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Perceived Vulnerability to Downside Risk

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Perceived Vulnerability to Downside Risk*

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Abstract

In this paper we propose an approach to vulnerability called perceived $vulnerability\ to\ downside\ risk$. We argue that the other concepts of vulnerability, though partially adhering to the focus axiom, do not exclusively consider downside risks in their measures. The reason for this is that most of them use a pre-determined threshold such as the poverty line as their benchmark for analysis. Instead, we opt for the current level of wellbeing of a household as reference point. Also, we propose to use subjective risk perception as the source of information for quantifying vulnerability since it overcomes some of the shortcomings connected to the reliance on information about the past. Finally, we apply the measure of perceived $vulnerability\ to\ downside\ risk$ to risk perception data from Thailand and Vietnam and find that households in the latter country tend to be more vulnerable than households in the former. Moreover, determinants of perceived $vulnerability\ to\ downside\ risk$ differ significantly between the two countries.

JEL Classification: D81, I31, I32, O12

Key words: Vulnerability, Risk, Risk Perception, Subjective Wellbeing

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1 Introduction

The World Bank put the concept of vulnerability in the spotlight of poverty research by presenting it in the World Development Report 2000/01 as an important component of combating poverty. According to the report "vulnerability measures the resilience against a shock – the likelihood that a shock will result in a decline in well-being" (World Bank, 2001).

The reason for assigning such a prominent position to, as well as for increased economists' interest in vulnerability is twofold: First, vulnerability impacts negatively on the wellbeing of households. Expressed differently, not only current conditions such as levels of income and consumption matter for actual welfare, but also the risks a household faces (and the (in)ability to prevent, mitigate, and cope with these).

Second, vulnerability is not only a dimension but also a cause of deprivation. For instance, poor households facing a risky future, i.e. vulnerability, are more likely to opt for stable, low-return sources of income than to invest in endeavours whose outcome is more uncertain. Though being a rationale choice, this behavior may trap households in poverty by rendering higher levels of income impossible. Therefore, attacking vulnerability has the potential to reduce poverty.

The concept of vulnerability (even of vulnerability to poverty) is distinct from the concept of poverty. Poor households may be non-vulnerable whereas non-poor households may face a risky future possibly pushing them below the poverty line. In Indonesia, for instance, the population share of the poor was rather low before the financial crisis took place during the second half of the 1990s. However, due to the crisis the share of the poor rose dramatically revealing that prior to the crisis numerous Indonesian households were non-poor but vulnerable to poverty (cf. Gaiha and Imai, 2009). Hence, when targeting policies to combat poverty it is important to identify not only the poor but also the part of the population which is at risk of becoming poor. Also, the required type of policy intervention may differ between poor and vulnerable beneficiaries. On the one hand, the creation of new sources of income might be the right "medicine" for the poor. On the other hand, the non-poor but vulnerable part of the population might rather be in need of insurance for their existing sources of income. Since standard poverty measures are not able to adequately identify the vulnerable part of the population researchers increasingly propose and discuss different measures of vulnerability.

With this paper we intend to add value to the ongoing debate about an appropriate concept and measure of vulnerability. It has been widely acknowledged that vulnerability as such has to focus on downside risk, i.e. on possible negative future outcomes (cf. Hoddinott and Quisumbing, 2003). We argue that the concepts proposed so far, though claiming to adhere to this principle, do not exclusively rely on downside risks. By choosing, for instance, the poverty line as their benchmark they allow all future outcomes beneath this reference point to impact on vulnerability. However, when assessing the impact of vulnerability on wellbeing it seems to be much more reasonable to determine a household's current status as the reference point. For example, the wellbeing of a currently poor household, who faces a possible future state of the world in which it is better off than now but still beneath the poverty line, is improved – as opposed to harmed – by this outlook. For the household such an outcome is a positive one since it relies on its own *status quo* as benchmark for any assessment and not on a threshold imposed from the outside such as the poverty line.

