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NatCats and Insurance in a Developing Economy - New Theoretical and Empirical Evidence

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NatCats and Insurance in a Developing Economy

- New Theoretical and Empirical Evidence

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Abstract

Our paper analyses the effect of natural catastrophes on insurance demand in a developing economy and the specific role of insurance regulation in this relationship. We base our analysis on a theoretical model as well as a panel regression using household survey level data for Vietnam and corresponding spatial measures of natural catastrophes. Vietnam is especially interesting for our analysis as it is strongly affected by natural catastrophes and experienced an enhancement of insurance regulation in recent years.

The theoretical results indicate that a loss experience should have a less positive effect in developing economies than in developed economies. In addition, an enhancement of insurance regulation should make the impact of a loss event on insurance demand more positive. These findings are confirmed in our empirical analysis: Overall natural catastrophes decrease insurance demand of affected households in Vietnam. The enhancement of insurance regulation not only increased insurance demand. It also reversed the effect of natural catastrophes on the property insurance demand of affected households.

Keywords: Insurance Penetration, Natural Catastrophes, Insurance Regulation.

JEL-Classifications: G22, G52, Q54.

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1 Introduction

Many developing economies are heavily exposed to natural catastrophes. According to Munich Re data, low and middle income countries¹ (below: low income countries) account for about 36% of global losses from relevant natural loss events between 2008 and 2017. However, while in high income countries about 45% of all losses from natural catastrophes were insured, in low income countries only 7% were insured. This is reflected in a low insurance penetration. While people in high income countries spend 0.6% of their income on property insurance, people in low income countries spend less than 0.3% of their income.²

Since there are indications that especially uninsured losses from natural catastrophes can cause high and long lasting economic costs, the low insurance penetration is a major concern.³ In order to address this issue, several international initiatives have been launched. In 2015, for example, the G7 Climate Risk Insurance Initiative was launched which then led to the InsuResilience Global Partnership for Climate and Disaster Risk Finance and Insurance Solutions, launched at the UN Climate Conference COP23 in 2017. Another example is the Global Index Insurance Facility, a program by World Bank. The goal of these initiatives is to protect more people from the financial consequences of natural catastrophes.

One reason for the low insurance penetration in developing economies is that in these countries insurance is relatively expensive. Following Table 1, property insurance buyers in low income countries can expect about 37 cents payouts on every euro insurance premium. In high income countries the expected payout is about 64 cents. This argument is supported by Grace et al. (2004), for example, which find empirical evidence for a higher price elasticity of the demand for catastrophe coverage.

Another important impact factor of insurance penetration are the institutional framework conditions. A sub pillar of the WEF's Global Competitive Index rates the institutions of each countries. These scores are highly correlated with insurance penetration (54% in 2017) and are significantly higher in high income countries than in low income countries.⁴ A lack of trust in insurance and institutions is major hurdle for higher insurance penetration.⁵ Hence, an enhancement of insurance regulation seems

¹Countries with per capita GNI up to 12,735 US\$.

²See Table 1.

³See e.g. Peter et al. (2012).

⁴See Table 1.

⁵Esho et al. 2004, Sirimanne et al. (2015), Petrolia et al. (2013) and Reynaud et al.

Table 1: Average Property Insurance Penetration and Loss Ratios in High and Low Income Countries (in %, source: Axco) and Score for Institutions (source: World Economic Forum, Global Competitive Index)

	Penetration		Loss Ratio		Institutions
	(2006-2017)	(1996-2018)	(2006-2017)	(1996-2018)	2018
Low Income Countries	0.27		37.32		49.4
Brazil		0.22		43.85	49.7
Egypt		0.07		43.26	48.1
Vietnam		0.11		31.28	49.5
High Income Countries	0.59		64.11		66.4
Germany		0.54		72.43	73.5
Japan		0.25		52.00	71.1
U.S.		0.90		61.50	74.6

to be an important step towards protecting more people from the financial consequences of natural catastrophes. Vietnam is a good example for this. The 2011 enhancement of insurance regulation was followed by a substantial increase in insurance penetration (see Figure 1).

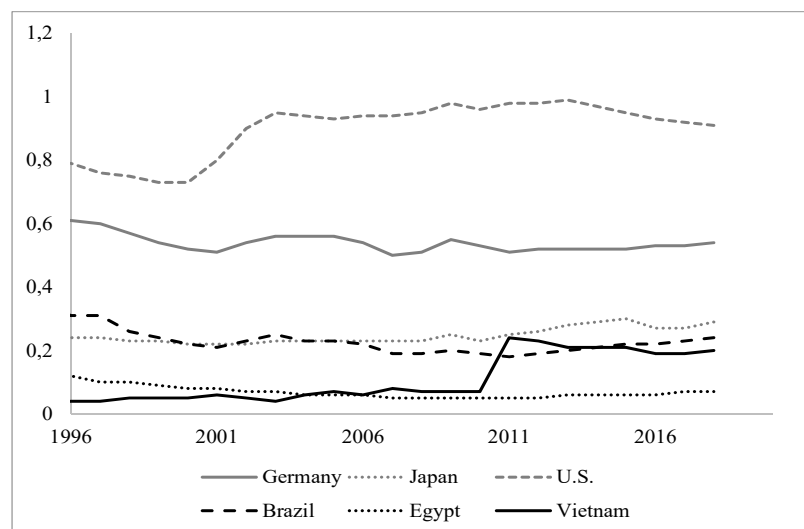
Loss experiences from natural catastrophes also have an effect on insurance demand. However, such an experience has effects that increase the demand and others that dampen it. Hence, it is not clear whether the net effect is positive or negative. On the one hand, the experience of a natural catastrophe might increase the subjective probability assessment of individuals and might therefore increase their willingness to pay. Botzen and van den Bergh (2012), for example, argue that individuals follow a Bayesian updating when assessing flood probabilities in the Netherlands. As a result, a higher frequency of natural catastrophes (e.g. due to climate change) might lead to a higher insurance demand.⁶ Furthermore, a positive experience with insurance in the aftermath of a natural catastrophe, can have a positive effect on insurance demand.

On the other hand, loss experiences from natural catastrophes might dampen the demand for insurance as uncovered losses tighten households' budgets and therefore their ability to pay (e.g. Seifert et al. 2013, Atreya et al. 2015, Cai and Song 2017). Losses might tighten budgets because they were not insured or because the insured loss is not compensated by a corresponding claims payment. The latter could in addition result in a negative experience with insurance and hence an additional dampening effect on insurance demand.

(2018).

⁶see also Seifert et al. (2013).

Figure 1: Development of Property Insurance Penetration (written premiums / GDP in %, source: Axco)



Following this reasoning, a natural catastrophe might result in a positive effect on insurance demand if insurance penetration is high and if a sufficient regulation assures a certain level of consumer protection and hence claim payments when they are appropriate. Given the lower level of insurance penetration and institutional framework conditions in low income countries, the effect of a natural catastrophe on insurance demand is likely more negative than in high income countries.

Our paper adds to the literature by analysing the effect of natural catastrophes on insurance demand in a developing economy and the specific role of insurance regulation in this relationship. Furthermore, we base our analysis on a theoretical model as well as a panel regression using household survey level data and spatial measures of natural catastrophes.

