-0.014***	-0.014***	-0.012**
	(0.002)	(0.002)	(0.005)	(0.005)
IG	0.068***	0.064***	0.062**	0.056**
	(0.024)	(0.024)	(0.024)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.340	0.417	0.386	0.500
Age children (mean)	-0.015***	-0.014***	-0.014***	-0.011**
	(0.002)	(0.002)	(0.005)	(0.005)
Local authority	0.056**	0.061***	0.056**	0.057**
	(0.023)	(0.023)	(0.025)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.331	0.414	0.383	0.501
Age children (mean)	-0.015***	-0.014***	-0.014***	-0.011**
	(0.002)	(0.002)	(0.005)	(0.005)
National authority	0.063**	0.071***	0.056**	0.058**
	(0.026)	(0.027)	(0.026)	(0.026)
No. of Observations	196	196	196	196
R-Squared	0.336	0.421	0.382	0.501
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

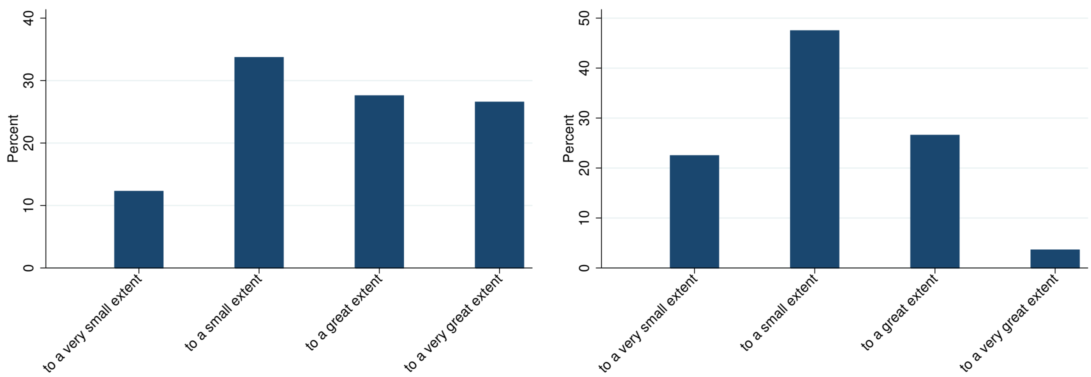
Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Trust in local people

Finally, one may argue that spatial diversification could also be correlated to the level of cooperation in the community. To check the robustness of our results to this alternative, we introduce variables accounting for the level of trust toward other persons in the community. We followed Grootaert (2004) and we measured the levels of trust toward relatives and neighbors through the following question: "*In general, how much do you trust [name]?*", where [name] was replaced by: "relatives", and "other persons of the community". 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". The distributions of the answers are provided in Figures 4.5a and 4.5b. We include separately each of these measures of trust in Equation 4.1 which is estimated using OLS estimator. We then successively add each measure of trust toward public authorities. We report the results in Tables 4.6 and 4.7 for trust in relatives, and neighbors, respectively. Without loss of generality, we estimate each specification without control variables or fixed-effects (column 1), by adding community fixed-effects only (column 2), by adding control variables only (column 3), and by adding both control variables and community fixed-effects (column 4). We note that, regardless of the specification, neither trust in relatives, nor trust in neighbors appears significant in the regressions, and the magnitude of the estimated coefficients is very close to zero. Regarding the coefficients associated to trust in public authorities, they remain highly similar to our previous findings.

Figure 4.6: Trust in relatives and neighbors

(a) Relatives (b) Neighbors



Source: Author's elaboration.

Table 4.6: OLS Regressions: Robustness Trust in relatives

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
Relatives	-0.005	-0.005	0.007	0.012
	(0.028)	(0.027)	(0.023)	(0.023)
No. of Observations	196	196	196	196
R-Squared	0.000	0.157	0.311	0.450
Relatives	-0.020	-0.016	-0.004	0.004
	(0.028)	(0.027)	(0.024)	(0.023)
IG	0.106***	0.093***	0.063**	0.056**
	(0.028)	(0.029)	(0.025)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.062	0.200	0.331	0.464
Relatives	-0.019	-0.019	-0.009	-0.003
	(0.030)	(0.028)	(0.025)	(0.025)
Local authority	0.063**	0.067**	0.064**	0.064**
	(0.031)	(0.031)	(0.025)	(0.024)
No. of Observations	196	196	196	196
R-Squared	0.020	0.177	0.331	0.467
Relatives	-0.017	-0.016	-0.006	0.000
	(0.029)	(0.027)	(0.024)	(0.024)
National authority	0.067**	0.071**	0.061**	0.062**
	(0.030)	(0.030)	(0.025)	(0.025)
No. of Observations	196	196	196	196
R-Squared	0.023	0.180	0.329	0.466
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4.7: OLS Regressions: Robustness Trust in neighbors

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
Neighbors	-0.008	0.005	0.009	0.023
	(0.034)	(0.032)	(0.031)	(0.030)
No. of Observations	196	196	196	196
R-Squared	0.000	0.157	0.311	0.451
Neighbors	-0.046	-0.027	-0.017	0.002
	(0.036)	(0.034)	(0.034)	(0.031)
IG	0.115***	0.098***	0.067**	0.056**
	(0.028)	(0.029)	(0.026)	(0.025)
No. of Observations	196	196	196	196
R-Squared	0.068	0.201	0.332	0.464
Neighbors	-0.036	-0.021	-0.021	-0.004
	(0.038)	(0.035)	(0.034)	(0.032)
Local authority	0.070**	0.069**	0.068**	0.064**
	(0.032)	(0.032)	(0.028)	(0.026)
No. of Observations	196	196	196	196
R-Squared	0.023	0.177	0.332	0.467
Neighbors	-0.026	-0.011	-0.010	0.007
	(0.035)	(0.032)	(0.032)	(0.030)
National authority	0.068**	0.070**	0.062**	0.061**
	(0.029)	(0.029)	(0.026)	(0.026)
No. of Observations	196	196	196	196
R-Squared	0.024	0.179	0.329	0.467
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

4.6 Discussion and Conclusions

This paper investigates how trust in public authorities could shape ex-ante migration decisions of households living in a natural hazard prone area. To that extent, this paper contributes to the burgeoning literature aiming at understanding the mitigating role of public authorities against natural disasters. In this respect, our paper complements the work of Chort and De La Rupelle (2017) who investigate the impact of two programs in Mexico on post-disaster migration. Our approach builds on an original dataset that we collected in Ecuador around Tungurahua volcano. Our results suggest that an increase of trust toward public authorities increases the ratio of children living in the same parish as their parents. This result is robust to the inclusion of control variables accounting for risk aversion, risk perception about future eruptions, trust in local people, and fertility decisions. Interestingly, although relying on different mechanisms, our results go in the same direction as Chort and De La Rupelle (2017) who also highlight the mitigating effect of public policies.

The idea that institutional quality is central in mitigating the impacts of natural disasters is of course long known (Kahn, 2005, among others). The contribution of the present paper is slightly different. In fact, while our work obviously encourage any improvement of institutional quality, it also highlights the importance to convince local people that public policies will be efficiently implemented. In this vein, the initiative to associate local people living around Mt. Tungurahua to the monitoring of the volcano, a system called 'vigias' (which can be translated to sentinels) certainly goes in the good direction. As underlined by Barclay et al. (2008), this participatory communication pathway from scientists to vigias, and vigias to their friends and family living in the community, results in an efficient and effective way to communicate risk information. These strong relationships have also engendered citizens'confidence in the system of vigias, scientists and authorities, resulting in prompt evacuations at times of high risk, and an increase in the uptake of risk information (Stone et al., 2014).

Nevertheless, our results also highlight a strong contradiction in the public policies implemented in this area. In fact, as stated earlier in the paper, the initial aim of the Ecuadorian government was to encourage people to leave the affected area. To do so, the government implemented a relocation program consisting in offering houses in the non-affected area in exchange for people to leave permanently the affected area. At the meantime, public authorities also put substantial efforts to improve the quality of their tools to mitigate the effects of eruptions. What we show in the present paper is that these efforts, apart from helping resident households to deal with these shocks, also give an incentive to children to stay in the affected area, increasing the number of people threatened by the volcano. Such a contradiction may also arise in various other contexts involving natural disasters that are likely to repeatedly affect specific areas, such as floods. Then, while this work encourages public authorities to provide people efficient tools to cope with natural disasters, it also opens the discussion on the design of consistent public policies that could both protect people from falling into poverty and insures an optimal land use planning.

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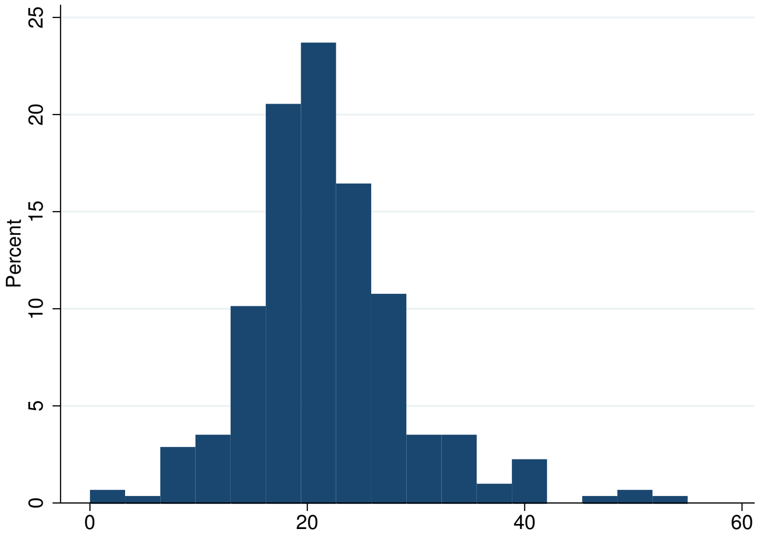
Appendix to chapter 4

Table C8: Children out of household summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Male	0.435	0.497	0	1	331
Age	36.089	10.316	3	71	326
Time left	14.556	9.081	0	50	320
Age left	21.726	7.257	0	55	317
Sparish	0.323	0.468	0	1	331
Sprovince	0.514	0.501	0	1	331
Ecuador	0.121	0.326	0	1	331
Abroad	0.042	0.202	0	1	331

Note: Male is a dummy variable taking the value one if the child is a male and zero otherwise; Age is the age of the child; Time left is the number of years since the child left his parent's household; Age left is the age at which he left his parents' household; Sparish is a dummy variable taking the value one if the child lives in the same parish as his parents and zero otherwise; Sprovince is a dummy variable taking the value one if the child lives in a different parish but in the same province as his parents and zero otherwise; Ecuador is a dummy variable taking the value one if the child lives in a different province but remains in the country and zero otherwise; Abroad is a dummy variable taking the value one if the child lives abroad and zero otherwise. *Source:* Author's elaboration.

Figure C7: Age left distribution



Source: Author's elaboration.

Table C9: T-test on children out of household's characteristics

	Migrant	Same parish	Difference/T-stat
Male	0.410	0.510	-0.0999*
			(-1.666)
Age	36.19	36.67	-0.481
			(-0.385)
Time left	14.82	14.17	0.650
			(0.590)
Age Left	21.37	22.50	-1.131
			(-1.291)

Note: Male is a dummy variable taking the value one if the child is a male and zero otherwise; Age is the age of the child; Time left is the number of years since the child left his parent's household; Age left is the age at which he left his parents' household. *Source:* Author's elaboration.

