1 Introduction

How natural disasters affect economic development became a burning issue over the last few years. In fact, according to the CRED (2015),[1] during the 2004-2013 period, natural disasters increased in frequency, though not monotonically, claiming 1.35 million of lives and causing USD 2,600 billion of losses. This increase was largely due to a sustained rise in the number of climate related disasters such as storms or floods. On the contrary, the number of geophysical disasters remain stable throughout the past 20 years. Among environmental hazards, volcanic eruptions seem marginal as they only represent one percent of the occurrence of natural disasters. However, despite the relatively low number of volcanic events, 800 million persons are considered to live under the threat of a volcano. Moreover, this threat is not homogeneously distributed around the globe, making countries as Indonesia, Philippines or Mexico extremely concerned about volcanic hazards. In developing countries, where people are the most vulnerable, eruptions can have a wide range of effects. For instance, ash fall, which affected more than two million persons over the last 20 years, may cause crop losses, animal deaths, roof collapses and may also affect individual health. Understanding the consequences of volcanic hazards on households' asset accumulation appears, therefore, as a main concern.

The recent empirical literature provides evidence on the impact of natural disasters on households' well-being. Results suggest an adverse effect on the short run, but remain ambiguous on the ability of households to recover on the long run. However, assets destruction or income loss are not the only way through which natural disasters affect households' asset accumulation. In fact, the theoretical literature has long highlighted the impact of risk exposure on investment decision. However, this ex-ante effect is undetermined both in its sign and its magnitude, and then remains an empirical question. In addition, a burgeoning literature has highlighted that affected people temporary change their risk perception about future shocks in the wake of natural disasters.

Quantifying these last two effects on capital accumulation, namely the ex-ante effect and the impact of changes in risk perception after a shock, is the aim of this paper. To this end, we focus on Indonesia, one of the most exposed and vulnerable country to volcanic risk in the world. Identifying these effects is beyond the possibilities of reduced form empirical models and calls for a structural approach. In fact, comparing households affected by volcanoes with non exposed households would not allow to disentangle the behavioral effect from the shock itself. Moreover, we are not aware of any micro data on households exposed to volcanic risk, which requires the use of simulations. We follow the method proposed by Elbers et al. (2007). In a first step, we estimate a stochastic growth model based on the Indonesian Family Life Survey dataset over the 1993-2007 period. 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, that are drawn from the literature based on fieldwork. Similarly, values to characterize changes in risk perception are drawn from the literature.

This paper makes three main contributions to the literature. First, while empirical papers focus on the ex-post consequences of natural disasters on households' well-being, 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. Third, our structural approach offers a long-run overview of the asset accumulation path while reduced form studies are limited by their data

[1] Center for Research on the Epidemiology of Disasters.

time span.

Our results show that the ex-ante effect of volcanic risk on investment is negative and relatively strong as it accounts for around one-third of the total cost. In addition, changes in risk perception after an eruption worsen the economic damages of income and asset losses. Indeed, changes in beliefs slow down the recovery process and have long lasting effects which incur non negligible losses in capital. 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 half of total losses.

The remainder of the paper is as follows. Next, we discuss the related literature. Section 3 describes the data and the sample characteristics. Section 4 exposes the model. Section 5 discusses the estimation methods. Section 6 is devoted to the characterization of volcanic hazard, the simulations and a discussion of the results. Finally, Section 7 concludes.

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 savings. 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 are 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.

Apart from the theoretical literature, numerous articles empirically investigate the impact of natural disasters on countries' growth and households' poverty. At the aggregate level, three types of conclusions emerge. First, some papers show that natural disasters promote growth through creative destruction or a "build back better" phenomena (Hallegatte and Dumas 2009), or through an increase in human capital accumulation (Skidmore and Toya 2002). Second, others defend the idea of a recovery to the trend. In other words, natural disasters are neutral toward growth as the temporary loss is recovered in the following years (Crowards 1999, Charvériat 2000). Finally, some papers argue that the GDP loss incurred by natural disasters cannot be recovered as the resources spent to build back are taken away from others more productive investments (Noy 2009, Hsiang and Jina 2014). At the microeconomic level, conclusions do not converge neither. On the one hand, some authors show the adverse impact of natural disasters. For instance, Rodriguez-Oreggia et al. (2013) investigate, 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. The long lasting effect of shocks on consumption growth has also been highlighted by Dercon (2004) in rural Ethiopia. Similarly, Arouri et al. (2015) conclude to adverse effects of natural disasters on welfare and poverty of rural households in Vietnam and highlight the role of credit and remittances in the resilience process. On the other hand, some papers conclude to a positive effect. Leiter et al. (2009) find that, in Europe, companies in regions hit by floods show higher growth of total assets than firms in non affected regions. 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.