The theoretical part models insurance demand of risk averse, expected utility maximizing households.⁷ In a dynamic setting (similar to Gollier, 2003), in each period there is a probability that a household suffers a loss. Households can buy insurance protection. However, the probability that the insurer really pays in a loss event is below 100% (like Doherty and Schlesinger's, 1990, non-performance risk). Furthermore, we assume that, depending on their loss experience, households adjust their subjective probability assessment regarding the loss event and the non-performance risk.

The results indicate that an enhancement of insurance regulation which reduces the non-performance risk, only increases aggregated insurance demand, if it also leads to a sufficient increase in trust in the insurance sector. Furthermore, our theoretical results indicate that the non-performance risk and the markup on fair premiums (expensive insurance) have a negative and the trust in insurance a positive effect on the impact of a loss event on insurance demand. This would imply that a loss experience has a less positive (or negative) effect in developing economies than in developed economies. In addition, an enhancement of insurance regulation would make the impact of a loss event on insurance demand more positive.

We base our empirical analysis on data on Vietnam. Vietnam is a developing economy with low loss ratios (i.e. expensive insurance) and low insurance penetration. What makes Vietnam especially interesting is, however, the fact that Vietnam is strongly affected by natural catastrophes (in particular storms) and experienced a change in regulation in recent years.

We use the "Thailand Vietnam Social Economic Panel" (TVSEP) for our empirical analysis. To the best of our knowledge, this household survey panel data has not yet been used to answer insurance questions. The

⁷See e.g. Rothschild and Stiglitz (1976).

data set includes information about insurance consumption at the household level. This enables us to evaluate the impact of natural catastrophes on the property insurance demand of affected individual households and how this impact is influenced by the change in regulation. Property insurance is offered to both companies and households by private insurers and usually covers all perils including natural disasters such as storms, flood and earthquake. In this paper, we focus only on property insurance demand of households.

While we use survey information on the "loss of income because of shocks" as a self reported indicator for whether a household was affected by a natural catastrophe, we are aware of the fact that such self-reported figures have to be handled with caution. Therefore, we also use spatial data on storms (the main kind of natural catastrophes in Vietnam) as an external measure of whether a household was hit by a natural catastrophe.

Our empirical results indicate that overall natural catastrophes decrease insurance demand of affected households. The 2011 enhancement of insurance regulation not only increased insurance demand of the households within our panel. It also reversed the effect of natural catastrophes on the property insurance demand of affected households. This result confirms the implications of our theoretical model and holds for self reported loss experience as well as external storm data.

Our paper is organized as follows: In the next section, we present the theoretical model and its implications. Section 3 give the overview of data that we apply for empirical estimations. In section 4, we present our panel regressions approach and empirical results. Section 5 provides our conclusions.

2 Theoretical Model

2.1 Basic Assumptions

Time is discrete and we are looking at three periods $t = 0, 1, 2$. There are many households (N) and in all three periods each household receives the income Y . In period $t = 1$ and $t = 2$, however, there is the probability $0 < \pi^x < 0.5$ to loose the amount $L = lY$. In addition, we assume that in $t = 1$ the subjective probability of household i to suffer the loss in $t = 2$ is influenced by its experience in $t = 1$ and that $\pi_{i,1}^x = \epsilon_i \pi^x$, where $\epsilon_i = \epsilon_h > 1$ if the household experiences a loss event and $\epsilon_i = \epsilon_l < 1$ if not. However, we also assume that in $t = 0$ households do not expect to change their probability assessment: $E(\pi_{i,1}^x) = \pi^x$.

We assume that households do not have the possibility to save money but can insure the loss event in the next period. The insurance of the amount $0 \leq I_{i,t} = \alpha_{i,t}L \leq L$ is assumed to cost $pI_{i,t} = p\alpha_{i,t}L$. However, the insurer only pays if the loss event is really covered by the insurance and if the insurer has a sufficient financial strength (is not insolvent). The probability of a compensation is $0 < \pi^z \leq 1$. Depending on the general trust in insurance and its experience with insurance, in t household i subjectively considers the probability for a compensation in $t+1$ to be $\pi_{i,t}^z = \gamma_{i,t}\pi^z$. We assume that in $t=0$, $\gamma_{i,0} = \gamma$ (general trust). In $t=1$, households change their subjective $\gamma_{i,1}$ to $\delta_l\gamma$ (with $\delta_l < 1$) if they have an uncovered loss event and to $\delta_h\gamma$ (with $\delta_h > 1$) if they have an insured loss event. However, we assume, again, that in $t=0$ households do not expect to change their probability assessment: $E_0(\pi_{i,1}^z) = \gamma\pi^z$.

We further assume that the insurance premium has a markup $m \geq 1$ to the actuarial fair premium ($p = m\pi^x\pi^z$), where $1 > m\pi^x\pi^z \geq \epsilon_h\delta_h\gamma\pi^x\pi^z$.

Hence, the timeline is as follows:

- **Period $t=0$:** All households are equal, receive the income Y and choose the same optimal degree of insurance coverage α_0 for the potential loss in period $t=1$. The remaining amount $Y(1-p\alpha_0l)$ is used for consumption.
- **Period $t=1$:** Now there are three different groups of households. Since we have assumed that the number of households is very large, the size of the different groups can be assumed to be equal to the expected size:
 - **The fraction $\pi^x\pi^z$ has an insured loss event** and therefore an available income of $Y_{i,1} = Y(1-l(1-\alpha_0))$. This group chooses the optimal insurance coverage $\alpha_{i,1}lY = \alpha_I lY$ and uses the remaining amount $Y_{i,1} - \alpha_{i,1}lY = Y(1-l(1-\alpha_0+p\alpha_I))$ for consumption. Given the loss experience, the individual probability perception changes to $\epsilon_h\pi^x\delta_h\gamma\pi^z$.
 - **The fraction $\pi^x(1-\pi^z)$ has an uninsured loss event** and therefore has an available income of $Y_{i,1} = Y(1-l)$. This group chooses the optimal insurance coverage $\alpha_{i,1}lY = \alpha_L lY$ and uses the remaining amount $Y_{i,1} - \alpha_{i,1}lY = Y(1-l(1+p\alpha_L))$ for consumption. Given the loss experience, the individual probability perception changes to $\epsilon_h\pi^x\delta_l\gamma\pi^z$.

- **The fraction $(1 - \pi^x)$ suffers no loss event** and therefore has an available income of $Y_{i,1} = Y$. This group chooses the optimal insurance coverage $\alpha_{i,1}lY = \alpha_N lY$ and uses the remaining amount $Y_{i,1} - \alpha_{i,1}lY = Y(1 - p\alpha_N l)$ for consumption. Given the loss experience, the individual probability perception changes to $\epsilon_l \pi^x \gamma \pi^z$.
- **Period $t = 2$:** Households can, again, be distinguished between suffering no loss event ($Y_{i,2} = Y$), an uninsured loss event ($Y_{i,2} = Y(1 - l)$) or an insured loss event ($Y_{i,2} = Y(1 - l(1 - \alpha_{i,1}))$). However, now the latter category has three subcategories including households with the three different loss histories and, hence, different levels of insurance coverage ($\alpha_{i,1} = \alpha_I, \alpha_L, \alpha_N$). Since $t = 2$ is the final period households do not buy any insurance and use their entire available income for consumption.