Table C10: OLS Regressions

	(1) SPchild	(2) SPchild	(3) SPchild	(4) SPchild
IG	0.101***	0.077**	0.037	0.027
	(0.033)	(0.036)	(0.029)	(0.029)
Local authority	-0.013	0.003	0.025	0.028
	(0.043)	(0.044)	(0.038)	(0.039)
National authority	0.018	0.025	0.020	0.027
	(0.041)	(0.043)	(0.037)	(0.039)
No. of Observations	196	196	196	196
R-Squared	0.060	0.200	0.337	0.472
Control variables	No	No	Yes	Yes
Community fixed effects	No	Yes	No	Yes

Note: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C11: T-test on childless and households with children's characteristics

	Childless households (N=33)	Households with children (N=196)	Difference/T-stat
Age (head)	58.24	54.98	3.258
			(1.014)
Educ (head)	1.121	1.123	-0.00186
			(-0.0180)
Male (head)	0.909	0.851	0.0578
			(0.882)
Migr (head)	0.242	0.323	-0.0807
			(-0.923)
Land	1.152	2.509	-1.357
			(-0.863)
Livestock	2.636	4.333	-1.697
			(-1.524)
Horses	0.152	0.272	-0.120
			(-0.867)
Finca	0.606	0.503	0.103
			(1.098)
Risk perception	3.667	3.313	0.354**
			(2.546)
Risk aversion	5.970	5.518	0.452
			(0.935)
IG	1.424	1.559	-0.135
			(-0.761)
Local authority	1.364	1.508	-0.144
			(-0.843)
National authority	1.273	1.328	-0.0555
			(-0.320)

Note: Age (head) is the age of the household head; Educ (head) is a categorical variable from 0 (no education) to 2 (secondary and upper) accounting for the household head's level of education; Male (head) is a dummy variable taking the value one if the household head is a male and zero otherwise; Migr (head) is a dummy variable taking the value one if the household head has lived in another place before and zero otherwise; Land is the surface of land owned by the household; Livestock is the number of farm animals owned by the household; Horses is the number of horses owned by the household; Finca is a dummy variable taking the value one if the household has a house out of the affected area and zero otherwise; Risk perception is a variable measuring the perceived likelihood of future eruptions ranging from 0 (no risk) to 3 (high risk); Risk aversion is a variable measuring the taste for risk of the household head ranging from 1 (hate risk) to 10 (love risk); IG is the level of trust of the household head in the Geophysical Institute ranging from 0 (low trust) to 3; Local authority is the level of trust of the household head in local authority ranging from 0 (low trust) to 3; National authority is the level of trust of the household head in national authority ranging from 0 (low trust) to 3. *Source*: Author's elaboration.

Chapter 5
Conclusions

Due to the increasing frequency of natural disasters over the last decade, their impacts on households have become a burning issue, especially in developing countries where people are highly vulnerable. In fact, the perspective that natural disasters may roll back decades of progress against poverty has triggered the attention of governments and international institutions. In addition, despite the abundant literature on the economics of risk, most of the existing results are hardly applicable to the case of natural hazards whose characteristics differ from 'traditional risks'. To fill this gap, a recent literature has emerged focusing on the impacts of natural disasters in developing countries. The present dissertation tries to contribute to this literature with the three empirical chapters previously exposed.

Chapter 2 of this dissertation focuses on the long-term effect of natural hazards on households' capital accumulation. While the existing empirical literature has investigated the impact of shocks on the quantity of assets held by individuals, these studies let aside the behavioral response to risk exposure, which was, however, widely highlighted in the theoretical literature. The main contribution of this chapter is therefore to focus on the impact of these changes in investment behaviors due to risk exposure rather than on the shocks themselves. In this aim, we rely on a structural approach which allows us to tackle the lack of data, and to disentangle the ex-ante from the ex-post effect. Our results show that volcanic risk exposure induces a change in investment decisions since exposed households prefer to increase their consumption rather than to invest in assets that could potentially be damaged by future eruptions. We also show that this effect is worsened by changes in risk perception after an eruption. This behavioral effect is quantitatively important since on the long run, a significant share of the wealth losses induced by volcanic risk is imputable to changes in investment behavior. In terms of public policy recommendations, our results suggest that increasing post disaster program duration could increase their efficiency as resources transfered right after the shock would rather be consumed than invested. In addition, since the ex-ante effect of risk is rarely taken into account, our results suggest that insurances against natural disasters could have important hidden benefits on households' growth and should therefore be supported.

Chapter 3 investigates the impact of a volcanic eruption on households' social capital. This paper contributes to the burgeoning literature on the impact of natural disasters on social behaviors which remains inconclusive both on the sign of the effect as well as on the underlying mechanisms at stake. In this aim, we use the survey that we conducted in June 2016 in Ecuador around Mt. Tungurahua and where we measured social capital along three dimensions, namely bilateral cooperation, the willingness to contribute to collective goods, and the levels of trust in public authorities. We augment this dataset with data on ash fall received in each community during the November 2015 eruption. We use the exogenous variation of ash thickness across communities to identify the causal effect of the eruption on social capital. 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, the shock has a negative effect, consistent with the moral hazard hypothesis. On the contrary, in the most heterogeneous communities, the eruption increases bilateral cooperation. Regarding the willingness to contribute to collective goods, we find a positive an unconditional effect of the shock intensity, consistent with the idea that a stronger shock increases the need for reconstruction. It is worth underlying that unlike bilateral cooperation, this effect is not conditional on the level of wealth inequality, suggesting an absence of moral hazard behavior that we explain through a greater social pressure. Finally, our results show an increase of the level of trust toward public authorities such as the Geophysical Institute, in charge of the monitoring of the volcano, and local authority. This result, already highlighted in the literature, might be explained by the fact that public authorities are more active in the most affected communities. In terms of public policy recommendations, this work mainly highlights the possibility, in some communities, of a break down of solidarity mechanisms. In other words, households are even more vulnerable in the wake of a natural disaster since they cannot count on their network to cope with other shocks. Consequently, supporting households against idiosyncratic shocks might be beneficial in the wake of a natural disaster.

Finally, Chapter 4 highlights the role of public authorities on migration decision of households living around Mount Tungurahua. This paper contributes to the burgeoning literature investigating the mitigating role of public authorities on natural disaster consequences. While the effects of public transfers on post-disaster migration have already been documented, our main contribution lies in the identification of the role of households' trust in public authorities on ex-ante migration decisions. Here again, we rely on the survey that we conducted around Tungurahua volcano where we measured both the household heads' levels of trust in the Geophysical Institute, local authority, and national authority; and their children spatial dispersion. To tackle the temporality issue, we include community fixed effects so that any intervention from public authorities at this level or above is partialled out. Our results suggest that trust in institutions is positively correlated to the ratio of children living in the same parish as their parents. In other words, the higher the household heads' levels of trust, the less children settle in a different parish. From a public policy perspective, our results naturally encourage any action aiming at improving institutional quality but also underline the necessity to setup transparent and intelligible public policies. In this vein, the initiative taken to associate local people to the monitoring of the volcano certainly goes in the right direction.

To conclude, while the three chapters developed in this dissertation may appear to deal with very different topics, they all have in common to study the behavioral response to volcanic risk. In that sense, this dissertation sheds light on a natural disaster which remains understudied in the economic literature and contributes to highlight an aspect of natural disasters largely ignored beyond academia, namely: its behavioral impact.

CHAPTER 6

Questionnaire

ENCUESTA SOBRE LA PERCEPCIÓN DEL RIESGO VOLCÁNICO
AÑO 2016

El objetivo de esta encuesta es conocer como ha sido su convivencia con el volcán Tungurahua desde que comenzó el último período eruptivo.

La información que nos entregue en esta encuesta es confidencial y sólo se utilizará con fines investigativos. Los datos serán publicados exclusivamente en compilaciones de conjunto de modo que no pueda ser violado el secreto comercial o patrimonial, ni individualizarse a las personas que los proporcionaron.

IDENTIFICACIÓN DE LA VIVIENDA SELECCIONADA
(en caso de doble residencia, anotar las dos ubicaciones)

UBICACIÓN GEOGRÁFICA VIVIENDA EN ZONA AFECTADA

CANTÓN	Penipe 1		Pelileo 3				1
PARROQUIA	Puela 1	Bilbao 2	Cotaló 4				2
COMUNIDAD			Cusúa 3	Chacauco 4	San Juan 5	Pillate 6	3

UBICACIÓN GEOGRÁFICA VIVIENDA EN ZONA DE REASENTAMIENTO

CANTÓN	Penipe 1	Pallatanga 2	Pelileo 3	4
BARRIO	Miduvi 1	Nuevo Bilbao 2	La Paz 3	5
COMUNIDAD				6

NOMBRES Y APELLIDOS DEL JEFE DEL HOGAR ______________________

NÚMERO DE CELULAR ______________________

ENCUESTADOR

Nombre : ______________________ 7

Fecha de visita al hogar		Hora de inicio	Hora de termino	Día	Mes	Año
	Primera visita	: 9	: 11	12	13	2016
	Segunda visita	:	:			2016

1. EXPOSICIÓN AL RIESGO VOLCÁNICO (y no a otro riesgo como riesgo climático, de salud etc…)

HACER ESTA SECCIÓN SÓLO EN LAS PARROQUIAS DE PUELA, BILBAO Y COTALÓ

Vamos a hablar de las consecuencias de la erupción del volcán Tungurahua de marzo del 2016 en su finca / vivienda en la zona de riesgo del volcán.

	Vivienda	**SÍ**	**NO**		
1	¿Su vivienda sufrió algún daño? ¿Cuáles habitaciones sufrieron daños? **(R.U.)**	1	2	**(PASE A P.7)**	16
2	El techo	1	2		17
3	Las paredes	1	2		18
4	Las ventanas	1	2		19
5	¿Y sus muebles o electrodomésticos sufrieron daños? **(R.U.)**	1	2		20
6	¿En cuánto dinero estima usted los daños que sufrió su vivienda y sus bienes? **(R.U.) (INDIQUE EL VALOR DE LOS DAÑOS EN DÓLARES, SI NO HAY GASTO MARQUE NINGUNO 98) (R.U.)**	**US$**_______ **Ninguno 98**			21
7	¿Se cortó la luz en su hogar? **(R.U.)**	1	2	No tiene luz 98	22

	Salud	**SÍ**	**NO**	
8	¿A raíz de la erupción, usted o algún miembro de su hogar enfermó y no pudo ir a trabajar? **(R.U.)**	1	2	23

	Cosechas		**Códigos**			
9	¿Tuvo pérdidas de su cosecha / cultivo? **(SI RESPONDE AFIRMATIVAMENTE)** ¿La pérdida fue total o parcial? **(R.U.)**	Pérdida total :	1			
		Pérdida parcial :	2			
		No tuvo pérdidas	97 **(PASE A P.16)**			24
		No tiene cultivos	98 **(PASE A P.16)**			
13	¿Qué porcentaje de la cosecha o pastizales se perdió? **(R.U.)**		%			25
14	¿Qué productos se perdieron en la cosecha? **(TARJETA A) (R.M.)**					26m
15	¿Cuánto dinero estima usted que ha perdido en sus cultivos desde marzo 2016 a causa de la caída de ceniza volcánica? **(INDIQUE EL VALOR EN DÓLARES, SI NO TUVO PÉRDIDAS EN DINERO MARQUE NO TUVO 98) (R.U.)**		**US$**_______ **No tuvo 98**			27
16	¿Sufrió daños su maquinaria agrícola? **(R.U.)**		SÍ 1	NO 2	No tiene 98	28