In addition to economic consequences, a recent literature has pointed out the effect of natural disasters on individual behaviors. Using experimental and survey data on Nicaragua and Peru, van den Berg et al. (2009) show that households reporting losses due to hurricane Mitch are more risk averse than others. Cameron and Shah (2015) run a similar study in Indonesia. Investigating the role of recurrent floods and earthquakes, they also conclude that being affected by such events lead to more risk averse behavior. They show that experiencing a natural disaster leads people to perceive the world as a much riskier place than it is actually. Reynaud and Aubert (2013) use the framework of the prospect theory and show that households having experienced a flood in Vietnam exhibit more risk aversion in the loss domain than unaffected people. Samphantharak and Chantarat (2015) study the impact of the 2011 mega flood on Thai farmers. In accordance with Cameron and Shah (2015), they find that affected individuals are more risk averse and overweight the probability of future floods. Studying the same disaster in Cambodia, Chantarat et al. (2015) find that affected farmers are more risk averse and less impatient than others. These papers also suggest that, as time goes by, differences in risk preferences are likely to vanish. This is confirmed by Becchetti et al. (2012) who do not find any significant differences in risk and time preferences seven years after the 2004 tsunami. Interestingly, these conclusions are supported by recent neurological research showing that increasing risk raises the level of cortisol (a steroid hormone) in the blood (Coates and Herbert 2008) which in turn, makes people more risk averse (Kandasamy et al. 2014). However some papers find opposite results. For instance, Ingwersen (2014) studies the impact of the 2004 tsunami on Indonesian households and finds evidence of a decrease in observed risk aversion among the affected population. Studies on developed countries such as Eckel et al. (2009), Hanaoka et al. (2015) and Page et al. (2014) reach similar conclusions. Regardless of the direction risk preferences shift, these empirical findings greatly challenged the standard assumption of stability of individual risk preference across time (Stigler and Becker 1977). Risk preferences play a key role in the resilience process as they determine a wide range of households' behaviors such as saving, adoption of self-insurance strategies (Dionne and Eeckhoudt 1985), and investment in human capital (Baez et al. 2010). To that extent, the consequences of changes in observed risk aversion deserve attention.

3 Data and Sample Characteristics

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. This event recalls that, with 142 volcanoes, Indonesia is the most exposed country to volcanic risk in the world. The risk is even strengthen by the great density of population leaving close to a volcano. In fact, 8.6 million inhabitants live in a perimeter of 10 km to the volcano, 68 million at 30 km and 179 million at 100 km which makes Indonesia not only the most exposed but also one of the most vulnerable country to volcanic hazards (Brown et al. 2015).

The Indonesian Family Life Survey (IFLS) is an on-going longitudinal survey in Indonesia. The sample is representative of about 83% of the Indonesian population and 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 use simulations and therefore to search for an additional dataset, which we present in Section 6, to characterize the volcanic risk. Thus, we decide to focus only on households that have similar characteristics to those actually living on the flanks volcanoes. Due to high soil fertility, areas around volcanoes are usually devoted to agricultural activities (Annen and Wagner 2003 and Muzayyanah et al. 2013). Then, we restrict the sample to self employed farmers in rural areas that have been observed over the four waves. We are left with a balanced dataset of 90 households for which we provide descriptive statistics in Table 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 or heavy equipment. In addition to farm activity, around 15% of the sample reports to have at least one non-farm business. The literature (Fafchamps and Lund 2003 among others) suggests that non-farm income can represent the main source of revenue for rural households. Then, we may worry that this extra-activity affects the level of investment in farm assets. To investigate whether it is the case or not, 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. This is consistent with the fact that non-farm business is rather exceptional as most households only report it once over the four waves.