We propose a perceived "$vulnerability\ to\ downside\ risk$" measure which incorporates this argument and exclusively relies on vulnerability in the proper meaning of the word. That is, it is only influenced by possible future outcomes which are below the current level of a household's wellbeing. While being different from other concepts in the choice of the relevant reference point the approach still belongs to "the class of measures where vulnerability is a probability weighted average of state-specific 'deprivation indices'..." (Calvo and Dercon, 2005).[1]

Commonly used approaches to empirically estimate vulnerability rely on information from the past in order to model future outlooks. For instance, Calvo and Dercon (2007) regress current consumption (from period t) on, *inter alia*, lagged consumption (from period t-1) and adverse shocks. They use the results from this step to predict vulnerability to poverty as it was in period t-1. In other words, a *backward* looking empirical method is used in order to estimate a *forward* looking measure. We argue that these empirical approaches – while certainly having their merits – are not the best choice to inform policy makers since they provide only insights into the vulnerability of households in the past.

Therefore, we apply the proposed measure of perceived $vulnerability\ to\ downside\ risk$ to the forward looking risk perception of households in period t. Certainly this approach relies on the subjective assessment of a household and it is questionable whether actual risk can properly be predicted in such a

[1] In this paper aggregation issues are – at least in the theoretical part – excluded and left of future research. However, when presenting results of the empirical application of the measure we use simple arithmetic means to reveal aggregate levels of vulnerability.

way. But it is not crucial whether subjective risk perception or information about past shocks is better in predicting the future; what rather counts is the question which one of both impacts more on a household's wellbeing and economic behavior. We argue that it is reasonable to assume that the former does so, i.e. that subjective risk perception is determining current wellbeing, as well as choices and therefore constitutes an appropriate source of information for quantifying vulnerability.

The remainder of this paper is structured as follows: Section 2 provides background information on vulnerability, risk and risk perception. In section 3 the new measure of vulnerability to downside risk and its properties are discussed. In section 4 the results of the measure's application to 3875 households from Thailand and Vietnam are presented. Finally, in the last section the findings of the paper are summarized and conclusions drawn.

2 Risk and Vulnerability

2.1 Risk and Concepts of Vulnerability

Risk plays a key role in economic development. Before elaborating on this, it is useful to define what we are talking about: Although technically risk does not have to have a negative connotation, in common practice such a meaning is typically attached to it. Harding (1998) defines risk as "a combination of the probability, or frequency, of occurrence of a defined hazard and the magnitude of the consequences of the occurrence: how often is a particular potentially harmful event going to occur, [and] what are the consequences of this occurrence?" In this paper we will follow this definition: Risk is a negative future event whose occurrence has a certain probability.[2]

Among economists it is widely acknowledged that a household's level of wellbeing is not only determined by its current status in terms of, for instance, income, consumption, education and health, but also by the risks it faces (cf. Ligon and Schechter, 2004). Having a certain income but fearing to lose the job does not feel as good as having the same income and a safe employment. Therefore, risk is an important component in the analysis of wellbeing.

[2] However, there might be negative future events which will – or are perceived to – certainly take place (probability of 100%) or not (probability of 0%). Since in these cases there is no notion of uncertainty anymore (at least concerning their probability of occurrence) these events will be labeled certainties as opposed to risks in section 3 of this paper.

Risk not only impacts on wellbeing but also influences behavior and decision making processes (cf., for instance, Gunning and Elbers, 2003, and Dercon, 2007). People exposed to risk apply risk management strategies in order to prevent them from happening (for example, by building a dam to protect the belongings against a flood), mitigate their impact (for example, by contracting insurance) and / or cope with them as soon as they occur (for example, by migrating in order to find a new job). In absence of functioning credit and insurance markets such a behavior possibly results in lower growth, as well as high and persistent poverty rates. Imagine, for instance, a currently poor household which faces two possibilities: either it plants a type of crop that will yield a certain but low return, or it opts for a type that possibly offers a much higher return but is also much more prone to weather shocks and thus to an even lower return. Assuming risk aversion and the absence of a functioning insurance market this household is likely to choose the former possibility at the expense of remaining poor due to a constantly low source of income. On an aggregated level such a behavior hampers economic growth.[3] Therefore, risk is to be considered in the fight against poverty and the design of growth supporting policies.