	Animales - (VACAS, CERDOS, BORREGOS, POLLOS)	**SÍ**	**NO**	**NO TIENE ANIMALES**	
17	¿Enfermaron sus animales a raíz de la caída de ceniza volcánica? **(R.U.)**	1	2 **(A P.19)**	98 **(A P.23)**	29
18	¿Cuántos animales se enfermaron? **(ESCRIBA LA CANTIDAD DE ANIMALES QUE ENFERMARON) (R.U.)**	Nº. _______			30
19	¿Se secó la leche de su ganado? **(R.U.)**	**SÍ**	**NO**	**NO TIENE GANADO LECHERO**	
		1	2	98	31
20	¿Se le murieron animales producto de la ceniza volcánica? **(R.U.)**	1	2 **(A P.22)**		32
21	¿Cuántos animales se le murieron? **(ESCRIBA LA CANTIDAD DE ANIMALES QUE MURIERON) (R.U.)**				33
22	¿Cuánto dinero estima usted que ha perdido en sus animales desde marzo 2016 a causa de la caída de ceniza volcánica? **(INDIQUE EL VALOR EN DÓLARES, SI NO TUVO PÉRDIDAS EN DINERO MARQUE NO TUVO 98) (R.U.)**	**US$**_______ **No tuvo 98**			34

TARJETA A	
Maíz	1
Fréjol	2
Papa	3
Zanahoria	4
Habas	5
Cebolla blanca	6
Zambo	7
Tomate de árbol	8
Manzana	9
Durazno	10
Claudia	11
Pera	12
Mora	13
Mandarina	14
Pastos	15
Otros (especificar) _______ _______ _______	

2. PERCEPCIÓN DE LOS RIESGOS VOLCÁNICOS
HACER ESTA SECCIÓN SÓLO EN LAS PARROQUIAS DE PUELA, BILBAO Y COTALÓ

23 ¿Qué tan peligroso considera usted que es el volcán Tungurahua? **(LEER ALTERNATIVAS) (R.U.)**

Muy peligroso	Peligroso	Poco peligroso	Nada peligroso
4	3	2	1

¿Y cuánto riesgo piensa usted que existe de que el volcán Tungurahua sea…? **(LEER ALTERNATIVAS) (R.U.)**

	Mucho	Algo	Poco	Nada
24 ¿Una amenaza de destrucción para su vivienda? **(R.U.)**	4	3	2	1
25 ¿Una amenaza de destrucción para sus cosechas? **(R.U.)**	4	3	2	1
26 ¿Un peligro para su salud? **(R.U.)**	4	3	2	1

27 ¿Usted ha observado algún beneficio sobre los cultivos o terrenos desde del inicio de la caída de ceniza desde el año 1999? **(R.U.)**

SÍ 1 NO 2 **(PASE A P.29)**

28 En caso afirmativo, ¿Cuáles? **(R.M.)**

Un aumento de la fertilidad de los suelos / tierra	1
Otros (Especifique) ____________________	
____________________	
____________________	

29 ¿Cuáles son sus principales fuentes de información sobre el volcán? **(R.M.)**

Autoridades	1
COE	2
Medios (Prensa local, radio, etc.)	3
Televisión	4
Vigías del volcán	5
Amigos y familia	6
Otras (Especifique) ____________________	

30 En base a su experiencia e información, ¿Cuánto riesgo cree usted que existe de que el volcán Tungurahua entre en erupción en los próximos doce meses? **(R.U.)**

Alto riesgo	4
Mediano riesgo	3
Bajo riesgo	2
Nulo riesgo	1

2. PERCEPCIÓN DE LOS RIESGOS VOLCÁNICOS

HACER ESTA SECCIÓN SÓLO EN LAS PARROQUIAS DE PUELA, BILBAO Y COTALÓ

31 ¿Cuando las autoridades emitieron la alerta roja del año 2010, usted y su familia evacuaron su casa? **(R.U.)**
Sí 1 **(PASE A P.33)**
No 2

32 ¿Por qué razón (es) no evacuó su casa? **(R.M.)**

No recibió la información de la alerta	1
No confía en las alertas	2
Pensó que la erupción no era peligrosa	3
Tuvo miedo que se le roben cosas	4
Otra (Especifique) ______________________________	

33 ¿Cuando las autoridades emitieron la alerta naranja de marzo de 2016, usted y su familia evacuaron su casa? **(R.U.)**
Sí 1 **(PASE A P.35)**
No 2

34 ¿Por qué razón (es) no evacuó su casa? **(R.M.)**

No recibió la información de la alerta	1
No confía en las alertas	2
Pensó que la erupción no era peligrosa	3
Tuvo miedo que se le roben cosas	4
Otra (Especifique) ______________________________	

35 ¿Durante la erupción de marzo de 2016, trasladó a sus hijos a otro hogar? **(R.U.)**
Sí 1
No 2
No tiene hijos 98

36 ¿Ha visto el mapa de peligros del volcán? **(R.U.)**

Sí 1 No 2 **(A P.39)**

37 ¿Me podría decir el color de la zona donde usted vive? **(R.U.)**

Color: ____________________

3. RESPUESTA DEL HOGAR A LA ERUPCIÓN VOLCÁNICA DE MARZO 2016
HACER ESTA SECCIÓN SÓLO EN LAS PARROQUIAS DE PUELA, BILBAO Y COTALÓ

Ahora vamos a hablar de cómo su hogar ha superado las consecuencias de la erupción del volcán Tungurahua de marzo de 2016

		SI	NO		
39	¿Recibieron ayuda del gobierno? **(R.U.)**	1	2	50	
40	¿Recibieron ayuda de ONG o iglesias? **(R.U.)**	1	2	51	
41	¿Gastaron ahorros? **(R.U.)**	1	2	NO TENÍAN AHORROS 98	52
42	¿Vendieron animales? **(R.U.)**	1	2	NO TENÍAN ANIMALES 98	53
43	¿Se realizaron mingas de ayuda? **(R.U.)**	1	2	54	
44	¿Obtuvieron préstamos de bancos o cooperativas? **(R.U.)**	1	2	55	
45	¿Obtuvieron préstamos de amigos o familiares? **(R.U.)**	1	2	56	
46	¿Recibieron dinero de amigos o familiares que viven en el extranjero? **(R.U.)**	1	2	57	
47	¿Recibieron dinero de amigos o familiares que viven en el país? **(R.U.)**	1	2	58	
48	¿Trabajaron en tierras de otras personas que no son de su familia? **(R.U.)**	1	2	59	
49	¿Vendieron tierras o terrenos propios? **(R.U.)**	1	2	NO TENÍAN TIERRAS 98	60
50	¿Redujeron gastos en salud o educación? **(R.U.)**	1	2	61	
51	¿Disminuyeron gastos en alimentación? **(R.U.)**	1	2	62	

3. RESPUESTA DEL HOGAR A LAS ERUPCIONES VOLCÁNICAS DESDE LA PRIMERA ERUPCIÓN DEL AÑO 1999

HACER ESTA SECCIÓN SÓLO EN LAS PARROQUIAS DE PUELA, BILBAO Y COTALÓ

¿Qué es lo que usted ha hecho para disminuir los problemas en los cultivos o los productos desde que empezó la caída de ceniza en el año 1999?

		SÍ	NO	NO TIENE CULTIVOS	
52 ¿Cambiaron de cultivos? **(R.U.)**		1	2 **(AP.55)**	**98 (PASE A P.55)**	63
53 ¿Cuáles son los cultivos que abandonaron? **(TARJETA A) (R.M.)**	**(CONSIGNAR CÓDIGO DE PRODUCTOS)**				64m
54 ¿Cuáles son los nuevos cultivos que tienen ahora? **(TARJETA A) (R.M.)**	**(CONSIGNAR CÓDIGO DE PRODUCTOS)**				65m
		SÍ	**NO**	**NO TUVO ANIMALES**	
55 ¿Abandonó la cría de animales? **(R.U.)**		1 **(A P.57)**	2	**98 (A P.57)**	66
56 ¿Redujo la actividad de cría de animales? **(R.U.)**		1	2		67

TARJETA A	
Maíz	1
Fréjol	2
Papa	3
Zanahoria	4
Habas	5
Cebolla blanca	6
Zambo	7
Tomate de árbol	8
Manzana	9
Durazno	10
Claudia	11
Pera	12
Mora	13
Mandarina	14
Pastos	15
Otros (especificar) ______ ______	

57 ¿Alguien de su hogar cambió de actividad económica debido a la caída de ceniza? **(SI RESPONDE AFIRMATIVAMENTE)** ¿Quién cambió de actividad? **(R.M.)**

58 ¿Cuál es la actividad que abandonó? **(R.U.) (ANOTE NOMBRE ACTIVIDAD)**

59 ¿Cuál es la nueva actividad que realiza ahora? **(R.U.) (ANOTE NOMBRE ACTIVIDAD)**

60 ¿Dónde desarrolla esta nueva actividad? **(R.U.)**

	QUIÉN CAMBIÓ (P.57) (R.M) 68m	**ACTIVIDAD ABANDONADA (P.58) (R.U)**	**NUEVA ACTIVIDAD (P.59) (R.U)**	**LUGAR NUEVA ACTIVIDAD (P.60) (R.U)** Misma parroquia 1 Otra provincia 4 Mismo cantón 2 Quito 5 Misma provincia 3 Extranjero 6
Jefe/a de hogar	1 71	75	76	1 2 3 4 5 6 77
Esposo/a del jefe de hogar	2 72	78	79	1 2 3 4 5 6 80
Hijos mayores de 18 años	3 73	81	82	1 2 3 4 5 6 83
Niños	4 74	84	85	1 2 3 4 5 6 86
Ninguno	98 **(A P.61)**			

61 ¿Usted seguirá viviendo en esta zona aunque el volcán Tungurahua siga permanentemente activo? **(R.U)**

Sí 1 No 2 **(A P.63)** 87

62 ¿Por qué razón va a seguir viviendo en esta zona? ¿Por alguna otra razón? **(R.M.)**

88m
______
______

4. RESPUESTA A LA EXPOSICIÓN A OTROS PROBLEMAS ECONÓMICOS EN EL AÑO 2015

HACER ESTA SECCIÓN A TODOS

¿Además de los problemas que tuvo producto de la erupción del volcán tuvo alguno de los siguientes problemas?