Table 1: Summary statistics

Variable	1993	1997	2000	2007
Household size	5.94 (1.99)	6.68 (2.18)	7.26 (2.28)	8.11 (2.72)
Dependency ratio	0.68 (0.60)	0.56 (0.48)	0.54 (0.49)	0.52 (0.49)
Age of household head	50.46 (11.77)	53.66 (11.49)	54.81 (10.85)	61.92 (10.33)
Share of male headed household	0.89 (0.32)	0.89 (0.32)	0.89 (0.31)	0.89 (0.31)
Share of 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)
Owning equipment	0.04 (0.21)	0.02 (0.15)	0.06 (0.25)	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)
Value of equipment (*ln*)	11.14 (1.98)	14.27 (1.63)	13.78 (2.72)	13.07 (2.01)
Non-farm business	0.16 (0.36)	0.11 (0.32)	0.16 (0.36)	0.17 (0.37)
Non-farm income (*ln*)	12.72 (2.69)	13.25 (1.39)	9.65 (6.41)	-

Notes: Mean values of variables. Standard deviations are in parentheses. Household size is the number of people by household; Dependency ratio is computed as the ratio between the number of householders younger than 15 and older than 64, over the number of householders between 15 and 64 years old; Share of male headed household is a dummy variable taking the value one if the household is headed by a male and zero otherwise; Share of 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 is a dummy variable taking the value one if the household owns land and zero otherwise; Owning livestock is a dummy variable taking the value one if the household owns livestock and zero otherwise; Owning tools is a dummy variable taking the value one if the household owns tools and zero otherwise; Owning tractor is a dummy variable taking the value one if the household owns a tractor and zero otherwise; Owning equipment is a dummy variable taking the value one if the household owns heavy equipment and zero otherwise; Value of land is the logarithm of the value of land (in Indonesian rupiahs) owned by the household. Value of livestock is the logarithm of the value of livestock (in Indonesian rupiahs) owned by the household. Value of tools is the logarithm of the value of tools (in Indonesian rupiahs) owned by the household. Value of tractor is the logarithm of the value of tractor (in Indonesian rupiahs) owned by the household. Value of equipment is the logarithm of the value of heavy equipment (in Indonesian rupiahs) owned by the household. 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. Non-farm income is the logarithm of the value (in Indonesian rupiahs) of non-farm income generated by the household. Source: author's elaboration on IFLS panel data.

4 The Model

We start from a standard stochastic Ramsey model in which households draw their income from a stochastic production process that involves one type of capital and labor. Income is affected by idiosyncratic shocks that are $i.i.d$ and drawn from a centered Gaussian distribution. Households are 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:

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

subject to:

$$c_{ht} + i_{ht} = s_{ht} y_{ht} \tag{2}$$

$$k_{ht+1} = (1-\delta)k_{ht} + i_{ht} \tag{3}$$

$$y_{ht} = a_h f(k_{ht}, l_{ht}) \tag{4}$$

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.

Despite being appealing in many ways, structural models are also extremely sensible to misspecifications. In light of the descriptive statistics exposed in the previous section, some assumptions call for clarifications. For instance, while the model only allows for a single type of capital, descriptive statistics show that households use several inputs in their farm business. Allowing for multiple assets in the production process would greatly increase the computational burden of estimating and simulating the model without bringing substantial benefits in the analysis. Indeed, all productive assets are likely to be affected by eruptions. We show in the next section how we aggregate the different types of assets into a single bundle of capital. We also assume that the unique income source is the farm business, an assumption that completely rules out any income diversification strategy. Although this assumption is challenged by a fraction of the sample, we show in the previous section that having an extra business does not influence farm assets accumulation (Table A1). Moreover, we assume that no risk pooling arrangements occurs between households, so that consumption smoothing is the only risk coping strategy available to households. However, informal risk sharing is well known to happen in developing countries (Townsend 1994 and many others). We believe, nevertheless, that this shortcoming is unlikely to affect our conclusions as informal risk pooling is vain against covariate shocks.

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 elasticities of capital and labor 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.