2.2 Optimal Insurance Demand

The households' utility from consumption is assumed to be $U[Y_{i,t} - I_{i,t}]$, where $U' > 0$ and $U'' < 0$. For simplicity, we assume that households value utility in the next period equally to utility in the present period (discount factor one). Hence, in period $t = 0$, expected utility (EU_0) is given by:

$$EU_0 = U[Y(1 - p\alpha_0 l)] + \pi^x \gamma \pi^z U[Y(1 - l(1 - \alpha_0 + p\alpha_I^e))] + \pi^x (1 - \gamma \pi^z) U[Y(1 - l(1 + p\alpha_L^e))] + (1 - \pi^x) U[Y(1 - p\alpha_N^e l)], \quad (1)$$

where α_I^e, α_L^e and α_N^e are the expected values of α_I, α_L and α_N .⁸ The first order condition for an optimum is given by:

$$\frac{U'[Y(1 - p\alpha_0 l)]}{U'[Y(1 - l(1 - \alpha_0 + p\alpha_I^e))]} = \frac{\pi^x \gamma \pi^z}{p} = \frac{\gamma}{m}. \quad (2)$$

Following (2), insurance demand depends positively on the trust in insurance (γ). With constant absolute risk aversion (CARA), the impact of π^x and π^z on α_0 is negative. With constant relative risk aversion (CRRA), however, the impact of the two probabilities on insurance demand in $t = 0$ is not clear.⁹ For CARA and reasonable levels of CRRA, insurance demand in $t = 0$ depends negatively on the insurance premium markup m .¹⁰ This result is

⁸Note that households do not expect to change their risk perception. Hence, the expected values of α are based on $E(\pi_{i,1}^x) = \pi^x$ and $E(\pi_{i,1}^z) = \gamma \pi^z$.

⁹See Appendix A.

¹⁰See Appendix C.

in line with the empirical fact that low loss ratios (i.e. high markups) are highly correlated with low insurance premiums.

In period $t = 1$ the maximization problem of household i is:

$$EU_{i,1} = U[Y_{i,1} - p\alpha_{i,1}lY] + \pi_{i,1}^x \pi_{i,1}^z U[Y(1 - l(1 - \alpha_{i,1}))] + \pi_{i,1}^x (1 - \pi_{i,1}^z) U[Y(1 - l)] + (1 - \pi_{i,1}^x) U[Y]. \quad (3)$$

Depending on whether household i has an insured loss (I), an uninsured loss (L) or no loss (N), the first order condition for an optimum is given by:

$$\frac{U'[Y(1 - l(1 - \alpha_0 + p\alpha_I))]}{U'[Y(1 - l(1 - \alpha_I))]} = \frac{\epsilon_h \delta_h \gamma}{m}, \quad (4)$$

$$\frac{U'[Y(1 - l(1 + p\alpha_L))]}{U'[Y(1 - l(1 - \alpha_L))]} = \frac{\epsilon_h \delta_l \gamma}{m} \quad (5)$$

and

$$\frac{U'[Y(1 - lp\alpha_N)]}{U'[Y(1 - l(1 - \alpha_N))]} = \frac{\epsilon_l \gamma}{m}. \quad (6)$$

As we can see, individual insurance demand in $t = 1$ depends positively on available income $Y_{i,1}$ and the probability assessment $\epsilon_i \gamma_i$. Hence, since $\alpha_0 \geq 0$ and $\delta_h > \delta_l$, insurance demand of a household with an insured loss is higher than the demand of a household with an uninsured loss ($\alpha_I > \alpha_L$). Whether a household with an insured loss also demands a higher insurance coverage (α_I) than a household with no loss experience (α_N), depends on the difference between $\epsilon_h \delta_h$ and ϵ_l as well on the insurance demand in $t = 0$ (α_0).

The fact that we are looking at a three period model allows us to calculate the dynamic effects of loss events on insurance demand while keeping the scope of the model limited. However, the three periods are very different: while in $t = 0$ there are only premium payments but no potential losses and in $t = 2$ there are only potential losses but no premium payments, in period $t = 1$ there are both: premium payments and potential losses. As the result, there is an artificial "savings" aspect of insurance which leads to a much higher insurance demand in $t = 0$ than in $t = 1$.

Since we have assumed that $\epsilon_h \delta_h \gamma < m$, the right hand side of conditions (2) to (6) are smaller than one. For the left hand side this implies that: $\alpha_0(1 + p) < 1 + p\alpha_I^e$, $\alpha_I(1 + p) < \alpha_0$, $\alpha_N(1 + p) < 1$ and, since $\alpha_i \geq 0$, that $\alpha_L = 0$. Hence, even with an actuarial fair premium and perfect information, insurance demand would always be lower than one. This results from the fact that in period $t = 2$, households do not have expenses for insurance

premiums and, therefore have a limited incentive to transfer capital from $t = 1$ into (contingent capital in) $t = 2$.

The effect of the probabilities π^x and π^z on individual insurance demand in $t = 1$ is given by:

$$\frac{d\alpha_I}{d\pi} = \left[-m\alpha_I + \frac{d\alpha_0}{d\pi} \right] \frac{\frac{U''[Z_I]}{U'[Z_I]}}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} \quad (7)$$

and

$$\frac{d\alpha_N}{d\pi} = -m\alpha_N \frac{\frac{U''[Z_N]}{U'[Z_N]}}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}}. \quad (8)$$

where $\pi = \pi^x \pi^z$, $Z_I = Y(1 - l(1 - \alpha_0 + p\alpha_I))$, $N_I = Y(1 - l(1 - \alpha_I))$, $Z_N = Y(1 - lp\alpha_N)$ and $N_N = Y(1 - l(1 - \alpha_N))$.

As we can see, α_N depends negatively on π . For CARA and CRRA, also α_I depends negatively on π .¹¹ Given that individual insurance demand depends negatively on π , it also depends negatively on the premium markup m . The corresponding derivatives are:

$$\frac{d\alpha_I}{dm} = \left[-\pi\alpha_I + \frac{d\alpha_0}{dm} \right] \frac{\frac{U''[Z_I]}{U'[Z_I]}}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} + \frac{1}{Ylm} \frac{1}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} < 0 \quad (9)$$

and

$$\frac{d\alpha_N}{dm} = -\pi\alpha_N \frac{\frac{U''[Z_N]}{U'[Z_N]}}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}} + \frac{1}{Ylm} \frac{1}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}} < 0. \quad (10)$$

2.3 Aggregated Insurance Demand

In $t = 1$, the aggregated insurance demand of the economy is given by:

$$N\alpha_1 = N\pi^x \pi^z \alpha_I + N(1 - \pi^x) \alpha_N \quad (11)$$

This aggregated demand depends positively on the individual insurance demand α_I and α_N and, hence, positively on γ and negatively on m . This finding is in line with the fact that trust in institutions and loss ratios are positively correlated with insurance penetration.¹² The impact of the likelihood that the insurer pays in the case of a loss event (π^z) is less obvious. It

¹¹See Appendix B.