63 ¿En el año 2015 usted se ha visto afectado por alguno de estos problemas? **(HACER PREGUNTAS UNA POR UNA) (R.U.)**

	SI	NO	
¿Pérdida de la cosecha por plaga, lluvia, peste, mala semilla?	1	2	**NO TUVO CULTIVOS 98**
¿Caída de los precios de productos agrícolas?	1	2	**NO TUVO CULTIVOS 98**
¿Alza de los precios de insumos agrícolas?	1	2	**NO TUVO CULTIVOS 98**
¿Enfermedad, robo o muerte de los animales y aves?	1	2	**NO TUVO ANIMALES Y AVES 98**
¿Enfermedad de algún miembro del hogar que impidió el trabajo?	1	2	
¿Muerte de algún miembro del hogar que contribuye a mantener el hogar?	1	2	
¿Pérdida de empleo de algún miembro del hogar?	1	2	
En caso de actividades no agrícolas, ¿caída de ventas o clientes?	1	2	
¿Dejó de recibir transferencias de dinero de amigos o familiares?	1	2	**NO RECIBE TRANSFERENCIAS 98**
Ninguna	**98 (A P.65)**		

64 ¿Cómo usted ha superado estas situaciones? **(HACER PREGUNTAS UNA POR UNA) (R.U.)**

	SI	NO	
¿Recibieron ayuda del gobierno?	1	2	
¿Recibieron ayuda de ONG, iglesias?	1	2	
¿Gastaron ahorros?	1	2	**NO TIENE AHORROS 98**
¿Vendieron animales?	1	2	**NO TIENE ANIMALES 98**
¿Pidieron ayuda a través de una minga?	1	2	
¿Obtuvieron préstamos de bancos o cooperativas?	1	2	
¿Obtuvieron préstamos de amigos o familiares?	1	2	
¿Recibieron dinero de amigos o familiares que viven en el extranjero?	1	2	
¿Recibieron dinero de amigos o familiares que viven en el país?	1	2	
¿Cobraron un seguro?	1	2	**NO TIENE SEGURO 98**
¿Trabajaron tierras de otros?	1	2	
¿Vendieron tierras / terrenos propios?	1	2	**NO TIENE TIERRAS 98**
¿Redujeron gastos en salud o educación?	1	2	
¿Disminuyeron gastos en alimentación?	1	2	

5. DEFINICIÓN DEL LUGAR DE RESIDENCIA ACTUAL DEL HOGAR
HACER ESTA SECCIÓN SOLO EN PUELA, BILBAO Y COTALÓ - VERIFICAR NÚMERO DE VIVIENDAS EN PRIMERA PÁGINA

65	66	67	68	69	70
¿DÓNDE TIENE SU(S) VIVIENDA(S)? (R.U.)	**¿Y CUÁL DE ESAS VIVIENDAS ES SU RESIDENCIA PRINCIPAL*? (R.U.)**	**¿LE HAN OFRECIDO UNA VIVIENDA EN UN REASENTAMIENTO? (R.U.)**	**¿EN CUÁL CANTÓN? (R.U.)**	**¿QUÉ TIPO DE VIVIENDA LE OFRECIERON ? (R.U.)**	**¿ACEPTARON LA CASA EN EL REASENTAMIENTO? (R.U.)**
Sólo en la finca / tierras……1 **(A P.67)** Sólo en la zona de reasentamiento……………..2 En la finca y zona de reasentamiento…............. 3 En la finca y en otro lugar………….……………… 4 Sólo en otro lugar………..5 **(A P.67)**	Finca…………………….....1 Reasentamiento 2 **(A P.72)** Otro lugar…………….....3	Sí 1 No 2 **(A P.74)**	Penipe…………………1 Pallatanga…………..2 Pelileo……………..……..3	Casa de cemento / bloque / ladrillo / loza.....1 Casa de adobe / teja..……………………….…2 Casa de madera………………….….….….…..…3 Otra (especifique) ________________ No sabe el tipo ……………………………………………97	Sí 1 **A P. 72** No 2

** La residencia principal es la residencia donde los miembros del hogar duermen más de cuatro noches la semana*

71	72		73
¿POR QUÉ NO ACEPTARON LA CASA EN EL REASENTAMIENTO? (R.M.)	**¿QUÉ MIEMBROS DEL HOGAR VIVEN EN EL HOGAR REASENTADO LA MAYOR PARTE DEL TIEMPO? (R.M.)**		**¿HACE CUÁNTO TIEMPO ESTAS PERSONAS VIVEN AHÍ? (R.U.)**
No abandona su tierra……………....1	Jefe del Hogar	1	
Muy lejos de sus tierras……………..2	Cónyuge	2	
No hay medios de trabajo…………..3	Hijos / Hijas	3	Años: ________
La casa no es de buena calidad…...4	Yerno / nuera	4	Meses: _______
Otro (especifique)	Madre / padre	5	
	Hermano / hermana	6	
(PASE A P.74)	Otro familiar	7	
	Otros no familiares	8	
	Nadie vive en reasentamiento	98	

5. DATOS DE LA VIVIENDA DE LA RESIDENCIA PRINCIPAL
HACER ESTA SECCIÓN A TODOS

74	75	76	77	78	80	81
¿EL MATERIAL PREDOMINANTE DEL TECHO DE LA VIVIENDA ES...? (R.U.)	**¿El estado del TECHO de la vivienda es...? (R.U.)**	**¿El material predominante de las PAREDES de la vivienda es…? (R.U.)**	**¿Cuántos cuartos tiene su vivienda para uso exlusivo del hogar incluyendo sala y comedor? (NO INCLUYA BAÑOS, COCINAS NI NEGOCIO) (R.U.)**	**¿Tiene cuartos adicionales fuera de la vivienda? (SI RESPONDE AFIRMATIVAMENTE) ¿Cuántos cuartos fuera de la vivienda tiene? (R.U.)**	**¿Y tiene este hogar cuartos exclusivamente para negocios familiares? (R.U.)**	**¿CUÁNTOS? (R.U.)**
Palma / paja / hoja……………..1 Eternit……………..…………..2 Zinc…………………………….3 Teja……………………......….4 Hormigón / loza / cemento…...5 Otro, ¿cuál? _________________________	Bueno.…....3 Regular… ...2 Malo….. …..1	Caña…………..….…………...1 Bahareque / carrizo……..…..2 Adobe / tapia……….……..…3 Hormigón / bloque / ladrillo..….4 Eternit / cemento…………..5 Madera………………………...6 Otro, ¿cuál? ________________________	Cuartos: _________	Cuartos: _________ Ninguno 98	Sí……....1 No….…2 **(A P.82)**	__________

82	83	84	
¿Cuál es la fuente principal de energía que ocupan en esta vivienda? (R.U.)	**¿De dónde obtiene el agua principalmente esta vivienda? (R.U.)**	**¿Cuántos de los siguientes aparatos en funcionamiento tiene esta vivienda? (SI NO TIENE CONSIGNE 98) (R.U.)**	
		EQUIPAMIENTO	**NÚMERO**
Empresa eléctrica pública……...…1	Red Pública… ………………....1	Televisión	_________ 98
Planta eléctrica privada…………...2	Pila / Pileta o llave pública …....2	Radio	_________ 98
Vela / candil / mechero / gas……...3	Agua entubada ………………..3	Lavadora	_________ 98
Ninguna……....………….....……98	Carro repartidor / triciclo ……..4	Refrigerador	_________ 98
	Pozo………………..………..5	Bicicleta	_________ 98
	Río / vertiente o acequia…...…6	Motocicleta	_________ 98
		DVD	_________ 98
		Equipo de Sonido	_________ 98
	Otro, ¿cuál?	Computadora	_________ 98
	________________________	Vehículo	_________ 98
		Otro (Especifique) ________________________________	

5. DATOS DE LA VIVIENDA SECUNDARIA
(SI EN P.65 RESPONDEN 3 o 4 HAGA ESTA SECCIÓN)
(SI LA CASA FUE DESTRUÍDA CONSIGNE DESTRUÍDA 97 Y PASE A P.95)

85	86	87	88	89	90	91
¿EL MATERIAL PREDOMINANTE DEL TECHO DE LA VIVIENDA ES...? (R.U.)	**¿El estado del TECHO de la vivienda es...? (R.U.)**	**¿El material predominante de las PAREDES de la vivienda es…? (R.U.)**	**¿Cuántos cuartos tiene su vivienda para uso exlusivo del hogar incuyendo sala y comedor? (NO INCLUYE BAÑOS, COCINAS NI NEGOCIO) (R.U.)**	**¿Tiene cuartos adicionales fuera de la vivienda? (SI RESPONDE AFIRMATIVAMENTE) ¿Cuántos cuartos fuera de la vivienda tiene? (R.U.)**	**¿Y tiene este hogar cuartos exclusivamente para negocios familiares? (R.U.)**	**¿CUÁNTOS? (R.U.)**
Palma / paja / hoja……………1 Asbesto……………………....2 Zinc……………………..…..3 Teja………………………...…4 Hormigón / loza / cemento…..5 Otro, ¿cuál? ______________________ Destruída ……………97 **(A P.95)**	Bueno..……3 Regular… ..2 Malo….. ….1	Caña……………….………...1 Bahareque…………………..2 Adobe / tapia……… ……..…3 Hormigón / bloque / ladrillo….4 Eternit / cemento…….…....5 Madera……………………....6 Otro, ¿cuál? ______________________	Cuartos: _________	Cuartos: _________ Ninguno 98	Sí……....1 No…..…2 **A P.92**	

92	93	94	
¿Cuál es la fuente principal de energía que ocupan en esta vivienda? (R.U.)	**¿De dónde obtiene el agua principalmente esta vivienda? (R.U.)**	**¿Cuántos de los siguientes aparatos en funcionamiento tiene esta vivienda? (SI NO TIENE CONSIGNE 98) (R.U.)**	
		EQUIPAMIENTO	**NÚMERO**
Empresa eléctrica pública……..….1	Red Pública… ………………...1	Televisión	_________ 98
Planta eléctrica privada…………...2	Pila / Pileta o llave pública ……2	Radio	_________ 98
Vela / candil / mechero / gas……..3	Agua entubada ….…..3	Lavadora	_________ 98
Ninguna……....…………...……98	Carro repartidor / triciclo ……..4	Refrigerador	_________ 98
	Pozo……………………..……….5	Bicicleta	_________ 98
	Río / vertiente o acequia….…..6	Motocicleta	_________ 98
		DVD	_________ 98
		Equipo de Sonido	_________ 98
	Otro, ¿cuál?	Computadora	_________ 98
		Vehículo	_________ 98
	______________________	Otro (Especifique) ______________________________	

6. CARACTERÍSTICAS DE LAS TIERRAS PROPIAS CULTIVADAS DIRECTAMENTE (RESPONDE EL JEFE / A DEL HOGAR)

95 **¿TUVO USTED O ALGÚN MIEMBRO DE SU HOGAR EN EL AÑO 2015 TERRENOS PROPIOS DESTINADOS A CULTIVOS Y/O GANADERÍA? (SI CONTESTA AFIRMATIVAMENTE) ¿DÓNDE ESTÁN UBICADOS ESOS TERRENOS? (SI NO TUVO CONSIGNE 98 Y PASE A P.111) NO TUVO 98 (A P.111)**

Ahora vamos a hablar de las tierras que usted cultivó o destinó a ganadería en el año 2015.