5.1 Production Function Parameters

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

$$y_{ht} = a_{ht} l_{ht}^{\gamma} \prod_{i=1}^{I} k_{iht}^{\alpha_i} \tag{5}$$

where y denotes farm income, a is the 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 usual objection to direct estimation of this equation is that output and inputs may be simultaneously determined. In fact, if the decision taker in the household has prior knowledge of a_{ht} at the time input decisions are made, endogeneity arises because inputs quantities will be partly determined by prior beliefs about its productivity. We assume that the productivity parameter is fixed in time, so that Equation 5 can be consistently estimated using the fixed-effects estimator. The convenient form of the Cobb-Douglas production function allows for log-linearization, which leads to the following equation to estimate:

$$\ln(y_{ht}) = \beta_0 + \gamma \ln(l_{ht}) + \sum_{i=1}^{I} \alpha_i \ln(k_{iht}) + \nu_h + \varepsilon_{ht} \tag{6}$$

where $\ln(a_h) = \beta_0 + \nu_h$ where ν_h is an household fixed effect and ε_{ht} is an $i.i.d$ error term. Productivity in level can then be obtained as $\widehat{TFP}_h = \exp(\hat{\beta}_0 + \hat{\nu}_h)$.

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 problematic. We follow the procedure proposed by Battese (1997) to estimate unbiased coefficients.[2]

Finally, we test for the constant returns to scale hypothesis, that is, whether the sum of input elasticities significantly differs from one. We could not reject this hypothesis at the 10% level. Then, we rewrite Equation 6 assuming constant returns to scale (i.e. farm income and productive assets are expressed in per-worker terms) and we estimate it using the fixed-effects estimator. Results are reported in Table 2.

[2]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: $k_{iht} = \max(k_{iht}, 1)$.

Table 2: Production function estimation under constant returns to scale

	(1)	(2)	(3)	(4)
	$\ln(y_{ht})$	$\ln(y_{ht})$	$\ln(y_{ht})$	$\ln(y_{ht})$
$\ln(land_{ht})$	0.54***	0.39***	0.37***	0.36***
	(8.30)	(5.89)	(5.71)	(5.54)
$\ln(tools_{ht})$		0.39***	0.36***	0.37***
		(5.91)	(5.83)	(5.90)
$\ln(livestock_{ht})$			0.17***	0.16***
			(3.03)	(2.91)
$\ln(tractor_{ht})$				0.03***
				(2.67)
$Constant$	5.44***	3.64***	2.03**	2.17**
	(5.70)	(4.86)	(2.39)	(2.45)
Households Fixed Effects	Yes	Yes	Yes	Yes
Nb. of Observations	360	360	360	360
Nb. of Groups	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. $\ln(equipment_{ht})$ was dropped due to lack of significance. To correct for zero values in explanatory variables, we apply the method proposed by Battese (1997). 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. In the full specification, we test for the constant returns to scale hypothesis. Using the delta method, we show that the sum of the coefficients was equal to 1.07 but not statistically different from one at the 10% level. 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 productive asset variables into a single bundle of capital per worker, k_{ht}^{ag}, that is used in the following estimations and simulations.[3] Table 3 reports summary statistics about the output of this first step estimation, namely the aggregate variable of capital, k_{ht}^{ag}, the household specific total factor productivity parameter TFP, and the elasticity parameter, α, of k_{ht}^{ag}.

[3] $k_{ht}^{ag} = \left(\prod_{i=1}^{I} k_{iht}^{\hat{\alpha}_i}\right)^{\frac{1}{\sum_i \mathbb{1}_{(k_{iht})}\hat{\alpha}_i}}$, 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.

Table 3: Summary statistics of production function estimation

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

Notes: $\hat{k}^{ag}_{ht}$ is an aggregate variable of capital per worker. The household specific productivity parameter is computed as: $\widehat{TFP}_h = \exp(\hat{\beta}_0 + \hat{\nu}_h)$. $\hat{\alpha}$ is the estimated elasticity of the aggregate capital variable $\hat{k}^{ag}_{ht}$. Source: Author's elaboration on IFLS panel data.