After having clarified the meaning of risk and its possible economic impact we will now turn to the area of research of which risk is the crucial ingredient: vulnerability. Subsequently to its introduction to a broad audience by the World Development Report 2000/01 the concept of vulnerability was widely applied and interpreted.[4] The numerous approaches to vulnerability can broadly be grouped into the following three categories: (i) vulnerability as expected poverty (VEP; cf., for example, Pritchett *et al.*, 2000, Chaudhuri *et al.*, 2002, and Kamanou and Morduch, 2004), (ii) vulnerability as low expected utility (VEU; cf. Ligon and Schechter, 2003) and (iii) vulnerability as uninsured exposure to risk (VER; cf., for example, Townsend, 1994, and Amin, Rai and Topa, 2003).

VEP measures the probability that a household will be below a pre-determined poverty line in the future. Expressed differently, this approach uses a benchmark – the poverty line z – and sets the probability that household h's consumption level in the future ($c_{h,t+1}$) will be below this benchmark equal to its actual degree of vulnerability:

(1) $$VEP_{ht} = \Pr\,(c_{h,t+1} \leq z).$$

[3] For empirical proof that risk management strategies can impact negatively on overall growth see, for example, Gunning and Elbers (2003).
[4] Note that already prior to this event vulnerability was a research topic of economists, although on a much smaller scale (cf. Calvo and Dercon, 2007). For a detailed discussion of different approaches to vulnerability see Hoddinott and Quisumbing, 2003.

By doing so the concept differs from the one put forward by the World Bank (cf. chapter 1). Certainly, it incorporates the resilience against shocks – but only against the shocks that push a household below the poverty line or keep it there. Instead, expected consumption shortfalls above the poverty line are not considered – even if they are much more pronounced than the former ones. Moreover, upward movements below the poverty line increase VEP. That is, an individual currently consuming half a dollar per day and expecting to consume 90 cents per day in future will be considered vulnerable although he or she faces and consumption increase by 80%.

VEP as presented in equation 1 does not account for risk sensitivity: Households are said to exhibit the same degree of vulnerability if they have the same expected outcome. However, uncertainty is likely to have a negative impact on wellbeing wherefore a household which will certainly receive the expected outcome should be less vulnerable than households facing different possible future outcomes. The severity of expected poverty is not considered, either. That is, a household with a 50% probability of being little below the poverty line has the same vulnerability as a household with a 50% probability of being far below the poverty line.

These shortcomings can easily be addressed by combining VEP with the Foster-Greer-Thorbecke (FGT; 1984) measures of poverty (cf. Hoddinott and Quisumbing, 2003). Assuming that $\sum_{i=1}^{N_h} p_{hi}$ reflects the sum of probabilities of all possible future scenarios faced by household h and $I_{hi}(\cdot)$ represents an indicator which equals one if $c_{hi,\,t+1} \leq z$ and zero otherwise equation 1 can be transformed into:

(2) $$VEP_{ht} = \sum_{i=1}^{N_h} p_{hi} \times I_{hi}(c_{hi,\,t+1} \leq z) \times \left(\frac{z - c_{hi,t+1}}{z}\right)^{\alpha}$$

Here, α captures risk attitudes and the type of poverty which is measured: households are risk averse if $\alpha > 1$, risk neutral if $\alpha = 1$, and risk proclivous if $0 < \alpha < 1$. Also, $\alpha = 0$ provides the expected poverty headcount, $\alpha = 1$ the expected poverty gap, and $\alpha > 1$ the expected severity of poverty.

Nonetheless, VEP based on FGT measures integrates households' risk attitudes only imperfectly: First, $\alpha > 1$ implies that absolute risk aversion is positively correlated with consumption (or any other measure of welfare; cf. Hoddinott and Quisumbing, 2003).[5] In the light of empirical findings regarding this matter such a property of risk attitude is highly unlikely (for an early example see Binswanger, 1981). Second, cases are possible in which VEP of a household decreases when moving from a certain

[5] In case of FGT measures absolute risk aversion is given by (α –1)z/(z-c) (cf. Hoddinott and Quisumbing, 2003).

consumption level just below the poverty line to an expected consumption level equal to the certain one but based on outcomes above and below it (for an example see Hoddinott and Quisumbing, 2003).