	95	96	97	98	99	100	101	102	103
CÓDIGO TERRENO	¿EN QUÉ COMUNIDAD SE UBICA? (R.U)	¿EN QUÉ PARROQUIA SE UBICA? (R.U)	¿CUÁL ES LA SUPERFICIE DE CADA TERRENO? (CONSIGNAR LA MEDIDA Y EL TAMAÑO QUE SEÑALE EL ENTREVISTADO YA SEA EN HECTÁREAS, CUADRAS, SOLARES, METROS, ETC.) (R.U.)	¿CUENTA CON AGUA DE RIEGO ESE TERRENO? (R.U.)	¿CUÁL ES LA CALIDAD DE SUELO DE ESTE TERRENO? (R.U.)	¿CUÁL ES LA INCLINACIÓN DE ESTE TERRENO? (R.U.)	¿TIENE TÍTULO DE PROPIEDAD? (R.U.)	¿CÓMO OBTUVO ESTE TERRENO? (R.M.)	¿HAY CONSTRUCCIONES EN ESTE TERRENO? (R.U.)
			CUADRA = 7400MTS HECTÁREA = 10.000 MTS	Sí 1 No 2	Muy bueno…….4 Bueno………….3 Malo…………….2 Muy malo……...1	Plana…………..1 Ladera………..2 Quebrada……..3 Mixta (ladera / plano)………...4	Sí 1 No 2	Compra……..1 Herencia……2 Usufructo…..3 Otro………...4 Donación…..5	Sí 1 No 2 **A P.105**
	COMUNIDAD	PARROQUIA	SUPERFICIE	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO
1				1 2	4 3 2 1	1 2 3 4	1 2	1 2 3 4 5	1 2
2				1 2	4 3 2 1	1 2 3 4	1 2	1 2 3 4 5	1 2
3				1 2	4 3 2 1	1 2 3 4	1 2	1 2 3 4 5	1 2
4				1 2	4 3 2 1	1 2 3 4	1 2	1 2 3 4 5	1 2

	104	105	106	107	108	109	110
CÓDIGO TERRENO	¿QUÉ TIPO DE CONSTRUCCIONES HAY? (R.M.)	¿SE DIFICULTA EL ACCESO AL TERRENO CUANDO LLUEVE? (R.U.)	¿CUÁNTOS MINUTOS DEMORA EN TRASLADARSE EN VEHÍCULO HASTA EL LUGAR DE VENTA DE LOS PRODUCTOS? (R.U.)	¿A QUÉ DISTANCIA SE ENCUENTRA ESTE TERRENO DE LA CARRETERA MÁS CERCANA? (R.U.)	¿CUÁNTOS MINUTOS SE DEMORA PARA IR AL CANTÓN MÁS CERCANO EN VEHÍCULO? (R.U.)	¿SI FUESE A VENDER TODO ESTE TERRENO, EN CUÁNTO DINERO LO VENDERÍA? (R.U.)	¿SI FUESE A ARRENDAR TODO ESTE TERRENO, EN CUÁNTO LO ARRENDARÍA ANUALMENTE? (R.U.)
	Casa de vivienda….1 Mediagua…..……...2 Galpón…………......3 Otro……………......4	Sí 1 No 2	SI NO VENDE LOS PRODUCTOS, COLOQUE 98 - SI VENDE EN EL MISMO LUGAR CONSIGNE CERO	Ej: 100 mts = 0,1km 500 mts = 0,5km			
	CÓDIGOS	CÓDIGO	MINUTOS	KMS	MINUTOS	DÓLARES	DÓLARES
1	1 2 3 4	1 2				$	$
2	1 2 3 4	1 2				$	$
3	1 2 3 4	1 2				$	$
4	1 2 3 4	1 2				$	$

6. CARACTERÍSTICAS DE LAS TIERRAS PROPIAS DADAS EN ARRIENDO O ENTREGADAS AL PARTIR Y USUFRUCTO

111 **¿TUVO USTED O ALGÚN MIEMBRO DE SU HOGAR EN EL AÑO 2015 TERRENOS PROPIOS QUE USTED HAYA DADO EN ARRIENDO O HAYA ENTREGADO AL PARTIR O HAYA DADO EN USUFRUCTO DESTINADOS A CULTIVOS Y/O GANADERÍA? (SI CONTESTA AFIRMATIVAMENTE) ¿DÓNDE ESTÁN UBICADOS ESOS TERRENOS) (SI NO TUVO CONSIGNE 98 Y PASE A P.133) NO TUVO 98 (A P.133)**

CÓDIGO TERRENO	111	112	113	114	115
	¿EN QUÉ COMUNIDAD SE UBICA? (R.U)	¿EN QUÉ PARROQUIA SE UBICA? (R.U)	¿CUÁL ES LA SUPERFICIE DE CADA TERRENO? (CONSIGNAR LA MEDIDA Y EL TAMAÑO QUE SEÑALE EL ENTREVISTADO YA SEA EN HECTÁREAS, CUADRAS, SOLARES, METROS, ETC.) (R.U.)	¿CUENTA CON AGUA DE RIEGO ESE TERRENO? (R.U.)	¿CUÁL ES LA CALIDAD DE SUELO DE ESTE TERRENO? (R.U.)
			CUADRA = 7.400MTS HECTÁREA = 10.000MTS	Sí 1 No 2	Muy bueno…………4 Bueno……………3 Malo………………2 Muy malo……………1
	COMUNIDAD	PARROQUIA	SUPERFICIE	CÓDIGO	CÓDIGO
5				1 2	4 3 2 1
6				1 2	4 3 2 1
7				1 2	4 3 2 1
8				1 2	4 3 2 1

CÓDIGO TERRENO	116	117	118	119	120	121
	¿CUÁL ES LA INCLINACIÓN DE ESTE TERRENO? (R.U.)	¿HAY CONSTRUCCIONES EN ESTE TERRENO? (R.U.)	¿QUÉ TIPO DE CONSTRUCCIONES HAY? (R.M.)	¿SE DIFICULTA EL ACCESO AL TERRENO CUANDO LLUEVE? (R.U.)	¿CUÁNTOS MINUTOS DEMORA EN TRASLADARSE EN VEHÍCULO HASTA EL LUGAR DE VENTA DE LOS PRODUCTOS? (R.U.)	¿A QUÉ DISTANCIA SE ENCUENTRA ESTE TERRENO DE LA CARRETERA MÁS CERCANA? (R.U.)
	Plana………………………………1 Ladera……………………………2 Quebrada…………………………3 Mixto (ladera y plano)………4	Sí 1 No 2 **AP.119**	Casa de vivienda…….1 Mediagua……………..2 Galpón…………………...3 Otro……………………...4	Sí 1 No 2	**SI NO VENDE LOS PRODUCTOS, COLOQUE 98 - SI VENDE EN EL MISMO LUGAR CONSIGNE CERO**	Ej: 100 mts = 0,1km 500 mts = 0,5km
	CÓDIGO	CÓDIGO	CÓDIGOS	CÓDIGO	MINUTOS	KM
5	1 2 3 4	1 2	1 2 3 4	1 2		
6	1 2 3 4	1 2	1 2 3 4	1 2		
7	1 2 3 4	1 2	1 2 3 4	1 2		
8	1 2 3 4	1 2	1 2 3 4	1 2		

6. CARACTERÍSTICAS DE LAS TIERRAS PROPIAS DADAS EN ARRIENDO O ENTREGADAS AL PARTIR Y USUFRUCTO

CONTINUACIÓN: TIERRAS PROPIAS DADAS EN ARRIENDO O ENTREGADAS AL PARTIR Y USUFRUCTO

CÓDIGO TERRENO	122 ¿CUÁNTOS MINUTOS SE DEMORA PARA IR AL CANTÓN MÁS CERCANO EN VEHÍCULO? (R.U.)	123 ¿POR ESTE TERRENO, LE PAGAN EN...? (R.U) Dinero............1 (A P.128) Cosecha.......2 Usufructo.....3 (A P.129)	124 ¿CUÁLES PRODUCTOS RECIBIÓ USTED AL PARTIR O COMO PAGO DEL ARRIENDO? (CONSIGNE TODOS LOS PRODUCTOS QUE RECIBIÓ COMO PARTE DE PAGO) (R.M.)	125 ¿QUÉ CANTIDAD DE PRODUCTOS RECIBIÓ USTED EN TOTAL AL PARTIR O COMO PAGO DEL ARRIENDO? (CONSIGNE EL PESO TOTAL DE TODOS LOS PRODUCTOS QUE RECIBIÓ EN P.124 COMO PARTE DE PAGO) (R.U.)
	MINUTOS	CÓDIGO	PRODUCTOS	KILOGRAMOS / LITROS / UNIDAD (ANIMALES)
5	1	1 2 3 2	3m	4 Kg________ / Lt________ / U ________ 6
6	7	1 2 3 8	9m	10 Kg________ / Lt________ / U ________ 12
7	13	1 2 3 14	15m	16 Kg________ / Lt________ / U ________ 18
8	19	1 2 3 20	21m	22 Kg________ / Lt________ / U ________ 24

CÓDIGO TERRENO	126 ¿CUÁL ES EL % DE LA COSECHA QUE REPRESENTAN ESOS PRODUCTOS? (R.U.)	127 ¿A CUÁNTO DINERO EQUIVALE ESA CANTIDAD DE PRODUCTOS? (R.U.) REGISTRAR VALOR Y PASAR A P.129	128 ¿CUÁNTO LE PAGAN POR EL ARRENDAMIENTO ANUAL DE ESTE TERRENO? (R.U.)	129 ¿A QUIÉN ARRENDÓ, DIO AL PARTIR O EN USUFRUCTO ESTE TERRENO? (R.U.) Pariente.........1 Vecino...........2 Otro (especifique) ________	130 ¿CUÁL ES LA DURACIÓN DE ESE CONTRATO? (R.U.)	131 ¿DESDE HACE CUÁNTO TIEMPO USTED DIO ESTE TERRENO EN ARRIENDO O AL PARTIR AL ARRENDATARIO ACTUAL? (R.U.)	132 ¿SI FUESE A VENDER TODO ESTE TERRENO, EN CUÁNTO DINERO LO VENDERÍA? (R.U.)
	PORCENTAJE	DÓLARES	DÓLARES	CÓDIGO	MESES	AÑOS / MESES	DÓLARES
5	% 25	$ 26	$ 27	1 2 ____________ 28	29	_____ / _____	$ 32
6	% 33	$ 34	$ 35	1 2 ____________ 36	37	_____ / _____	$ 40
7	% 41	$ 42	$ 43	1 2 ____________ 44	45	_____ / _____	$ 48
8	% 49	$ 50	$ 51	1 2 ____________ 52	53	_____ / _____	$ 56

6. CARACTERÍSTICAS DE LAS TIERRAS TOMADAS EN ARRIENDO O AL PARTIR O RECIBIDAS EN USUFRUCTO

138 ¿FUE USTED O ALGÚN MIEMBRO DE SU HOGAR EN EL AÑO 2015 ARRENDATARIO O RECIBIÓ TERRENOS DE OTROS AL PARTIR DESTINADOS AL CULTIVO Y/O GANADERÍA? (SI CONTESTA AFIRMATIVAMENTE) ¿DÓNDE ESTÁN UBICADOS ESTOS TERRENOS) (SI NO TUVO CONSIGNE 98 Y PASE A P.154) NO TIENE 98 (A P.154)

CÓDIGO TERRENO	133	134	135	136	137	138	139	140	141
	¿EN QUÉ COMUNIDAD SE UBICA? (R.U)	¿EN QUÉ PARROQUIA SE UBICA? (R.U)	¿CUÁL ES LA SUPERFICIE DE CADA TERRENO? (ESPECIFICAR EN METROS CUADRADOS) (R.U.)	¿CUENTA CON AGUA DE RIEGO ESE TERRENO? (R.U.)	¿CUÁL ES LA CALIDAD DE SUELO DE ESTE TERRENO? (R.U.)	¿CUÁL ES LA INCLINACIÓN DE ESTE TERRENO? (R.U.)	¿A QUÉ DISTANCIA SE ENCUENTRA ESTE TERRENO DE LA CARRETERA MÁS CERCANA? (R.U.)	¿SE DIFICULTA EL ACCESO AL TERRENO CUANDO LLUEVE? (R.U.)	¿CUÁNTOS MINUTOS SE DEMORA PARA IR AL CANTÓN MÁS CERCANO EN VEHÍCULO? (R.U.)
			CUADRA = 7.400MTS HECTÁREA = 10.000MTS	Sí 1 No 2	Muy bueno...4 Bueno.........3 Malo........2 Muy mal......1	Plana.....................1 Ladera...................2 Quebrada...............3 Mixto(Ladera / Plano).4		Sí 1 No 2	
	COMUNIDAD	PARROQUIA	SUPERFICIE	CÓDIGO	CÓDIGO	CÓDIGO	KMS	CÓDIGO	MINUTOS
9	57	58	59	1 2 60	4 3 2 1 61	1 2 3 4 62	63	1 2 64	65
10	66	67	68	1 2 69	4 3 2 1 70	1 2 3 4 71	72	1 2 73	74
11	75	76	77	1 2 78	4 3 2 1 79	1 2 3 4 80	81	1 2 82	83
12	84	85	86	1 2 87	4 3 2 1 88	1 2 3 4 89	90	1 2 91	92