5.2 Accumulation Parameters

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

$$u(c) = \begin{cases} \dfrac{(c - c_{min})^{1-\sigma}}{1-\sigma} & \text{if } \sigma \neq 1 \\ \log(c - c_{min}) & \text{if } \sigma = 1 \end{cases} \tag{7}$$

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.[4] This gives a household 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 $k^{ag}_{h,1993}$.[5] 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:

$$\log L = -\frac{n}{2}\log(2\pi) - \frac{n}{2}\log\left(\zeta^2\right) - \frac{1}{2\zeta^2}\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{j=1}^{J}\left\{\left(k^{ag}_{h,t+1} - \psi_{hs}(k^{ag}_{h,t})\right) * \left(Pr(s_{h,t} = j)\right)\right\}^2 \tag{8}$$

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

[4] See Appendix B for details.

[5] Each increment is simulated 500 times.

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 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 a large number of times and we derive the standard errors of the second regression parameters.

Table 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 IFLS4. In fact, most households head reported a discount factor smaller than 0.64 (Appendix C). It is well established that the discount factor is partly determined by the market rate of substitution (Pender 1996). As households in rural areas have difficulties to access credit market, it is then expected to find a large discount rate. 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. The minimum consumption parameter is equal to 362 but suffers from low precision.

6 Simulations of Volcanic Risk

This section is devoted to the simulations of the model based on the previously estimated parameters. Simulations aims 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 6.1, and changes in risk perception which is done in Section 6.2. Section 6.3 formally exposes how volcanic risk and changes in risk perception enter the model. Results and a discussion are provided in Section 6.4.

6.1 Characterization of Volcanic Risk

Volcanic hazard can be characterized by two dimensions: the distribution of eruptions and the economic damages they incur. These two dimensions are treated in Section 6.1.1 and Section 6.1.2, respectively.

6.1.1 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 to eight discrete scale, to measure the size of explosive eruptions. One shortcoming of this index is that ash, lava, lava bombs and ignimbrite are all treated alike. Despite this limit, the VEI remains a useful index to rank 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 5, and 507 eruptions for which summary statistics are reported in Table 6.[6]

Table 5: List of active volcanoes between 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.

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

Table 6: Summary statistics of Indonesian eruptions between 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.

Volcanic eruptions, as others natural disasters are rare and of high magnitude. Thus, unlike most articles related to stochastic growth, we cannot assume the normality of shocks. Rather, the volcanologic literature suggests that volcanic eruptions follow extreme value or log-logistic distributions (Mendoza-Rosas and De la Cruz-Reyna 2008, Dzierma and Wehrmann 2010). The volcanic shock distribution is discrete and then can be written under the form of a Markov chain. The transition matrix is estimated by maximum likelihood. It can be shown that the maximum likelihood parameter (the probability of going from state i to state j) is the ratio of the number of times we transit from state i to state j over the number of times we were in i. Then, no assumption is made regarding the distribution. With such specification, the Markov chain allows for an auto-correlation of order one of the eruption process. Whether observing an eruption at a period influences the probability of observing another at the next period is known as the Independence of repose times hypothesis in the volcanologic literature. Studies on Mexico (Mendoza-Rosas and De la Cruz-Reyna 2008) or Chile (Dzierma and Wehrmann 2010) do not find evidence of serial correlation and conclude to the independence of repose times. To match this result, the steady-state distribution of the Markov chain is obtained. The optimization problem is run with the BFGS algorithm and the following transition matrix, π^v, is obtained:

Table 7: Steady-state probability transition matrix for 1900-2015

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

In line with the usual pattern of extreme value distributions, most weight is concentrated in the first column (VEI 0) which stands for the "no eruption" state of nature. In addition, as the VEI increases, the associated probability decreases, which captures the phenomenon that the strongest eruptions are also the rarest.