VEU – proposed by Ligon and Schechter (2002, 2003) – redresses this weakness. As opposed to VEP, this concept puts "expected utility" at the core of its analysis. It sets the vulnerability of household h (VEU_h) equal to the difference between the household's utility derived from certainty-equivalent consumption (z_{CE}) and the household's expected utility derived from its consumption (c_h):

(3) $$VEU_h = U_h(z_{CE}) - EU_h(c_h)$$

By assuming U_h to be a weakly concave, strictly increasing function VEU accounts for risk preferences and is thus suited for quantifying the welfare loss provoked by risk. Another useful feature of VEU is that vulnerability can be decomposed into a poverty-, a covariate risk-, and an idiosyncratic risk-component as shown in equation 4 (cf. Ligon and Schechter, 2003):

(4) $$VEU_h = [U_h(z_{CE}) - U_h(Ec_h)] \quad \text{(poverty component)}$$

$$+\{U_h(Ec_h) - EU_h[E(c_h|x_t)]\} \quad \text{(covariate risk-component)}$$

$$+\{EU_h[E(c_h|x_t)] - EU_h(c_h)\} \quad \text{(idiosyncratic risk-component)}$$

where $E(c_h|x_t)$ equals the expected value of consumption given a vector of covariant variables x_t.

However, these advantages come at the cost of allowing possible positive outcomes to compensate for the vulnerability increasing effect of possible negative outcomes. Such a property is not desirable because a household might be labeled "non vulnerable" although in at least one possible future state of the world it faces severe destitution. Also, there is no reference to the poverty line – the relevant threshold is $U_h(z_{CE})$ – wherefore VEU does not qualify for identifying the part of the population threatened by poverty.

The last point also holds true for VER which measures whether idiosyncratic and covariate shocks impact on consumption. That is, this concept is not able to identify those threatened by poverty, either. In sharp contrast to every other approach to vulnerability not levels but only changes of consumption matter in the case of VER. When applied econometrically, idiosyncratic and covariate shocks are usually instrumented by the growth rate of average household income ($\Delta\, y_{htv}$) and the growth rate of average village income ($\Delta\big(\overline{ln\; y_{tv}}\big)$), respectively, of household h in village v at time t as shown in equation 5:

(5) $$\Delta \ln c_{htv} = \alpha + \beta \ln \Delta\, y_{htv} + \gamma \Delta\big(\overline{ln\; y_{tv}}\big) + \delta X_{htv} + \Delta\, \varepsilon_{htv}$$

where $\Delta \ln c_{htv}$ denotes the growth rate of consumption per capita between periods t and t-1 and X_{htv} reflects a vector of household characteristics. VER rises with an increasing β. Complete risk sharing is implied by $\beta = 0$. The coefficient γ captures the impact of covariate shocks on consumption.

Although there is a wide range of differing approaches to vulnerability there seem to be at least two characteristics most strands of literature agree upon (cf. Calvo and Dercon, 2005):

1. Vulnerability is a forward-looking concept analyzing something *ex-ante*, and therefore dealing with uncertainties, and not *ex-post* as static poverty measures, which consider actual facts, do.
2. Vulnerability always refers to something negative. That is, vulnerability is concerned with “bad” future outcomes faced by households.

These two similarities are at the root of more recent attempts to narrow the multitude of interpretations of vulnerability to a clearly defined and more commonly accepted concept – or, in other words, to end what Hoddinott and Quisumbing (2003) called the “let a hundred flowers bloom” stage of vulnerability research. Calvo and Dercon (2005), for instance, present an axiomatic approach to vulnerability in whose framework vulnerability is a probability weighted average of future states of the world-specific indices of deprivation. They explicitly refer to $vulnerability\ to\ poverty$, i.e. they do not take into account states of the world above the poverty line. The $vulnerability\ to\ poverty$ of household h is calculated as shown in equation 6:

(6) $$Vulnerability\ to\ Poverty_{\,h} = 1 - \left(\textstyle\sum_{i=1}^{N_h} p_{hi} \times x_{hi}{}^{\alpha}\right),$$

where α ranges between zero and one, p_{hi} denotes the probability of state of the world i to occur and x_{hi} is a state specific degree of deprivation which equals $\frac{\tilde{y}_{hi}}{z}$. $\tilde{y}_{hi}$ is a censored outcome measure. That is, all outcomes where y_{hi} is above the poverty line z are censored at z and consequently do not change the vulnerability measure. The closer (further away) α moves to (from) one the less (more) risk aversion is assumed. By not allowing α to rise beyond one Calvo and Dercon (2005) discard the possibility of risk proclivity.