¹²See section 1.

has a positive direct impact on α_1 since it reduces the fraction of the households with the lowest insurance demand ($\alpha_L = 0$). In addition, however, there is a negative indirect effect as π^z lowers individual insurance demand α_I and α_N . The overall effect is positive if:

$$\frac{d\alpha_1}{d\pi^z} = \pi^x \alpha_I + \pi \pi^x \frac{\partial \alpha_I}{\partial \pi} + (1 - \pi^x) \pi^x \frac{\partial \alpha_N}{\partial \pi} > 0, \quad (12)$$

or

$$\alpha_I \frac{\frac{U''[N_I]}{U'[N_I]}}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} - \alpha_N \frac{m(1 - \pi^x) \frac{U''[Z_N]}{U'[Z_N]}}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}} > -\frac{\partial \alpha_0}{\partial \pi} \frac{\pi \frac{U''[Z_I]}{U'[Z_I]}}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}}, \quad (13)$$

where $\partial \pi / \partial \pi^z = \pi^x$ and $\partial \alpha_0 / \partial \pi$ is given by equation (31) in Appendix A. As we can see, this condition is only fulfilled if α_N is sufficiently low relative to α_I . For illustration we assume a standard ln utility function, $l = 0.7$, $\pi^x = 0.1$, $m = 1.25$, $\gamma = 0.95$ and $\delta_h = 1.1$. For "normal" levels of ϵ_l (i.e. about 0.9), the aggregated demand α_1 depends negatively on π^z . Only if the absence of a loss event reduces the subjective probability very strongly (ϵ_l lower than about 0.44), total demand would depend positively on π^z .

Given the negative impact of the premium markup m and the positive effect of trust in insurance γ , we can expect a lower insurance penetration in developing economies than in developed economies.¹³ Furthermore, our results indicate that an enhancement of insurance regulation which increases the probability that an insurer pays in a loss event (higher π^z), only increases aggregated insurance demand, if it also leads to a sufficient increase in trust in the insurance sector (higher γ).

2.4 The Effect of a Loss Event

The insurance demand of a household with no loss event is given by α_N . The insurance demand of a household which is affected depends on whether the loss event is covered by the insurance or not. The fraction π^z of the affected household has the high insurance demand α_I and the fraction $1 - \pi^z$ has no insurance demand $\alpha_L = 0$. Hence, overall, the experience of a loss event has a positive effect on insurance demand if:

$$\pi^z \alpha_I > \alpha_N. \quad (14)$$

Hence, the loss event has more likely a positive effect on insurance demand if the probability that the insurer pays in a loss event (π^z) is high and

¹³See section 1.

α_I is high relative to α_N . As mentioned above, the latter depends on the difference between $\epsilon_h \delta_h$ and ϵ_l as well on the insurance demand in $t = 0$ (α_0).

However, the probability π^z not only has the direct positive effect on the impact of a loss event on insurance demand. It also has a negative effect on the individual insurance demand α_I , α_N and α_0 . Hence, the overall effect of π^z is only positive if:

$$\alpha_I + \pi \frac{\partial \alpha_I}{\partial \pi} > \pi^x \frac{\partial \alpha_N}{\partial \pi}, \quad (15)$$

or

$$\alpha_I \frac{\frac{U''[N_I]}{U'[N_I]}}{p \frac{U'''[Z_I]}{U'[Z_I]} + \frac{U'''[N_I]}{U'[N_I]}} + \alpha_N \frac{m\pi^x \frac{U''[Z_N]}{U'[Z_N]}}{p \frac{U'''[Z_N]}{U'[Z_N]} + \frac{U'''[N_N]}{U'[N_N]}} > -\frac{\partial \alpha_0}{\partial \pi} \frac{\pi \frac{U''[Z_I]}{U'[Z_I]}}{p \frac{U'''[Z_I]}{U'[Z_I]} + \frac{U'''[N_I]}{U'[N_I]}}. \quad (16)$$

As we can see, the condition for a positive effect of π^z on the impact of a loss experience is very similar to (13). The only difference is that condition (16) depends positively on α_N (multiplied by $m\pi^x$) and not negatively (multiplied by $-m[1 - \pi^x]$). For $\alpha_N > 0$, this implies that condition (16) is much more likely fulfilled and definitely fulfilled if condition (13) is fulfilled. It would only be not fulfilled if α_I and α_N are much smaller than α_0 . In our model this would be the case if insurance is very expensive and that, therefore, the mentioned "artificial three period saving effect" is very strong. Hence, we can assume that π^z usually has a positive effect on the impact of a loss event on insurance demand.

For illustration we look at the above example: We assume a standard ln-utility function, $l = 0.7$, $\pi^x = 0.1$, $\gamma = 0.95$, $\delta_h = 1.1$ and $\epsilon_l = 0.9$. For $m = 1.25$ condition (16) is fulfilled. For $m = 1.8$, however, it would only be fulfilled if π^z is below 0.8.

The effect of the trust in insurance (γ) on the impact of a loss event on insurance demand (condition 14) is positive if:

$$\pi^z \frac{\partial \alpha_I}{\partial \gamma} > \frac{\partial \alpha_N}{\partial \gamma} \quad (17)$$

This condition is more likely fulfilled if π^z is high. For CARA utility, for example, it would be fulfilled if:

$$\pi^z > \frac{1 + p + p^2}{2 + 3p + p^2} \quad (18)$$

For $\pi^x = 0.1$ and $m = 1.25$, for example, the threshold for π^z would be about 0.49. If we assume a standard ln-utility function, $l = 0.7$, $\pi^x = 0.1$,

$m = 1.25$, $\delta_h = 1.1$, $\epsilon_l = 0.9$ and $\pi^z = 0.5$, trust γ would have a negative effect on condition (14). For $\pi^z = 0.9$, trust would have a positive effect if $\gamma > 0.6$.

The effect of the markup on insurance premiums (m) on the impact of a loss event on insurance demand (condition 14) is negative if:

$$\pi^z \frac{\partial \alpha_I}{\partial m} < \frac{\partial \alpha_N}{\partial m} \quad (19)$$

or

$$\begin{aligned} \left[-\pi \alpha_I + \frac{d\alpha_0}{dm} \right] \frac{\pi^z \frac{U''[Z_I]}{U'[Z_I]}}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} + \frac{\pi^z}{Ylm} \frac{1}{p \frac{U''[Z_I]}{U'[Z_I]} + \frac{U''[N_I]}{U'[N_I]}} < \\ -\pi \alpha_N \frac{\frac{U''[Z_N]}{U'[Z_N]}}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}} + \frac{1}{Ylm} \frac{1}{p \frac{U''[Z_N]}{U'[Z_N]} + \frac{U''[N_N]}{U'[N_N]}} \end{aligned} \quad (20)$$

For CARA utility this condition is fulfilled if:

$$\frac{1 - \pi^z}{\pi^z} < Ylm R_A \left[\pi^x (\pi^z \alpha_I - \alpha_N) - \frac{d\alpha_0}{dm} \right], \quad (21)$$

where R_A is the degree of CARA. As we can see, this condition is fulfilled if π^z is high and if α_I is high relative to α_N . If we assume a standard ln-utility function, $l = 0.7$, $\pi^x = 0.1$, $\gamma = 0.95$, $\delta_h = 1.1$, $\epsilon_l = 0.9$ and $\pi^z = 0.9$, the markup m would have a negative effect on condition (14).¹⁴ For a low $\pi^z = 0.5$, the effect of m would turn positive if m is larger than about 1.3.

Even though the effects of the different parameters on the impact of a loss event on demand are not unambiguous, we can assume that π^z and γ usually have a positive effect and m a negative. This would imply that the a loss experience has a more positive effect in developed economies than in developing economies and that an enhancement of insurance regulation (higher π^z and γ) makes the impact of a loss event on insurance demand more positive.

3 Data

For our empirical estimation of the effect of natural catastrophes on insurance demand in developing economies we look at data for Vietnam. Typical for a developing economy, insurance penetration is relatively low and premiums are relatively high in Vietnam.¹⁵ What makes Vietnam particular

¹⁴Up to a degree of m which would not allow for a positive α_I (about $m = 1.9$).