CÓDIGO TERRENO	142	143	144	145	146	147
	¿HAY CONSTRUC-CIONES EN ESTE TERRENO? (R.U.)	¿QUÉ TIPO DE CONSTRUCCIONES HAY? (R.M.)	¿CÓMO PAGA USTED POR ESTE TERRENO...? (R.U.)	¿CUÁLES PRODUCTOS DIO USTED COMO PAGO DEL ARRIENDO? (CONSIGNE TODOS LOS PRODUCTOS QUE ENTREGÓ COMO PARTE DE PAGO) (R.M.)	¿QUÉ CANTIDAD DE PRODUCTOS DIO USTED EN TOTAL COMO PAGO DEL ARRIENDO? (CONSIGNE EL PESO TOTAL DE TODOS LOS PRODUCTOS QUE ENTREGÓ EN P.145 COMO PARTE DE PAGO) (R.U.)	¿CUÁL ES EL % DE SU COSECHA QUE REPRESENTAN ESOS PRODUCTOS? (R.U.)
	Sí 1 No 2 **AP.144**	Casa de vivienda ....1 Mediagua................2 Galpón..................3 Otro.......................4	Dinero..........1 **(AP.149)** Cosecha.....2 Usufructo....3 **(A P.150)**			
	CÓDIGO	CÓDIGO	CÓDIGO	PRODUCTOS	KG/LTS/UNIDAD	PORCENTAJE
9	1 2 93	1 2 3 4 94m	1 2 3 95	96m	Kg________ / Lt_________ / U ________	100
10	1 2 101	1 2 3 4 102m	1 2 3 103	104m	Kg________ / Lt_________ / U ________	108
11	1 2 109	1 2 3 4 110m	1 2 3 111	112m	Kg________ / Lt_________ / U ________	116
12	1 2 117	1 2 3 4 118m	1 2 3 119	120m	Kg________ / Lt_________ / U ________	124

6. CARACTERÍSTICAS DE LAS TIERRAS TOMADAS EN ARRIENDO O AL PARTIR

CÓDIGO TERRENO	148	149	150	151	152	153
	¿A CUÁNTO DINERO EQUIVALE ESA CANTIDAD DE PRODUCTOS? (R.U.) REGISTRAR VALOR Y PASAR (A P.150)	¿CUANTO PAGA USTED POR EL ARRENDAMIENTO ANUAL DE ESTE TERRENO? (R.U.)	¿QUIÉN LE DIO EN ARRIENDO ESTE TERRENO? (R.U.) Pariente……...1 Vecino……..…2 Otro…..………3	¿CUÁL ES LA DURACIÓN DE ESE CONTRATO? (R.U.)	¿DESDE CUÁNDO USTED ALQUILA ESTE TERRENO AL PROPIETARIO ACTUAL? (R.U.)	¿SI FUESE A COMPRAR ESTE TERRENO, EN CUÁNTO LO COMPRARÍA? (R.U.)
	DÓLARES	DÓLARES	CÓDIGO	AÑOS / MESES	AÑOS / MESES	DÓLARES
9	$	$	1 2 3	______ / ______	______ / ______	$
10	$	$	1 2 3	______ / ______	______ / ______	$
11	$	$	1 2 3	______ / ______	______ / ______	$
12	$	$	1 2 3	______ / ______	______ / ______	$

7. ACTIVIDAD AGRÍCOLA : COSECHA Y PRÁCTICAS DE CULTIVO REALIZADAS EN EL AÑO 2015

154 (SI NO TUVO TERRENOS EN LAS SECCIONES ANTERIORES CONSIGNE 98 Y PASE A PREGUNTA 168)   NO TUVO TERRENOS 98 (A P.168)

HACER P.154 A P.160 SI RESPONDIÓ P.95 A P.110 SOBRE TERRENOS PROPIOS Y CULTIVADOS POR EL HOGAR

CÓDIGO TERRENO	154	155	156	157	158	159	160
	¿CUÁL ES LA PRINCIPAL ACTIVIDAD QUE USTED REALIZÓ EN ESTE TERRENO EN EL AÑO 2015? (R.U.)	¿CUÁL FUE EL PRINCIPAL CULTIVO QUE USTED COSECHÓ? (R.U.)	¿CUÁNTAS VECES COSECHÓ EN 2015? (R.U.)	¿CUÁL FUE LA SUPERFICIE COSECHADA? (CONSIGNAR EN METROS CUADRADOS) (R.U.)	¿CUÁL FUE LA CANTIDAD TOTAL COSECHADA DE ESTE PRODUCTO? (CONSIGNAR EN KILOS) (R.U.)	¿QUÉ CANTIDAD TOTAL DE FERTILIZANTES QUÍMICOS HA UTILIZADO? (R.U.)	¿REALIZA ROTACIÓN DE CULTIVOS EN ESTE TERRENO? (R.U.)
	AGRÍCOLA……………….......1 GANADERA / PASTOS….….2 **A P.168** AGRÍCOLA / GANADERA….3 TIERRA EN DESCANSO…......4 **A P.168** **HAGA PREGUNTAS PARA TODOS LOS 3 TIPOS DE TERRENOS ANTES DE PASAR A P.168**	**SI NO HA COSECHADO CONSIGNE 98 Y PASE A P.160**				**Si no ha utilizado consignar 98**	Sí 1 No 2
	CÓDIGO	NOMBRE DE CULTIVO	VECES	SUPERFICIE M2	KILOS	EQUIVALENCIA EN KG	CÓDIGO
1	1 2 3 4						1 2
2	1 2 3 4						1 2
3	1 2 3 4						1 2
4	1 2 3 4						1 2

HACER P.154a A P.160a SI RESPONDIÓ P.111 A P.132 SOBRE TERRENOS DE PROPIEDAD DEL HOGAR QUE DIO EN ARRIENDO, AL PARTIR O EN USUFRUCTO

	154a	155a	156a	157a	158a	159a	160a
5	1 2 3 4						1 2
6	1 2 3 4						1 2
7	1 2 3 4						1 2
8	1 2 3 4						1 2

HACER P.161 A P.167 SI RESPONDIÓ P.133 A P.153 SOBRE TERRENOS DE PROPIEDAD DE OTRAS PERSONAS QUE ARRENDÓ O TOMÓ AL PARTIR EL HOGAR

CÓDIGO TERRENO	161	162	163	164	165	166	167
	¿CUÁL ES LA PRINCIPAL ACTIVIDAD QUE USTED REALIZÓ EN ESTE TERRENO EN 2015? (R.U.)	¿CUÁL FUE EL PRINCIPAL CULTIVO QUE USTED COSECHÓ? (R.U.)	¿CUÁNTAS VECES COSECHÓ EN 2015? (R.U.)	¿CUÁL FUE LA SUPERFICIE COSECHADA? (CONSIGNAR EN METROS CUADRADOS) (R.U.)	¿CUÁL FUE LA COSECHA TOTAL DE ESTE PRODUCTO? (CONSIGNAR EN KILOS) (R.U.)	¿QUÉ CANTIDAD DE FERTILIZANTES QUÍMICOS HA UTILIZADO? (R.U.)	¿REALIZA ROTACIÓN DE CULTIVOS EN ESTE TERRENO? (R.U.)
	AGRÍCOLA……………......1 GANADERA……………......2 **(A P.168)** AGRÍCOLA / GANADERA...3	**SI NO HA COSECHADO CONSIGNE 98 PASE A P.167**				**Si no ha utilizado consignar 98**	Sí 1 No 2
	CÓDIGO	NOMBRE DE CULTIVO	VECES	SUPERFICIE M2	KILOS	EQUIVALENCIA EN KG	CÓDIGO
9	1 2 3						1 2
10	1 2 3						1 2
11	1 2 3						1 2
12	1 2 3						1 2

8. CAPITAL FÍSICO

168		169
¿QUE TIPO DE ANIMALES HA CRIADO USTED EN EL AÑO 2015? (R.M.)		**¿CUANTAS CABEZAS TENÍA EN EL 2015? (R.U.)**
NOMBRE DE ANIMALES		**CANTIDAD**
NINGUNO	98 **(A P.170)**	
GANADO VACUNO (VACAS)	1	
CABALLOS, BURROS, MULAS	2	
LLAMAS	3	
GANADO OVINO (BORREGOS)	4	
GANADO PORCINO (CERDOS)	5	
AVES Y ANIMALES DE CORRAL (GALLINAS, CUYES,CONEJOS)	6	
OTROS (Especifique) ______________________________		

	170			171
	¿ACTUALMENTE USTED TIENE? (R.U.)			**(SOLO PARA LOS EQUIPOS QUE TENGA EN P.170) ¿CUÁNTOS TIENE EN FUNCIONAMIENTO? (R.U)**
	(MARCAR CON UN CÍRCULO LA RESPUESTA EN EL CASILLERO CORRESPONDIENTE)			
		SI	**NO**	**NÚMERO**
1	ARADO ACCIONADO POR ENERGÍA HUMANA	1	2	
2	ARADO PARA ANIMALES	1	2	
4	FUMIGADORA	1	2	
5	MOTOCULTIVADORA	1	2	
6	TRACTOR	1	2	
8	SEMBRADORA	1	2	
9	COSECHADORA	1	2	
10	TRILLADORA	1	2	
11	MOTOR PARA BOMBEO DE AGUA	1	2	
12	MÁQUINA PARA RIEGO POR ASPERSIÓN	1	2	
13	CAMIÓN, CAMIONETA	1	2	
14	OTRO (Especificar) _________________________________	1	2	

11. AHORROS Y CRÉDITO

172	
¿USTED O ALGÚN MIEMBRO DE SU FAMILIA TIENE AHORROS? (SI CONTESTA AFIRMATIVAMENTE) ¿EN QUÉ TIPO DE INSTITUCIÓN TIENE SUS AHORROS? (R.M.)	
No tiene	98
Banco	1
Cooperativa	2
Caja de Ahorro	3
Amigo / pariente fuera del hogar	4
Cajas solidarias / Rueda	5
En su casa	6
Otro (especificar)_______________________________	

173	174
¿CONTRAJO SU HOGAR EN EL AÑO 2015 DEUDAS POR CRÉDITOS O PRÉSTAMOS? (R.U)	**¿CUÁNTO DINERO DEBE EL HOGAR POR ESOS CRÉDITOS O PRÉSTAMOS? (R.U)**
Sí 1 No 2 **(A P.175)**	**US $** ____________ Ya está pagado 98

9. CAPITAL SOCIAL : CONFIANZA Y SOLIDARIDAD

175 En general, ¿qué tanto confía usted en las siguientes personas? **(LEER ALTERNATIVAS) (R.U.)**

	Mucho	Algo	Poco	Nada
Parientes	4	3	2	1
Otra persona de su comunidad	4	3	2	1
Otra persona de su conocimiento	4	3	2	1
Vigías del volcán	4	3	2	1
Autoridades locales	4	3	2	1
Autoridades nacionales	4	3	2	1
Instituto Geofísico	4	3	2	1

17

HACER P.176 SOLO EN PUELA, BILBAO Y COTALÓ

176 ¿Después del inicio de las erupciones del volcán Tungurahua en el año 1999, su opinión sobre la bondad de las siguientes personas es...? **(LEER ALTERNATIVAS) (R.U.)**