6.1.2 Economic Damages of Volcanic Eruptions

Agriculture is particularly vulnerable to the physical and chemical effects of tephra fall, which may directly impact crops, soil, animal health, farm infrastructure and machinery (Wilson et al. 2007, Wilson et al. 2010, Wilson et al. 2011, and Magill et al. 2013). Characterizing the risk requires to convert the physical measure of the eruption (the VEI) into a measure of economic losses. Ideally, these values would be drawn from the literature for each VEI. However, few fieldwork has been done to collect data on agricultural losses following volcanic eruptions in Indonesia, and most of it focus on major eruptions. For instance, Ilham and Priyanti (2013) investigate the 2010 Merapi eruption (VEI 4) and find that it causes the death of 50% of cattle heads in three cooperatives around Merapi volcano. Chandra et al. (2015) study the agricultural impact of cold lahar of the 2014 eruption of Mont Kelut (VEI 4). They find that people living along the stream get between 60% and 65% of their land damaged. To the best of our knowledge, no study investigates agricultural losses for smaller eruptions in Indonesia. Then, remaining values, namely for VEI ranging between one and three, are drawn from a simple loss function. That is, a function that links the strength of an eruption to the percentage of wealth damaged. We propose three functional forms for this function that are calibrated to match the two extreme values of the distribution, namely no damage when no eruption occurs and 60% of loss for a VEI 4 eruption. 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. 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. Values for each specification are reported in Table 8. The three loss functions are then used in simulations (Section 6.4) to test the sensitivity of our results.

Table 8: Economic losses

VEI	Exponential loss function	Linear loss function	Logarithmic loss function
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.

6.2 Evolution of Beliefs

The growing literature about natural disasters and risk perception suggests that, being affected by such shocks not only incurs income losses or asset destructions but also change people's beliefs. A large share of the literature concludes to an adverse, and rather long lasting, effect of disasters on observed risk aversion. 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 9.

Table 9: Difference in probabilities of natural disasters occurence

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.

One year after having experienced a shock (t+1), 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.

6.3 Simulation Method

To investigate how volcanic risk affects investment we augment the model presented in Section 4 with volcanic shocks. That is, written in a Bellman equation form, the household maximization problem becomes:

$$V_{ht}(s_{ht}, \Upsilon_t, k_{ht}) = \max_{k_{ht+1}} u(\Upsilon_t s_{ht} y_{ht} + \Upsilon_t(1-\delta)k_{ht} - k_{ht+1}) + \beta\pi V_{ht+1}(s_{ht+1}, \Upsilon_{t+1}, k_{ht+1}) \quad (9)$$

where the volcanic shock, denoted Υ, affects income and assets, and the transition matrix, π, captures the joint distribution of income shock, s, and volcanic eruptions, Υ. [7,8]

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 9. 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.

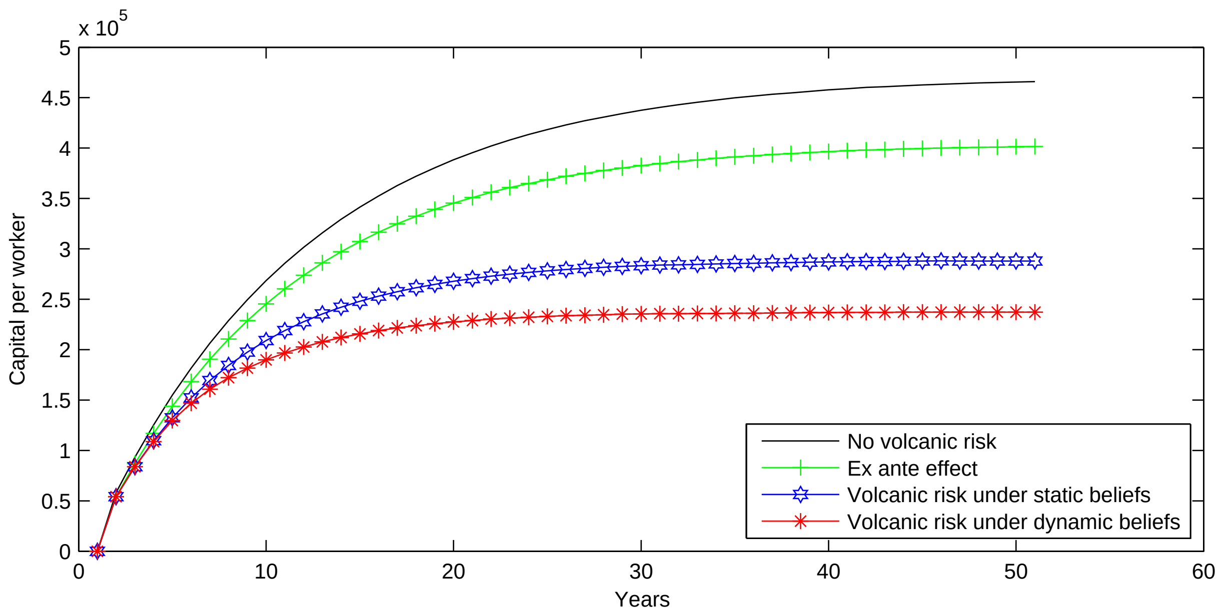
[7] Υ_t is a discrete variable describing the five states of nature (from VEI 0 to VEI 4) and to which we assign values such that Υ_t = (1 - *Economic damages*) where *Economic damages* is drawn from Table 8.