¹⁵See section 1.

interesting for our evaluation is the fact that Vietnam is strongly affected by natural catastrophes; in particular storms. Furthermore, the country experienced an enhancement of insurance regulation in 2011, followed by a substantial increase in insurance penetration.¹⁶ We evaluate whether this changes the relationship between the experience of a natural catastrophe and insurance demand as suggested by our theoretical model.

On October 24th 2010, the Vietnamese government imposed decision 61/2010/QH12 that become valid on 1st July 2011 requires a more rigid regulation and supervision of insurance companies. Concretely the enhanced regulation is imposing higher capital standards on insurers to make sure that they fulfil their obligations to their customers. Moreover, insurance companies must extract 5% of their annual net profit to establish compulsory reserves. In addition, a policyholder protection fund was established to protect the benefits of customers. The insurance enterprises or foreign branches must contribute to this fund and the contribution is made until the value of the fund is equivalent to 5 % of the total assets of non-life insurance enterprise. This should lead to a higher probability of a claims payment following a loss event (higher π^z) but also more trust in the insurance industry (higher γ). According to our theoretical model, the latter should lead to a higher insurance penetration. The higher insurance penetration (theoretical and observed) should lead to a relatively more positive reaction of insurance demand to the experience of a loss event.

In the following we present the concrete data for empirical analyses of insurance demand in Vietnam. We use household level panel data, including insurance demand and household characteristics as well as spatial data on catastrophic storms.

3.1 Household Data

The Thailand Vietnam Socio Economic Panel (TVSEP)¹⁷ is a repeated household survey for Thailand and Vietnam conducted in six waves during the period 2007 to 2017.¹⁸ As discussed above, in this paper, we focus on data for Vietnam. In Vietnam 2200 households in 3 provinces were asked

¹⁶According to Axco data, written premiums for property insurance jumped from an average of 0.07% of GDP in the years 2004 to 2010 to an average of 0.21% in the years 2011 to 2017.

¹⁷The TVSEP is a long-term research project financed by the Deutsche Forschungsgemeinschaft (DFG). The website of the project provides more information <https://www.tvsep.de/overview-tvsep.html>

¹⁸In 2007, 2008, 2010, 2013, 2016 and 2017.

about: demographics, occupation, income, expenditures, insurance, shocks and other issues.

As our dependent variable we construct a dummy variable signalling whether a household bought property insurance or not. The variable has the value one if a household declares to have spent a positive amount for property insurance in last 12 months. If the amount is zero, the value of our dummy variable is zero.¹⁹

We are interested in the effect of natural catastrophes on insurance demand. The TVSEP provides a self reported loss of income as a result of a shock event measured in 2005 US PPP. This variable is the estimated loss due to household damage, drought, flood and typhoon, reported by the household. On the one hand, this variable signals to which extent available income is reduced by a shock and should therefore have a negative effect. On the other hand, the variable signals whether a household has been affected by a shock. According to our theoretical considerations, it is not clear whether this variable should have a positive or negative impact on insurance demand. However, the impact should become more positive after the change in regulation.

The TVSEP also includes a number of variables that can be used as right hand variables. Since most of the variables do not show much changes over time (e.g. occupation), they are, however, already covered by household fixed effects which are used in the estimation. We therefore only use total income measured in 2005 US PPP. According to our theoretical model, insurance demand should be positively related to current income. Hence, we expect a positive impact in our regression analysis. This is also in line with the findings in Akter et al. (2008).

3.2 Storm Data and Measures of Storm

Regarding storm data, we apply the Best Track dataset of tropical cyclones at Western Pacific that is collected jointly by the National Oceanic and Atmospheric Administration (NOAA), the Tropical Prediction Center (Atlantic and eastern North Pacific hurricanes) and the Joint Typhoon Warning Center (for the West Pacific, South Pacific, South Indian and North Indian hurricane basins).^{20 21} It provides information on the hurricane's geographic

¹⁹About 72% of the observations have the value zero. Therefore we decided to use the dummy variable instead of the actual amount.

²⁰The best track storm data were downloaded from weather.unisys.com on 28.03.2018. Recently, this link is not accessible

²¹This dataset has been used in several papers such as Yang (2005 and 2008), Hsiang and Jina (2014), Ouattara and Strobl (2014), Berlemann (2016), Mahajan and Yang (2017) or

coordinates, time and maximal wind speed in knots of six-hourly storm intervals. Since Vietnam is mainly affected by hurricanes in the Western Pacific, we employ only the best track data in from this ocean.

We use of Best Track hurricane data from 2006 to 2017 and combine this data with micro data in the period 2007 to 2017. Since the TVSEP asks households for information about the time span 1st May in previous year to 30th April in current year, we also track storms that occurred in this period. We only consider six-hourly storm intervals with a wind speed of at least 34kt (39 mph or 17 m/s) since those with wind speed under 34kt are classified as tropical depressions.²² ²³ We construct the storm's trajectory by drawing a line to connect all the storm's eyes and create 50 km distance buffer around the storm's trajectory.²⁴ Since we know in which commune the households from the TVSEP are living, we can identify the households which are living in a commune that is located within the 50km buffer. These households are more likely to be heavily affected by the storm.

Table 2 presents the descriptive statistics for the dependent variable (household bought property insurance) and the different dependent variables for the six-year panel.

Table 2: Descriptive statistics table for variables in six-year panel dataset and the matched external storm data (Observations: 12172)

	Mean	Std. Dev.	Min	Max
Household bought property insurance (1. Yes, 0. No)	.2936	.4554	0	1
Total income (US PPP)	7177.313	9113.803	-30387.54	153167.1
Regulation (1. Yes, 0. No)	.4749	.4994	0	1
Reported loss of income (US PPP)	418.522	1338.89	0	19771.86
Reported loss of income * Regulation	154.3255	878.9875	0	19504
External Storms (1. Yes, 0. No)	.1067	.3087	0	1
External Storms * Regulation (1. Yes, 0. No)	.0165	.1274	0	1

Berleemann and Wenzel (2018)

²²https://www.prh.noaa.gov/cphc/pages/FAQ/Basic_Definitions.php

²³Berleemann (2016), Berleemann and Wenzel (2018), Yang (2008), Keller and DeVecchio (2016) provide detail information about cyclones and their structure

²⁴According to Hsu and Yan (1998), from data of 59 hurricanes from 1983 to 1979 hit US coastline, 90% of them fall into categories 2 and 4 and their radius of maximum wind mean is around 48 km with standard deviation of 3 km.

4 Empirical Estimation

4.1 Panel Regression Approach

We are interested in studying the impact of natural catastrophes on the demand for property insurance in Vietnam. As explained in section 3, the dependent variable (B_{it}) is a dummy variable that takes value of one if household i in year t bought property insurance and zero otherwise. We apply a Linear Probability Model in panel data using household fixed effect. The probability of buying property insurance is a linear function of the households' total income X_{it} , self-reported loss of income L_{it} , the external shocks S_{it} (the storm) that occurred in the commune of household i in year t . To control for unobserved factors we include the parameters a_i which are constant over time (household fixed effect).