	Mucho mejor que antes	Mejor que antes	Igual	Peor que antes	Mucho peor que antes
Parientes	5	4	3	2	1
Otra persona de su comunidad	5	4	3	2	1
Otra persona de su conocimiento	5	4	3	2	1
Vigías del volcán	5	4	3	2	1
Autoridades locales	5	4	3	2	1
Autoridades nacionales	5	4	3	2	1
Instituto Geofísico	5	4	3	2	1

177 ¿Participa usted en asociaciones u organizaciones locales como ...? **(R.U.)**

	SÍ	**NO**
Cooperativa agrícola	1	2
Comité Barrial / Comunitario	1	2
Iglesia	1	2
Grupo de ahorro	1	2

178 En general, ¿qué tan de acuerdo o en desacuerdo está usted con las siguientes afirmaciones? **(R.U.)**

	Totalmente de acuerdo	De acuerdo	Ni de acuerdo, ni en desacuerdo	En desacuerdo	Totalmente en desacuerdo
La mayoría de las personas en la comunidad están dispuestos a ayudarlo a usted si lo necesita	5	4	3	2	1
En esta comunidad, las personas no tienen confianza para prestar y pedir dinero prestado	5	4	3	2	1

9. CAPITAL SOCIAL : RED SOCIAL Y COOPERACIÓN

179 Si usted necesitase una pequeña cantidad de dinero como por ejemplo para pagar los gastos de su hogar para una semana, ¿Cuántas personas que no viven en su hogar cree que podrían ayudarle? **(R.U.)**

Cantidad: ☐

180 Si usted tiene un problema grave como la perdida total de la cosecha o animales, ¿cuántas personas que no viven en su hogar cree que podrían ayudarle? **(R.U.)**

Cantidad: ☐

181 En el año 2015, ¿cuántas personas que tuvieron problemas económicos le pidieron su ayuda? **(R.U.)**

Cantidad: ☐

	SI	**NO**
182 ¿En el año 2015 regaló dinero a amigos o familiares? **(R.U.)**	1	2
183 ¿En el año 2015 prestó dinero a amigos o familiares? **(R.U.)**	1	2

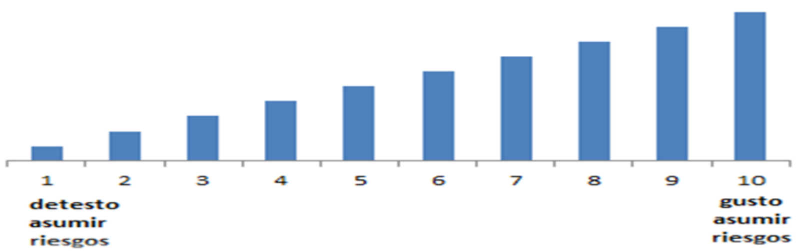
184 En general ¿Qué cantidad de personas en su comunidad contribuyen con tiempo o dinero a actividades comunes tales como la reparación de una carretera, mingas, etc., por ejemplo? **(R.U.)**

Todo el mundo	1
Más de la mitad	2
Casi la mitad	3
Menos de la mitad	4
Nadie	98

185 Supongamos que alguien de la comunidad enferme gravemente. ¿Qué tan probable es que algunas personas de la comunidad se reúnan para ayudarle? **(LEER ALTERNATIVAS) (R.U.)**

Muy probable	4
Probable	3
Poco probable	2
Nada probable	1

186 **En una escala de 1 a 10 donde 1 es Detesto asumir riesgos y 10 es Me gusta asumir riesgos. ¿Cómo evaluaría usted su disposición a tomar riesgos? (R.U.)**



10. CARACTERÍSTICAS DE LOS MIEMBROS DEL HOGAR

	187	188	189	190		191	192	193
CÓDIGO IDENTIFICACIÓN	AHORA HAREMOS UNA LISTA COMPLETA DE LAS PERSONAS QUE COMEN Y DUERMEN EN ESTE HOGAR (INCLUYENDO VIVIENDA EN ZONA DE REASENTAMIENTO) COMENZANDO POR EL JEFE DE HOGAR HASTA EL DE MENOR EDAD.	**¿CUÁL ES LA RELACIÓN DE PARENTESCO CON EL JEFE DEL HOGAR? (R.U.)**	**SEXO (R.U.)**	**¿QUÉ EDAD TIENE EN AÑOS CUMPLIDOS? (R.U.)**		**¿CUÁL ES EL ESTADO CIVIL O CONYUGAL? (R.U.)**	**¿ESTA PERSONA DUERME EN LA VIVIENDA PRINCIPAL? (R.U.)**	**¿DÓNDE DUERME ESTA PERSONA? (R.U.)**
		Jefe / Jefa de hogar..........1 Esposa (o)……………......2 Hijo (a)……..……..........3 Yerno / Nuera……..….....4 Padres / Suegros…..…....5 Otros parientes……….... 6 Otros No Parientes……....7	Hombre …...1 Mujer ……...2		PARA MENORES DE UN AÑO	PARA 12 AÑOS DE EDAD Y MÁS Unión libre……….....1 Casado (a)……......2 Viudo (a)…………..3 Divorciado (a).........4 Separado (a)…….. 5 Soltero (a)……..... 6	Todas las noches….. 1 **A P.194** Parte de la semana.....2 No duerme aquí……...3	Sólo en la finca…..…………1 Sólo en la zona de reasentamiento…..…………..2 Sólo en otro lugar……………………..…...3
	NOMBRE	CÓDIGO	CÓDIGO	AÑOS	MESES	CÓDIGO	CÓDIGO	CÓDIGO
1		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
2		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
3		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
4		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
5		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
6		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
7		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
8		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
9		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
10		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
11		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3
12		1 2 3 4 5 6 7	1 2			1 2 3 4 5 6	1 2 3	1 2 3

* En caso de doble residencia hacer la lista de todas las personas que viven en las dos viviendas

11. OCUPACIÓN DE LOS MIEMBROS DEL HOGAR DE 10 AÑOS Y MÁS (HOGAR PRINCIPAL Y HOGAR REASENTADO) EN EL AÑO 2015

CÓDIGO IDENTIFICACIÓN	194	195	196	197	198	199	200
	¿TRABAJÓ EN SU CHACRA Y / O CRIANZA DE SUS ANIMALES? (R.U.)	¿SE DEDICÓ A UN NEGOCIO O EMPRESA DE COMERCIO? (R.U.)	¿PREPARÓ ALIMENTOS, COSIÓ O TEJIÓ PRENDAS PARA LA VENTA? (R.U.)	¿PRESTÓ ALGÚN SERVICIO PROFESIONAL, O REALIZÓ ALGUNA ACTIVIDAD A CAMBIO DE PAGO? (R.U.)	¿TRABAJÓ PARA UNA EMPRESA, EL GOBIERNO, UN PATRÓN, U OTRO PARTICULAR? (R.U.)	EXAMINAR LAS RESPUESTAS DE PREGUNTAS 194 A 198	¿QUÉ ESTUVO HACIENDO? (R.U.)
		TRABAJO INDEPENDIENTE NO AGRÍCOLA O PROPIO DEL HOGAR					
	Sí…….1 No…...2	Sí…….1 No…...2	Sí…….1 No…...2	Sí…….1 No…...2	Sí…….1 No…...2	SI TODAS LAS RESPUESTAS PARA UNA PERSONA SON NEGATIVAS, CONTINÚE CON LA PREGUNTA SIGUIENTE, CASO CONTRARIO CIRCULE 1 EN LA FILA QUE APLIQUE Y PASE A LA SIGUIENTE SECCIÓN	Estudiando……...……..….1 Quehaceres del hogar..….2 Vivía de sus rentas….…..3 Enfermo o incapacitado….4 Servicio Militar ……….…..5 Buscando empleo………..6 Otro (Especificar) ____________________
	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO
1	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
3	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
4	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
5	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
6	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
7	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
8	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
9	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
10	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
11	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________
12	1 2	1 2	1 2	1 2	1 2	1	1 2 3 4 5 6 __________

12. TRABAJO DEPENDIENTE O ASALARIADO DE LOS MIEMBROS DEL HOGAR MAYORES DE 10 AÑOS Y MÁS

SÓLO PARA QUIENES EN P.198 HAYAN RESPONDIDO "SÍ"

CODIGO IDENTIF	201		202		203		204		205		206	
	POR FAVOR DÍGAME LAS DOS PRINCIPALES LABORES QUE CADA MIEMBRO DEL HOGAR MAYOR DE 10 AÑOS REALIZÓ DURANTE EL AÑO 2015 (R.M.)		¿A QUÉ ACTIVIDAD SE DEDICA EL NEGOCIO, LA EMPRESA U ORGANISMO EN EL QUE USTED TRABAJÓ? (R.U.)		¿A QUÉ SECTOR PERTENECE LA EMPRESA, EL NEGOCIO, U ORGANISMO EN EL QUE USTED TRABAJÓ? (R.U.)		¿EN LA OCUPACION, TAREA O LABOR, TRABAJÓ COMO…? (LEER ALTERNATIVAS) (R.U.)		¿DÓNDE SE UBICA LA EMPRESA, NEGOCIO U ORGANISMO EN EL QUE USTED TRABAJÓ? (R.U.)		¿CUÁNTO SE DEMORA USTED EN LLEGAR A SU TRABAJO? (R.U.)	
					Sector publico…1 Sector privado..2		Empleado permanente…….1 Empleado temporal……..…2 Empleado eventual…..……..3		Mismo pueblo……..……..1 Cantón más cerca……....2 Misma parroquia………..3 Mismo cantón…....……..4 Misma provincia……........5 Otra provincia.….............6 Quito……………….…..…7			
	OCUPACIÓN PRINCIPAL	OCUPACIÓN SECUNDARIA	ACTIVIDAD PRINCIPAL	ACTIVIDAD SECUNDARIA	OCUP 1	OCUP 2	OCUP 1	OCUP 2	OCUP 1	OCUP 2	MN 1	MN 2
1					1 2	1 2	1 2 3	1 2 3				
2					1 2	1 2	1 2 3	1 2 3				
3					1 2	1 2	1 2 3	1 2 3				
4					1 2	1 2	1 2 3	1 2 3				
5					1 2	1 2	1 2 3	1 2 3				
6					1 2	1 2	1 2 3	1 2 3				
7					1 2	1 2	1 2 3	1 2 3				
8					1 2	1 2	1 2 3	1 2 3				
9					1 2	1 2	1 2 3	1 2 3				
10					1 2	1 2	1 2 3	1 2 3				
11					1 2	1 2	1 2 3	1 2 3				
12					1 2	1 2	1 2 3	1 2 3				

Empleado permanente : no tiene tiempo fijo de terminación
Empleado temporal : tiene tiempo fijo de terminación (3 meses o mas)
Empleado eventual : (menos de 3 meses)