Among the axioms proposed within the context of $vulnerability\ to\ poverty$ the following two stand out and are of relevance for later sections of this paper:[6]

- The axiom of risk sensitivity implies that while keeping the expected outcome constant an increase in uncertainty faced by a household should be reflected in a higher degree of vulnerability.
- The focus axiom is supposed to ensure that the vulnerability measure is exclusively sensitive to negative future outcomes. Possible positive future outcomes must not be reflected in the measure.[7] In other words, this axiom guarantees that a household is not labeled "non vulnerable" although in a possible future state of the world it faces severe destitution (as it could be, for example, in the case of VEU). Since Calvo and Dercon (2005) are concerned with $vulnerability\ to\ poverty$ they interpret the axiom as being adhered to if exclusively outcomes below the poverty line impact on their measure.

Due to the focus axiom and its interpretation the concept of $vulnerability\ to\ poverty$ shares two important characteristics with VEP: First, consumption changes above the poverty line are not accounted for. Second, an expected increase of consumption of poor households *raises* vulnerability as long as the level of future consumption is still below the poverty line.

2.2 Contributions of Perceived Risk to the Measurement of Vulnerability

Besides theoretical aspects of approaches to vulnerability their empirical application is of major concern for economists. When measuring vulnerability the need for numerous considerations arises. The most important one is arguably related to the forward looking character which vulnerability measures have to adopt. How can something be quantified *ex-ante* when future events are still uncertain? On the one hand, probabilities have to be attached to each future state of the world. On the other hand, the outcome of each of these states has to be quantified. These requirements pose demands on the quantity and quality of data which are extremely – if not too – high. Therefore, researchers tend to rely on

[6] The axioms on which is not elaborated are: (i) axiom of symmetry over states, (ii) axiom of continuity and differentiability, (iii) axiom of scale invariance, (iv) axiom of normalization, (v) axiom of the probability-dependent effect of outcomes, (vi) axiom of probability transfer, and (vii) axiom of constant relative or absolute risk sensitivity. For a in depth discussion of them see Calvo and Dercon (2005).

[7] Calvo and Dercon (2005) offer the following example to illustrate the need for the focus axiom: "…let us imagine that the poor buy each week a state lottery ticket – they spend a very small sum of money, but 'you never know', and there is a 0.001 percent chance of winning to the top prize of $10,000. The following 'policy' measure would make these households less vulnerable [if the focus axiom was not applied] …: increase the top prize to $10 million!"

stringent assumptions when measuring vulnerability empirically: Chaudhuri et al. (2002), for instance, present a procedure to estimate VEP empirically with cross-sectional data which – given the paucity of panel data from developing countries – is already a merit of its own. More precisely, the authors interpret the cross-sectional variation of the sampled households' consumption as the time series variation of household-specific consumption. That is, they assume very stringently that both variations are alike. Another common approach to predict the future draws on information from the past. For example, Calvo and Dercon (2007) infer from passed shocks the future risks a household faces. That is, they implicitly assume that shocks will evolve over time and space just as they did beforehand. However, there is good reason to believe that this assumption does not hold true for real life: For example, a household which suffered from a drought in the past does not face a corresponding risk if meanwhile a reliable irrigation system was built.

Certainly, it is important to identify households which *have* suffered from shocks. But what the concept of vulnerability really is supposed to add to ongoing research and the provision of policy advice is a tool to properly target households which *will* suffer from shocks. Since adverse events from the past are not equal to future threats the vulnerability of a household is not constant over time. In fact, it is as dynamic as the concept of vulnerability itself. Therefore, it is preferable to rely on *forward* looking information when computing a measure of vulnerability.