The first model is given by the following equation.

$$P(B_{it} = 1|X_{it}, L_{it}, a_i) = F(X_{it}, L_{it}, a_i) \quad (22)$$

We also want to control for regulatory factors, i.e. the change in insurance regulation in Vietnam in 2011. Therefore we create dummy variable R_t that takes value of one if year is after 2011 and zero otherwise. We introduce the interaction between the self-reported loss in income L_{it} and regulatory change in the first model to investigate the combined effect of these factors on insurance penetration.

$$P(B_{it} = 1|X_{it}, L_{it}, R_t, a_i) = F(X_{it}, L_{it}, R_t, L_{it} * R_t, a_i) \quad (23)$$

Since, we also want to compare results using external storm data and self-reported data, we conduct the regressions applying the same method but using storm variable. The following equations describe these estimations.

$$P(B_{it} = 1|X_{it}, S_{it}, a_i) = F(X_{it}, S_{it}, a_i) \quad (24)$$

$$P(B_{it} = 1|X_{it}, S_{it}, R_t, a_i) = F(X_{it}, S_{it}, R_t, S_{it} * R_t, a_i) \quad (25)$$

For all these regressions, we employ solely two-year panel data in 2010 and 2013 because the surveys in these two years provide the closest data before and after the change in insurance regulation in 2011.

Furthermore, we conduct several robustness checks to confirm the stability of our findings. Firstly, instead of using Linear Probability model, we apply Conditional fixed-effects Logistic method because one might argue that Linear Probability model has some shortcomings such as a probability

can not be related to the independent variables for all their possible values or prediction value sometimes could less than zero or greater than one.²⁵ Therefore, by using this logit approach we aim to examine the stability of our results under the model that is specially designed for binary dependent variable. Moreover, we also conduct the Linear Probability Model estimations using data in four years by adding data in 2008 and 2016 and in six years by adding data in 2007, 2008, 2016 and 2017.

4.2 Empirical results

The results of our Linear Probability Model regression described in section 4.1 are presented in Table 3. Column (1) and column (2) present the result using the loss of income that was reported by the households. In column (1), as expected, households that have an increases im income are more likely to buy property insurance in this period. However, the self-reported loss income has a negative and statistically significant effect on the probability of buying property insurance. These findings are confirmed by the robustness checks when we apply the Conditional Logistic method and when we apply the same estimation approach but use the data in four years and six years. The results are shown in the column (1) in Tables 4, 5 and 6 in the Appendix D.

Table 3: Factors impact on property insurance demand in Vietnam

	<i>Dependent variable:</i>			
	Household bought property insurance			
	<i>Linear Probability Model</i>			
	(1)	(2)	(3)	(4)
Total income (US PPP)	0.00000645*** (0.00000160)	0.00000327** (0.00000152)	0.00000627*** (0.00000159)	0.00000338** (0.00000149)
Regulation		0.263*** (0.0138)		0.224*** (0.0143)
Reported loss of income (US PPP)	-0.0000293*** (0.0000105)	-0.0000153 (0.00000993)		
Reported loss of income * Regulation		0.0000683*** (0.0000203)		
External storms			-0.252*** (0.0304)	-0.123*** (0.0305)
External storms * Regulation				0.328*** (0.0465)
Household fixed effect	Yes	Yes	Yes	Yes
R^2	0.0134	0.213	0.0499	0.231
Observations	4064	4064	4064	4064

Standard errors in parentheses

Linear Probability Model regressions using data in 2 years 2010 and 2013

*p<0.1; **p<0.05; ***p<0.01

²⁵See e.g. Wooldridge (2009).

We are also interested in whether the change in insurance regulation impact on the insurance demand. Column (2) shows that the change in insurance regulation has positive and statistically significant effect on the insurance penetration. Moreover, the interaction between this loss and the change in regulation has the positive effect. It means the effect is negative before insurance regulation was changed and it is positive after the change. According to our theory described in section 2, this behavior could be explained by the loss of available income as well as the potentially negative experience with insurance if insurance regulation is rather lax.

These results are also confirmed by the robustness tests that are presented in the columns (2) of Tables 4, 5 and 6 in Appendix D. However, the loss in income in the aftermath of the shocks turns out to be statistically insignificant. When we change to Conditional fixed-effects Logistic method, the coefficient of variable loss of the income also remains statistically insignificant. This result is shown in the column (2) in Table 4.²⁶

One might argue that the self-reported loss data in the survey could be biased because the households could over-estimate or under-estimate their damage. In order to deal with this problem, we combine household survey data and external data. Column (3) and column (4) in Table 3 show the results using the external storm data. The result of our estimation in column (3) indicates that if households are located in the area near the eyes of a storm, the probability of buying property insurance decreases by 0.252. This finding confirms the results using internal data explained before. Moreover, when we apply Conditional fixed-effects Logistic method or when we employ data in four years or six years, this result remains qualitatively. These stability test results are shown in columns (3) of the Tables 4, 5 and 6 in Appendix D.

The effect of interaction between storms and the change in regulation are shown in the fourth column of Table 3. The results are in line with the results using self-reported losses: We find that before there was change in insurance regulation households living close to a storm's eye are less likely to buy insurance than others. However, after the change in insurance regulation, these households are more likely to buy insurance.

These results reflect our theoretical findings and are also in line with Petrolia, Landry and Coble (2013) that credibility of insurance providers contributes importantly on insurance demand against natural shocks. Our findings also support Reynaud, Nguyen and Aubert (2018) that the belief

²⁶However, in the regressions using four year panel data and six year panel data, variable loss of the income has negative and statistically significant.

in the ability of institutions increases the willing to pay for flood insurance in Vietnam. These findings demonstrate the important role of legal factor on insurance penetration and are in line with our theoretical results. Also Esho et al. (2004) conclude that legal factors play an important role in encouraging insurance demand. Statistics from macro level also show the dramatic increase in property insurance premium in 2011.²⁷

In all robustness tests in Appendix D, our main findings about the effect of the changing in insurance regulation and the effect of the interaction between storms and changing in insurance regulation remain qualitatively.
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5 Conclusions

Natural catastrophes can significantly harm the living standards of affected households and can have long lasting economic effects. Insurance could potentially help to protect households from the financial consequences of these events. Yet risks are uninsured to a large extent, especially in developing economies. While it seems to be an established assumption that the experience of a loss event has an influence on insurance demand, it is not clear whether this influence should increase or decrease demand. On the positive side, the experience of a natural catastrophe might lead to a subjective revaluation of risks and therefore to a higher attractiveness of insurance. On the negative side, however, losses from a natural catastrophe limit households budgets and, hence, ability to buy insurance.

In this paper we analyse the effect of natural catastrophes on the insurance demand of affected households. Given the special need for more protection, we focus our analysis on (a) developing economy(/ies). Our main contribution to the existing literature, however, is that we analyse the role of insurance regulation in this relationship and that we base our analysis on a theoretical model as well as on empirical household panel regressions.

Our theoretical results indicate that an enhancement of regulation does only increase insurance penetration if a reduction of the insurers' non-performance risk is accompanied by a sufficient increase in trust in insurance. Nevertheless, the non-performance risk and the markup on fair insurance premiums should have a negative effect on the impact of a loss event on insurance demand while trust in insurance should have a positive effect. This

²⁷See e.g. Axco data.

²⁸However, the coefficient of variable storm turns out to be statistically insignificant in the table 4 and 6.

would imply that the a loss experience has a more positive effect in developed economies than in developing economies and that an enhancement of insurance regulation makes the impact of a loss event on insurance demand more positive.