[8] 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 6.1.1.

6.4 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 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 1. Table 10 proposes a sum-up of the findings for the three loss functions.

Figure 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 simulation.

Table 10: Average loss of capital stock

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

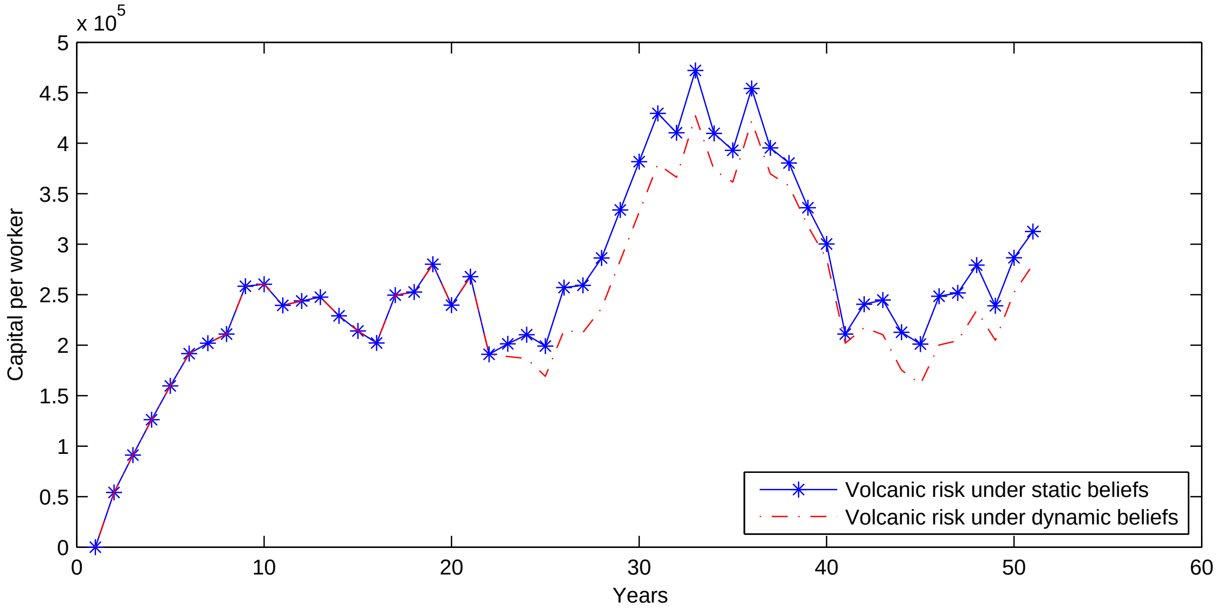
Notes: Average loss of capital, $\hat{k}^{ag}_{ht}$, over the 50-year period for 200,000 simulations under three scenarios and three loss functions. Losses in level are reported in parentheses. Losses in percentage and in level measure the deviation from the "No volcanic risk" scenario. Source: Author's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

First, we note that the ex-ante effect is negative. In other words, being exposed to volcanic hazard without experiencing any eruption has a negative impact on capital accumulation. Let recall that the sign of this effect was a priori undetermined. In fact, following Gunning (2010), the impact of a wealth risk on saving could be negative, null or positive depending on the risk aversion coefficient. Then, observing precautionary saving was not out of order. The literature about natural disasters often refers to the risk vulnerability concept of Gollier and Pratt (1996), probably because it deals with unfair risk. It is worth noting that predictions from this framework differ from our results. In fact, in this framework, adding an unfair background risk makes risk-averse agents behave in a more risk-averse way. In the standard portfolio problem, agents would lower the optimal quantity of a risky investment. On the contrary, in a single asset framework as we develop here, we would expect savings to increase. This difference is explained by the fact that, unlike Gollier and Pratt (1996), we model the background risk (the volcanic risk) as multiplicative and not as an additive one.