Forward looking information can be obtained, *inter alia*, by asking households directly about their risk perception, i.e. about the perceived probabilities and – in case they really occur – perceived severities of risks.[8] In addition to the avoidance of retrospective information there are other reasons in favor of using data on risk perception. Recall that risks and vulnerability are important because of two aspects: their negative effect on current wellbeing, as well as their impact on economic behavior (and therefore on future wellbeing). Wellbeing is obviously subjective. Imagine a household fears, i.e. perceives the risk of, a drought. Even if researchers "objectively" estimate a very low probability for the drought to occur the household remains fearing something – with all its negative implications for current wellbeing. In turn, if a household expects good weather conditions its current wellbeing will not be negatively influenced, neither by its subjective perception nor by an analysis of scientists who claim that there is a high danger of a drought.[9] Concerning vulnerability's impact on behavior imagine again a household fears a drought.

[8] For an in depth discussion of subjective risk perception and its measurement see De Weerdt, 2005.
[9] Note that this holds true even if the below discussed heuristic of availability appears.

This perceived risk may provoke the household to apply risk management strategies such as investment in drought-resistant, low-return income sources no matter how the actual risk looks like.[10]

In spite of these advantages the use of data on perceived risks comes at the cost of stringent assumptions – as the other empirical approaches to vulnerability do. For instance, there are the so called heuristics of probabilities which explain why risk perception may not be a good predictor of actual risk. According to Botterill and Mazur (2004) all households which are exposed to uncertainty rely on these heuristics. They define the latter as "speculative frameworks that … [households] … use to guide their investigation of possible solutions to problems or to make sense of the world". The three major heuristics are identified by Kahnemann, Slovic and Tversky (1982):

- The heuristic of representativeness implies that a person regards a certain sequence of events as being more likely than another although both sequences have the same probability. For example, when playing roulette in a casino people tend to bet on red if several previous times black won. However, the probability of red and black remains all the time equal and unchanged. Similarly, when asked about risks respondents may tend to assign a low probability to one of the risks if they assigned high probabilities to several previous ones – no matter whether outside the interview they perceive the risk in question as being likely or not.
- The heuristic of adjustment (or anchoring) provokes the respondent to stick to any value which he or she may have in mind beforehand. Thus, if a certain value is suggested to the respondent during the interview he or she may succumb to the heuristic of adjustment and state this value disproportionally often.
- The heuristic of availability provokes a person to consider past experiences when assigning probabilities to possible future events. Consequently, a respondent is more likely to expect an illness to take place with a high probability if his or her household was prone to this kind of shock during the past.

The heuristic of availability is not that problematic because even if it is present the enumerator still surveys the *de facto* perceived risk of the respondent. Instead, the heuristics of adjustment and of representativeness may provoke the respondent not to state his or her *de facto* perceived risk. Also, respondents in developing countries with limited formal schooling may have difficulties to report their

[10] Note that this holds true even if the below discussed heuristic of availability appears. Authors who recognize that perceived instead of actual risk determine the behavior of households include De Weerdt (2005) and Dercon (2007).

perceived risks in terms of probabilities and severities. Nonetheless, experience shows that even in developing countries it is possible to elicit high quality information of this type with the help of a well designed questionnaire, as well as carefully trained enumerators (cf., for example, Attanasio, 2009).

3 Vulnerability to Downside Risk

3.1 Theoretical Considerations Regarding a Measure of Vulnerability to Downside Risk

In this section we propose a measure of perceived $vulnerability\ to\ downside\ risk$ which chooses a household's current status of wellbeing instead of a pre-determined threshold such as the poverty line as reference point. The rationale behind this is twofold: First, the paternalism inherent in the poverty line is avoided. By using the latter as benchmark people are said to feel deprived as long as they are below it. However, why should these people compare changes in their wellbeing to a threshold they may not even be aware of?

Second, by determining the poverty line to be the relevant reference point households without a probability of falling below it are labeled "non vulnerable" regardless of how much their level of wellbeing may decrease in future. Consequently, the question arises why a household which is likely to fall from high above the poverty line to very close above it should be entirely "non vulnerable" whereas a household which is likely to fall much less, namely from right above the poverty line to right below it, is vulnerable?

Due to the newly chosen reference point the measure of perceived $vulnerability\ to\ downside\ risk$ is based on a re-interpretation of the focus axiom: Now, with this axiom is complied if, and only if, the vulnerability measure in question is exclusively affected by future states of the world in which a household finds itself below its current level of wellbeing.