The empirical analysis show that the enhancement of insurance regulation in Vietnam was followed by a substantial increase in insurance demand. Moreover, we find that before there was change in insurance regulation households affected by a storm were less likely to buy insurance than others. However, after the change in insurance regulation, these households were more likely to buy insurance. This confirms our theoretical results.

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A Impact of Claim-Payment Probability $\pi^x \pi^z$ on α_0

In order to calculate the impact of $\pi^x \pi^z$ on α_0 we first calculate the total differential of equation (2):

$$\begin{aligned}
& -\frac{p l Y U''[Z_0] U'[N_0] + l Y U'[Z_0] U''[N_0]}{U'[N_0]^2} d\alpha_0 \\
& -\frac{m \alpha_0 l Y U''[Z_0] U'[N_0] - m \alpha_I^e l Y U'[Z_0] U''[N_0]}{U'[N_0]^2} d\pi \\
& + \frac{p l Y U'[Z_0] U''[N_0]}{U'[N_0]^2} d\alpha_I^e = 0
\end{aligned} \tag{26}$$

or

$$\begin{aligned}
& \left\{ p U''[Z_0] + \frac{\gamma}{m} U''[N_0] \right\} \frac{d\alpha_0}{d\pi} = -m \alpha_0 U''[Z_0] \\
& + \gamma \alpha_I^e U''[N_0] + \gamma \pi U''[N_0] \frac{d\alpha_I^e}{d\pi},
\end{aligned} \tag{27}$$

where $\pi = \pi^x \pi^z$, $Z_0 = Y(1 - p\alpha_0 l)$, $N_0 = Y(1 - l(1 - \alpha_0 + p\alpha_I^e))$ and, hence, $U'[Z_0]/U'[N_0] = \gamma/m$. Since α_I^e depends on π , we also have to calculate the total differential of the expected equation (4) which is given by:

$$-\frac{p l Y U''[Z_I^e] U'[N_I^e] + l Y U'[Z_I^e] U''[N_I^e]}{U'[N_I^e]^2} d\alpha_I^e - \frac{m \alpha_I^e l Y U''[Z_I^e]}{U'[N_I^e]} d\pi + \frac{l Y U''[Z_I^e]}{U'[N_I^e]} d\alpha_0 = 0 \quad (28)$$

or

$$\frac{d\alpha_I^e}{d\pi} = -\frac{m \alpha_I^e U''[N_0]}{p U''[N_0] + \frac{\gamma}{m} U''[N_I^e]} + \frac{U''[N_0]}{p U''[N_0] + \frac{\gamma}{m} U''[N_I^e]} \frac{d\alpha_0}{d\pi}, \quad (29)$$

where $N_I^e = Y(1 - l(1 - \alpha_I^e))$, $Z_I^e = Y(1 - l(1 - \alpha_0 + p\alpha_I^e))$ and, hence, $Z_I^e = N_0$. By inserting this derivative in equation 27, we get:

$$\left\{ p U''[Z_0] + \frac{\gamma}{m} U''[N_0] \right\} \frac{d\alpha_0}{d\pi} = -m \alpha_0 U''[Z_0] + \gamma \alpha_I^e U''[N_0] - \frac{m \alpha_I^e \gamma \pi U''[N_0]^2}{p U''[N_0] + \frac{\gamma}{m} U''[N_I^e]} + \frac{\gamma \pi U''[N_0]^2}{p U''[N_0] + \frac{\gamma}{m} U''[N_I^e]} \frac{d\alpha_0}{d\pi}, \quad (30)$$

or

$$\left\{ p^2 \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_0]}{U'[N_0]} + p \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_I^e]}{U'[N_I^e]} + \frac{U''[N_0]}{U'[N_0]} \frac{U''[N_I^e]}{U'[N_I^e]} \right\} \frac{d\alpha_0}{d\pi} = -\alpha_0 m p \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_0]}{U'[N_0]} - \alpha_0 m \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_I^e]}{U'[N_I^e]} + \alpha_I^e m \frac{U''[N_0]}{U'[N_0]} \frac{U''[N_I^e]}{U'[N_I^e]} \quad (31)$$

The left hand side of this derivative is positive. Therefore, α_0 depends negatively on π if the right hand side is negative. If we assume constant absolute risk aversion with $R_A = -U''[W]/U'[W]$, this is given if:

$$-\alpha_0 m p R_A^2 - \alpha_0 m R_A^2 + \alpha_I^e m R_A^2 < 0 \quad (32)$$

or

$$(1 + p)\alpha_0 > \alpha_I^e \quad (33)$$

Since $m > 1$ the expected equation (4) implies that $\alpha_0 > (1 + p)\alpha_I^e$. Hence, the condition is always fulfilled. This implies that for constant relative risk aversion, α_0 depends negatively on π .

If we assume constant relative risk aversion with $R_R = -WU''[W]/U'[W]$, the condition for a negative impact of π on α_0 is:

$$-\alpha_0 mp \frac{R_R^2}{Z_0 N_0} - \alpha_0 m \frac{R_R^2}{Z_0 N_I^e} + \alpha_I^e m \frac{R_R^2}{N_0 N_I^e} < 0 \quad (34)$$

or

$$\alpha_0(1-l)(1+p) + \alpha_0 l(\alpha_I^e p + \alpha_0) > \alpha_I^e \quad (35)$$

As we can see, whether this condition is fulfilled, depends negatively on l and positively on p , α_0 as well as the fraction α_0/α_I^e . Hence, with constant relative risk aversion it is not clear whether insurance demand in $t = 0$ depends positively or negatively on π . It is also not clear whether in low income countries (high p and low α_0) the relationship is more or less likely to be negative.

B Impact of Claim-Payment Probability $\pi^x \pi^z$ on α_I

The deviation of α_I with regard to $\pi = \pi^x \pi^z$ is given by equation (7). As we can see, α_I depends negatively on π if:

$$m\alpha_I > \frac{d\alpha_0}{d\pi} \quad (36)$$

As shown in Appendix A, $d\alpha_0/d\pi$ is negative for CARA. Hence, for CARA this condition is fulfilled and also α_I depends negatively on π .

To calculate the impact under CRRA we replace $d\alpha_0/d\pi$ by the CRRA version of equation (31) and get:

$$\alpha_I(p^2 N_I^e + p N_0 + Z_0) > -\alpha_0 p N_I^e - \alpha_0 N_0 + \alpha_I^e Z_0, \quad (37)$$

where $Z_0 = Y(1 - p\alpha_0 l)$, $N_0 = Y(1 - l(1 - \alpha_0 + p\alpha_I^e))$ and $N_I^e = Y(1 - l(1 - \alpha_I^e))$.

Since we assume that households do not expect to change their probability assessment and that $\gamma < \epsilon_h \delta_h$, the actual α_I is higher than the expected α_I^e . Hence, the above condition is fulfilled and for CRRA α_I depends negatively on π .