13. EDUCACIÓN DE LOS MIEMBROS DEL HOGAR : ESCOLARIDAD (DESDE 4 AÑOS EN ADELANTE)

CÓDIGO IDENTIFICACIÓN	207	208	209	210	211	212	213	214
	¿DURANTE EL AÑO 2015 USTED ASISTIÓ A ALGÚN CENTRO DE ENSEÑANZA? (R.U.)	¿Por que razón no se matriculó? (R.U.)	¿CUÁL ES EL ÚLTIMO NIVEL DE ESTUDIOS QUE APROBÓ? (R.U.)	SI LA RESPUESTA A LA PREGUNTA 209 FUE 6, 8 ó 9 PREGUNTE ¿EN ESE ÚLTIMO NIVEL OBTUVO UN TÍTULO? (R.U.)	¿HACE CUÁNTOS AÑOS DEJÓ DE ESTUDIAR? (R.U.)	¿REPITIÓ ALGUNOS AÑOS? (R.U.)	¿CUÁNTAS VECES? (R.U.)	¿QUÉ GRADOS O CURSOS? (R.M.)
	Sí 1 **(A P.209)** No 2	Edad……………………1 Falta de dinero…………2 Trabajo…………………3 Lab. Domésticas…………4 Terminó estudios…………5 No le interesa……………6 Enfermedad………………7 Embarazo…………………8 Discapacidad……………9 Otro, ¿cuál?______________	Ninguno…………………………98 **(A P.215)** Centro de alfabetización………1 **(A P.211)** Pre primaria……………………2 **(A P.211)** Primaria incompleta……………3 **(A P.211)** Primaria completa………………4 **(A P.211)** Secundaria incompleta…………5 **(A P.211)** Secundaria completa……………6 Universidad incompleta…………7 **(A P.211)** Universidad completa……………8 Maestría / Post grado……………9	Sí 1 No 2	SI SIGUE ESTUDIANDO CONSIGNE **50**	Sí 1 No 2 **A P.215**		ESPECIFICAR EN GRADOS O CURSOS
	CÓDIGO	CÓDIGO	CÓDIGO	CÓDIGO	AÑO	CÓDIGO	VECES	GRADO (S)
1	1 2 173	1 2 3 4 5 6 7 8 9 ______ 174	1 2 3 4 5 6 7 8 9 98 175	1 2 176	______ 50 177	1 2 178	179	180
2	1 2 181	1 2 3 4 5 6 7 8 9 ______ 182	1 2 3 4 5 6 7 8 9 98 183	1 2 184	______ 50 185	1 2 186	187	188
3	1 2 189	1 2 3 4 5 6 7 8 9 ______ 190	1 2 3 4 5 6 7 8 9 98 191	1 2 192	______ 50 193	1 2 194	195	196
4	1 2 197	1 2 3 4 5 6 7 8 9 ______ 198	1 2 3 4 5 6 7 8 9 98 199	1 2 200	______ 50 201	1 2 202	203	204
5	1 2 205	1 2 3 4 5 6 7 8 9 ______ 206	1 2 3 4 5 6 7 8 9 98 207	1 2 208	______ 50 209	1 2 210	211	212
6	1 2 213	1 2 3 4 5 6 7 8 9 ______ 214	1 2 3 4 5 6 7 8 9 98 215	1 2 216	______ 50 217	1 2 218	219	220
7	1 2 221	1 2 3 4 5 6 7 8 9 ______ 222	1 2 3 4 5 6 7 8 9 98 223	1 2 224	______ 50 225	1 2 226	227	228
8	1 2 229	1 2 3 4 5 6 7 8 9 ______ 230	1 2 3 4 5 6 7 8 9 98 231	1 2 232	______ 50 233	1 2 234	235	236
9	1 2 237	1 2 3 4 5 6 7 8 9 ______ 238	1 2 3 4 5 6 7 8 9 98 239	1 2 240	______ 50 241	1 2 242	243	244
10	1 2 245	1 2 3 4 5 6 7 8 9 ______ 246	1 2 3 4 5 6 7 8 9 98 247	1 2 248	______ 50 249	1 2 250	251	252
11	1 2 253	1 2 3 4 5 6 7 8 9 ______ 254	1 2 3 4 5 6 7 8 9 98 255	1 2 256	______ 50 257	1 2 258	259	260
12	1 2 261	1 2 3 4 5 6 7 8 9 ______ 262	1 2 3 4 5 6 7 8 9 98 263	1 2 264	______ 50 265	1 2 266	267	268

14. MIGRACIÓN DE LOS MIEMBROS DEL HOGAR (PARA TODOS LOS ADULTOS MAYORES DE 18 AÑOS)

CÓDIGO IDENTIFICACIÓN	215		216		217	218		219	220	221	222
	¿EN QUÉ PARROQUIA NACIÓ USTED? (R.U.) SI NACIERON EN LA PARROQUIA DE LA ENCUESTA, CONSIGNE EL NOMBRE DE ÉSTA Y PASE A P.217		¿EN QUÉ CIUDAD SE UBICA ESTA PARROQUIA DONDE NACIÓ? (R.U.)		¿HA VIVIDO USTED EN OTRO LUGAR ANTES DE VENIRSE A VIVIR AL LUGAR (O LUGARES) DE RESIDENCIA ACTUAL? (R.U.) Sí 1 No 2 **A P.220**	¿EN QUÉ CIUDAD VIVÍA USTED ANTES DE VENIRSE VIVIR AL LUGAR (O LUGARES) DE RESIDENCIA ACTUAL? (R.U.)		¿POR QUÉ RAZÓN VINO USTED A VIVIR AL LUGAR (O LUGARES) DE RESIDENCIA ACTUAL? (R.U.) Por empleo.........1 Volcán...............2 Familiar...............3 Salud...............4 Otra razón ________	(SOLO PARA JEFE DE HOGAR. OTROS PASE A SECCIÓN 16) ¿HA PASADO USTED ALGUNA VEZ MÁS DE UN AÑO FUERA DE SU HOGAR? (R.U.) Sí 1 No 2 **A P.223**	¿DÓNDE? (R.U.)	¿POR QUÉ RAZÓN? (R.U.)
	NOMBRE	CÓDIGO	NOMBRE	CÓDIGO	CÓDIGO	NOMBRE	CÓDIGO	CÓDIGO	CÓDIGO	LOCALIDAD	RAZÓN
1	13		14		1 2 15	16		1 2 3 4 ______ 17	1 2 18	19	20
2	21		22		1 2 23	24		1 2 3 4 ______ 25			
3	26		27		1 2 28	29		1 2 3 4 ______ 30			
4	31		32		1 2 33	34		1 2 3 4 ______ 35			
5	36		37		1 2 38	39		1 2 3 4 ______ 40			
6	41		42		1 2 43	44		1 2 3 4 ______ 45			
7	46		47		1 2 48	49		1 2 3 4 ______ 50			
8	51		52		1 2 53	54		1 2 3 4 ______ 55			
9	56		57		1 2 58	59		1 2 3 4 ______ 60			
10	61		62		1 2 63	64		1 2 3 4 ______ 65			
11	66		67		1 2 68	69		1 2 3 4 ______ 70			
12	71		72		1 2 73	74		1 2 3 4 ______ 75			

15. TRABAJO INDEPENDIENTE : INFORMACIÓN DE LOS NEGOCIOS QUE TIENE EL HOGAR

SI ALGUNA DE LAS RESPUESTAS A LAS PREGUNTAS 195 A 197 ES AFIRMATIVA HAGA ESTAS PREGUNTAS

223	224	225
¿CUÁLES FUERON LOS DIFERENTES NEGOCIOS O EMPRESAS DE COMERCIO, INDUSTRIA, SERVICIOS O PROFESIONES QUE EL HOGAR HA DESARROLLADO EN EL AÑO 2015? (R.M.)	**¿Y DE ÉSTAS (P.223), CUÁL FUE LA MÁS IMPORTANTE PARA EL HOGAR? (R.U.)**	**¿DÓNDE FUNCIONABA ESTA EMPRESA O NEGOCIO (P.224)...? (LEER ALTERNATIVAS) (R.U.)**
1		En el hogar…..……………1
2		En otro local fijo…........2
3		Se desplaza…………..……3

226	227
¿ESTA EMPRESA, NEGOCIO, O TRABAJO SUFRIÓ DAÑOS POR LA ERUPCIÓN DE MARZO DE 2016? (R.U.)	**¿EN CUÁNTO DINERO ESTIMA USTED LOS DAÑOS A SU EMPRESA, NEGOCIOS Y A SUS BIENES? (R.U.)**
Sí 1 No 2 **A P.228**	$ ______________

16. CARACTERÍSTICAS DE LA FAMILIA DEL JEFE DEL HOGAR QUE NO VIVEN EN EL HOGAR ENCUESTADO

	228	229	230	231	232	233			
CÓDIGO IDENTIFICACIÓN	AHORA HAREMOS UNA LISTA DE LAS PERSONAS DE LA FAMILIA DEL JEFE / A DE HOGAR QUE NO VIVEN EN SU HOGAR PRINCIPAL NI EN SU HOGAR EN ZONA DE REASENTAMIENTO	¿CUÁL ES LA RELACIÓN DE PARENTESCO CON EL JEFE DEL HOGAR? (R.U.)	SEXO (R.U.)	¿QUÉ EDAD TIENE EN AÑOS CUMPLIDOS? (R.U.)	¿CUÁL ES SU ESTADO CIVIL O CONYUGAL? (R.U.)	¿DÓNDE VIVEN? (R.U.)			
	PREGUNTAR POR PADRES, HERMANOS, HIJOS, EX ESPOSO/A QUE NO VIVAN EN EL HOGAR DEL JEFE DE HOGAR ENCUESTADO	Padre, madre.......1 Esposa (o)……...2 Hijo (a)…………...3 Hermano (a)…….4 Otro…………..…..5	Hombre 1 Mujer 2	SI ES MENOR DE UN AÑO COLOCAR 98	PARA 12 AÑOS DE EDAD Y MÁS Unión libre……..1 Casado (a)……...2 Viudo (a)………..3 Divorciado (a).....4 Separado (a)….. 5 Soltero (a)…….. 6	Misma parroquia Sí 1 **A P.234** No 2	Otra parroquia / ciudad (Escriba el nombre de la parroquia / ciudad)	Otra provincia (Escriba el nombre de la provincia)	Extrajero (Escriba el nombre del país)
	NOMBRE	CÓDIGO	CÓDIGO	AÑOS	CÓDIGO	CÓDIGO	NOMBRE	NOMBRE	NOMBRE
1		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
2		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
3		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
4		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
5		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
6		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
7		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
8		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
9		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
10		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
11		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			
12		1 2 3 4 5	1 2		1 2 3 4 5 6	1 2			

16. CARACTERÍSTICAS DE LA FAMILIA DEL JEFE DEL HOGAR QUE NO VIVEN EN EL HOGAR ENCUESTADO

		234	235	236	237
	CÓDIGO IDENTIFICACIÓN	¿HACE CUÁNTOS AÑOS DEJARON DE VIVIR CON USTED? (R.U.)	¿A QUÉ SE DEDICAN? (R.U.) Estudian…………………………1 Trabajan…………………………2 Otro (Especif.)_____________	¿En el año 2015 _____ (nombre) le ha enviado o entregado dinero o especies? (R.U.) Sí 1 No 2 **TERMINE**	¿POR QUÉ MONTO EN TOTAL? (R.U.)
		AÑO	CÓDIGO	CÓDIGO	MONTO
191	1	203	1 2 ________ 204	1 2 205	$ 206
192	2	207	1 2 ________ 208	1 2 209	$ 210
193	3	211	1 2 ________ 212	1 2 213	$ 214
194	4	215	1 2 ________ 216	1 2 217	$ 218
195	5	219	1 2 ________ 220	1 2 221	$ 222
196	6	223	1 2 ________ 224	1 2 225	$ 226
197	7	227	1 2 ________ 228	1 2 229	$ 230
198	8	231	1 2 ________ 232	1 2 233	$ 234
199	9	235	1 2 ________ 236	1 2 237	$ 238
200	10	239	1 2 ________ 240	1 2 241	$ 242
201	11	243	1 2 ________ 244	1 2 245	$ 246
202	12	247	1 2 ________ 248	1 2 249	$ 250