As already indicated in chapter 2 other concepts of vulnerability do not adhere to the focus axiom in the aforementioned sense. By choosing the poverty line as their benchmark they allow all future outcomes beneath this reference point to impact on vulnerability. However, when assessing the impact of vulnerability on current wellbeing it seems to be much more reasonable to determine a household's current status as the reference point. For example, the wellbeing of a currently poor household that faces a possible future state of the world in which it is better off than now but still beneath the poverty line, is increased – as opposed to harmed – by this outlook. For the household such an outcome is a positive one since it relies on its own *status quo* as benchmark and not on a threshold imposed from the outside such as the poverty line. Moreover, the possibility to increase its welfare certainly does not provoke the household to opt for a second best choice like, for instance, investing in certain but low-return sources of income. That is, the household is not likely to impair its future wellbeing by current economic behaviour which is induced by its future outlook. However, $vulnerability\ to\ poverty$ and VEP would not just be affected by such a positive outcome, they would even *increase* because of it.

By contrast, the measure of perceived $vulnerability\ to\ downside\ risk$ presented below exclusively relies on vulnerability in the proper meaning of the word and therefore adheres to the re-interpreted focus axiom. Certainly, this implies that also outcomes above the poverty line can impact on vulnerability wherefore, in terms of pro-poor policy targeting, such a measure is not useful since the ones threatened by poverty are not identified. But even for poverty reduction the inclusion of households above the poverty line seems reasonable: By concentrating on decreasing degrees of vulnerability in all parts of society (instead of only in potentially poor parts) one allows all households to redirect resources from risk management strategies to growth enhancing activities. It is widely acknowledged that the latter play a crucial role for poverty reduction.

Furthermore, regarding (pro-poor) policy design the information whether a household faces upside or downside risk is crucial. On the one hand, a policy intervention to reduce exposure to downside risk would have to focus on the strengthening of risk prevention, mitigation and coping capacities. Vulnerable households identified by a measure which is exclusively sensitive to downside risk would be unambiguously in need of such policies. On the other hand, households facing upside risks would benefit more from policies that could boost their expected positive development (e.g. by lowering input costs if the "risk" was the launch of an own business). Vulnerable households identified by the measures of $vulnerability\ to\ poverty$ and VEP, respectively, would be in need either of the former type of policies (currently non-poor households threatened by poverty, as well as currently poor households threatened by more poverty) or of the latter one (currently poor households "threatened" by less poverty). What sort of policy mix would be the most adequate one in such a situation is not properly revealed by these measures.

3.2 The Measure of Vulnerability to Downside Risk

The proposed measure of perceived $vulnerability\ to\ downside\ risk$ assigns an index of deprivation d_{hi} – with 0 implying no deprivation and 1 implying the highest possible deprivation – to every state of the world i a household h possibly experiences in the future and weighs it with its probability of occurrence p_{hi}. Thereafter all obtained products are added up. Thus, for N_h possible future states of the world the vulnerability of household h (V_h) is given by equation 7:[11]

(7) $$V_h = \sum_{i=1}^{N_h}(d_{hi}{}^{\alpha} \times p_{hi})\text{, with}$$

$$0 \leq d_{hi} \leq 1 \quad \text{and} \quad \sum_{i=1}^{N_h} p_{hi} = 1.$$[12]

α is a parameter measuring risk attitudes. If $\alpha > 1$ risk aversion is assumed and the measure is risk sensitive. Instead, a kind of "risk loving loss aversion" is implied if $0 < \alpha < 1$. In the case of $\alpha = 1$ risk and loss neutrality is assumed. [13] Choosing an appropriate α is not as easy as it might appear at first glance: On the one hand, there is good reason to assume risk aversion as proposed by most studies.[14] On the other hand, in the case of perceived $vulnerability\ to\ downside\ risk$ the degree of deprivation assigned to each relevant state of the world quantifies a loss in welfare – as opposed to a certain level thereof. Taking the literature on risk attitudes into account households might prefer having the choice between a low and a high loss (since their wellbeing rises as the lowest possible loss declines) than having a certain mean loss.[15] In such a case risk proclivity (i.e. $0 < \alpha < 1$) should be assumed since it assigns a higher degree of vulnerability to a certain mean loss and thus implies loss averse households.[16]