C Impact of Markup m

In line with appendix A, we calculate the impact of m on α_0 by calculating the total differential of equation (2):

$$\left\{ pU''[Z_0] + \frac{\gamma}{m}U''[N_0] \right\} lY \frac{d\alpha_0}{dm} = \frac{\gamma}{m^2}U'[N_0] - \pi\alpha_0 lY U''[Z_0] + \frac{\gamma\pi\alpha_I^e lY}{m}U''[N_0] + \gamma\pi lY U''[N_0] \frac{d\alpha_I^e}{dm}, \quad (38)$$

where $\pi = \pi^x \pi^z$, $Z_0 = Y(1 - p\alpha_0 l)$, $N_0 = Y(1 - l(1 - \alpha_0 + p\alpha_I^e))$ and, hence, $U'[Z_0]/U'[N_0] = \gamma/m$. Since α_I^e depends on m , we also have to calculate the total differential of the expected equation (4) which is given by:²⁹

$$\gamma\pi lY \frac{d\alpha_I^e}{dm} = \frac{\frac{\gamma}{m^2}U'[N_I^e] - \pi\alpha_I^e lY U''[N_0]}{\frac{m}{\gamma}U''[N_0] + \frac{1}{p}U''[N_I^e]} + \frac{lY U''[N_0]}{\frac{m}{\gamma}U''[N_0] + \frac{1}{p}U''[N_I^e]} \frac{d\alpha_0}{dm}, \quad (39)$$

where $N_I^e = Y(1 - l(1 - \alpha_I^e))$, $Z_I^e = Y(1 - l(1 - \alpha_0 + p\alpha_I^e))$ and, hence, $Z_I^e = N_0$. By inserting this derivative in equation 38, we get:

$$\begin{aligned} & \left\{ p \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_0]}{U'[N_0]} + \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_I^e]}{U'[N_I^e]} + \frac{1}{p} \frac{U''[N_0]}{U'[N_0]} \frac{U''[N_I^e]}{U'[N_I^e]} \right\} lY \frac{d\alpha_0}{dm} \\ &= \frac{1}{m} \left\{ 2 \frac{U''[N_0]}{U'[N_0]} + \frac{1}{p} \frac{U''[N_I^e]}{U'[N_I^e]} \right\} \\ & - \frac{lY}{m} \left\{ \alpha_0 p \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_0]}{U'[N_0]} + \alpha_0 \frac{U''[Z_0]}{U'[Z_0]} \frac{U''[N_I^e]}{U'[N_I^e]} - \alpha_I^e \frac{U''[N_0]}{U'[N_0]} \frac{U''[N_I^e]}{U'[N_I^e]} \right\} \quad (40) \end{aligned}$$

The left hand side of this derivative is positive. Therefore, α_0 depends negatively on m if the right hand side is negative. As we can see, the differential looks very similar to (31). The main difference is the first term on the right hand side of differential equation. Since this factor is negative, the impact of m on α_0 is more likely to be negative than the impact of π .

If we assume constant absolute risk aversion with $R_A = -U''[W]/U'[W]$, this is given if:

$$2 + \frac{1}{p} + lY R_A \{ \alpha_0(1 + p) - \alpha_I^e \} > 0 \quad (41)$$

Since $m > 1$ the expected equation (4) implies that $\alpha_0 > (1 + p)\alpha_I^e$. Hence, the condition is always fulfilled. This implies that for constant relative risk aversion, α_0 depends negatively on m .

²⁹Since we assume that households do not expect to change their probability assessment, the right hand side of (4) is equal to γ/m .

If we assume constant relative risk aversion with $R_R = -WU''[W]/U'[W]$, the condition for a negative impact of m on α_0 is:

$$l\alpha_I^e \left(1 - \frac{1}{pR_R}\right) < l\alpha_0 \frac{(1+p)(1-l) + l\alpha_0}{1 - pl\alpha_0} + \frac{1}{pR_R} [(1-l)(1+p+\pi) + l\alpha_0] \quad (42)$$

As we can see, whether this condition is fulfilled, depends negatively on the risk aversion R_R . For $R_R \rightarrow \infty$, this condition is only fulfilled if $\partial\alpha_0/\partial\pi < 0$. For more realistic levels of risk aversion, however, the condition is always fulfilled and α_0 depends negatively on m . If we assume, for example, $R_R = 1/p$ (with $\pi = 0.1$ and $m = 2$, this would imply $R_R = 5$), we get the following condition:

$$l\alpha_I^e (1 - \pi) < l\alpha_0 \left\{ 1 + \frac{(1+p)(1-l) + l\alpha_0}{1 - pl\alpha_0} \right\} + (1-l)(1+p+\pi). \quad (43)$$

Since $\alpha_0 > \alpha_I^e$, this condition is fulfilled.

D Tables

Table 4: Factors impact on property insurance demand in Vietnam using Conditional fixed-effects Logistic

	<i>Dependent variable:</i>			
	Household bought property insurance			
	<i>Conditional fixed-effects Logistic</i>			
	(1)	(2)	(3)	(4)
Total income (US PPP)	0.0000322*** (0.00000851)	0.0000226** (0.0000104)	0.0000339*** (0.00000901)	0.0000229** (0.0000105)
Regulation		1.724*** (0.115)		1.678*** (0.132)
Reported loss of income (US PPP)	-0.000152*** (0.0000578)	-0.000161 (0.000126)		
Reported loss of income * Regulation		0.000332* (0.000200)		
External storm			-1.094*** (0.146)	-0.142 (0.227)
External storm * Regulation				0.888** (0.393)
Household fixed effect	Yes	Yes	Yes	Yes
Log likelihood	-520.3	-303.9	-492.1	-302.8
Observations	1536	1536	1536	1536

Standard errors in parentheses

Regressions using data in 2 years 2010 and 2013

*p<0.1; **p<0.05; ***p<0.01

Table 5: Factors impact on property insurance demand in Vietnam using data in four years

	<i>Dependent variable:</i>			
	Household bought property insurance			
	<i>Linear Probability Model</i>			
	(1)	(2)	(3)	(4)
Total income (US PPP)	0.00000826*** (0.000000949)	0.00000480*** (0.000000823)	0.00000736*** (0.000000924)	0.00000478*** (0.000000824)
Regulation		0.321*** (0.0101)		0.315*** (0.0101)
Reported loss of income (US PPP)	0.000000456 (0.00000502)	-0.0000174*** (0.00000511)		
Reported loss of income * Regulation		0.0000384*** (0.00000706)		
External storm			-0.201*** (0.0139)	-0.0877*** (0.0141)
External storm * Regulation				0.133*** (0.0368)
Household fixed effect	Yes	Yes	Yes	Yes
R^2	0.0199	0.210	0.0456	0.211
Observations	8088	8088	8088	8088

Standard errors in parentheses

Linear Probability Model regressions using data in 4 years 2008, 2010, 2013 and 2016

*p<0.1; **p<0.05; ***p<0.01

Table 6: Factors impact on property insurance demand in Vietnam using data in six years

	<i>Dependent variable:</i>			
	Household bought property insurance			
	<i>Linear Probability Model</i>			
	(1)	(2)	(3)	(4)
Total income (US PPP)	0.00000925*** (0.000000739)	0.00000446*** (0.000000580)	0.00000895*** (0.000000733)	0.00000458*** (0.000000583)
Regulation		0.342*** (0.00867)		0.362*** (0.00856)
Reported loss of income (US PPP)	-0.0000194*** (0.00000396)	-0.0000303*** (0.00000339)		
Reported loss of income * Regulation		0.0000550*** (0.00000513)		
External storm			-0.114*** (0.0113)	0.00591 (0.0107)
External storm * Regulation				0.101*** (0.0336)
Household fixed effect	Yes	Yes	Yes	Yes
R^2	0.0319	0.239	0.0357	0.233
Observations	12172	12172	12172	12172

Standard errors in parentheses

Linear Probability Model regressions using data in 6 years 2007, 2008, 2010, 2013, 2016 and 2017

*p<0.1; **p<0.05; ***p<0.01