Second, light should be shed on the magnitude of the ex-ante effect. On the long run, the ex-ante effect accounts for around one-third of the total cost incurred by volcanic risk under static beliefs. This finding is robust to the three loss functions as losses range between 32% and 40% across specifications. Once again, this finding is an empirical one as it depends on the estimated parameters of the model. 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 effect of volcanic risk on investment behavior, being exposed to volcano still represents an important impediment to household's asset accumulation. 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 10).

In addition, simulation outcomes (Figure 1) 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 costs in terms of growth. 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. Table 11 reports the difference in the levels of capital between static beliefs and dynamic beliefs on a seven-year period. Table 12 shows this difference over a 18-year period.

Figure 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 simulation.

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. Let recall that this path is drawn from the actual distribution of Indonesian eruptions over the 1900-2015 period. It is interesting to note that changes in risk perception after an eruption affect investment on the short run but also have long lasting effects. In fact, Table 11 shows that over-weighting the probability of future disasters decreases the level of investment such that 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 11), Table 12 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 explanation to the empirical microeconomic literature, such as Dercon (2004) and Carter et al. (2007), which highlights long lasting effects of natural disasters.

Table 11: 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 12: Long-term difference in capital quantity after an eruption

Time from eruption	[t+1, t+3]	[t+4, t+6]	[t+7, t+9]	[t+10, t+12]	[t+13, t+15]	[t+16, t+18]
Difference in capital	-11%	-17%	-13 %	-10 %	-7%	-5%

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

Overall, on the long run, changes in saving behavior (due both to the ex-ante effect of risk and changes in beliefs) account for half of the total loss of capital incurred by volcanic hazard (Table 13).

Table 13: Loss repartition

% of losses due to	Exponential loss function	Linear loss function	Logarithmic loss function
Saving 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. Saving 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.

7 Conclusions

In this paper, we investigate how being exposed to volcanic hazard would affect households' asset accumulation through the channel of saving behavior. To do so, we focus on Indonesia, one of the most exposed country to volcanic risk. Identifying the ex-ante effect and the impact of changes in beliefs on investment requires to use a structural approach. We set up a standard stochastic Ramsey model, that is estimated with household survey data. Then, the model is simulated under several cases to investigate the ex-ante effect of volcanic risk and the impact of changes in risk perception after a shock.

Our results show that, on the long run, being exposed to volcanic risk leads to a decrease in investment. This ex-ante effect is rather strong in magnitude as it lowers the quantity of capital by 7% to 17% depending on the loss function specification. In other words, being exposed to volcanic risk accounts for around one-third of the total cost of volcanic risk under static beliefs. In addition, changes in beliefs in the magnitude estimated in the literature incur severe impediments to the recovery process. Overall, changes in saving behavior, namely both the ex-ante effect and the changes in risk perception, account for half of the total cost incurred by volcanic risk.

If anything, this paper suggests two recommendations in terms of public policy, that apply beyond the particular case of volcano. Let recall that offering risk management tools to households, such as 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. Consequently, this paper suggests that risk management tools against natural disasters should be supported. 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 aid could make the recovery process more efficient.

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Appendix A: 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) $ln(equipment_{ht})$	(5) $ln(tractor_{ht})$
Non-Farm Business$_{ht}$	0.277	-0.0780	0.305	-0.325	0.535*
	(0.66)	(-0.41)	(0.51)	(-1.15)	(1.77)
Constant	13.17***	10.79***	5.637***	1.600**	-0.533
	(11.67)	(21.07)	(3.53)	(2.10)	(-0.65)
Households Fixed Effects	Yes	Yes	Yes	Yes	Yes
No. of Observations	360	360	360	360	360
No. of Groups	90	90	90	90	90
R-Squared	0.002	0.001	0.001	0.006	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.

Appendix B: Solving the Stochastic Ramsey Model

Estimating the deep parameters of the model requires to solve the stochastic Ramsey model. We explain the procedure below, although Elbers et al. (2007) already provide a detailed description of their method in their appendix.

The household maximization problem, exposed in the Section 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 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.

Appendix C: 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 year 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.