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[11] Note that this measure belongs to "the class of measures where vulnerability is a probability weighted average of state-specific 'deprivation indices'..." (cf. Calvo and Dercon, 2005). Also note that there is no such thing as an arbitrarily chosen threshold which the measure must surpass in order to assign a household to the group of vulnerable – as there is in the case of VEP. All households facing at least one state of the world in which they are worse off than currently are vulnerable to downside risk. They only differ in their degrees of vulnerability. To determine from which degree of vulnerability onwards a household should be in the focus of policy intervention is not the task of this paper but rather the one of policy makers.

[12] Consequently, the highest degree of vulnerability household h may face equals one, the lowest zero: $V_{h\,max} = 1$ if d_{h1} equals 1 and occurs with certainty, i.e. with a probability p_{h1} of 1; and $V_{h\,min} = 0$ if all d_{hi} equal 0 or every d_{hi} above 0 occurs with a probability p_{hi} of 0. The axiom of "normalization" which Calvo and Dercon (2005) establish "to facilitate interpretation and comparability" is adhered to by these closed boundaries.

[13] Note that $\alpha = 0$ is not advisable since each index of deprivation would equal one in such a case. Consequently, the measure would not adhere to the axiom of probability transfer established by Calvo and Dercon (2005). This axiom requires that the vulnerability measure decreases (increases) if probability from an index of deprivation is transferred to another, lower (higher) index of deprivation.

[14] In fact, the whole concept of VEU as proposed by Ligon and Schechter (2002, 2003) relies on the assumption of risk averse households.

[15] Unfortunately, empirical evidence on loss aversion in developing countries is almost not existent (regarding developed countries see, for instance, Barberis, Huang and Thaler, 2006). However, Dercon (2007) points out that during the 1984-85 famine in Ethiopia pastoralists desperately kept their livestock although selling (or consuming) it would have yielded the certain outcome of mitigating their starvation. A preference towards losing little (by keeping the livestock as long as possible) instead of much might have provoked such a loss adverse behavior.

[16] For a thorough discussion of vulnerability and loss aversion see Günther and Maier (2008).

Under the assumption that household h faces X_h downside risks with a probability of between 0% and 100%, as well as C_h downside certainties with probabilities of 0% or 100% the total number of possible future events the household is exposed to equals $C_h + X_h$. With the help of X_h the number of relevant future states of the world faced by household h (N_h) is derived via equation 8.

(8) $$N_h = \sum_{j=0}^{X_h} \frac{X_h!}{(X_h - j)!j!}$$

To exemplify equation 8, imagine a household h that faces 1 downside certainty a and 3 downside risks b, c, and d (i.e. $C_h = 1$ and $X_h = 3$). This household faces the following $\sum_{j=0}^{3} \frac{3!}{(3-j)!j!} = 8$ relevant future states of the world:

- $\frac{3!}{(3-0)!0!} = 1$ state of the world in which only a occurs;
- $\frac{3!}{(3-1)!1!} = 3$ states of the world in which a and one risk occur (i.e. a and b; a and c; a and d);
- $\frac{3!}{(3-2)!2!} = 3$ states of the world in which a and two risks occur (i.e. a, b and c; a, b and d; a, c and d;); and
- $\frac{3!}{(3-3)!3!} = 1$ state of the world in which a and all risks occur (i.e. a, b, c and d).

The index of deprivation assigned to household h in state of the world i in which all downside certainties with a probability of 100% (c), as well as x downside risks take place is given by (i) the sum of the impact severities of all downside certainties on a specific dimension of wellbeing ($\sum_{k=1}^{C_h} s_{hk}$), as well as by (ii) the sum of the impact severities of all risks occurring in the respective state of the world ($\sum_{j=0}^{x_{hi}} s_{hij}$; cf. equation 9[17]).

(9) $$d_{hi} = \sum_{k=1}^{C_h} s_{hk} + \sum_{j=0}^{x_{hi}} s_{hij} \ ,$$

If $d_{hi} > 0$ household's h wellbeing in the state of the world i is lower than its current one. As d_{hi} increases further away from zero household's h outlook worsens.

With regard to the probability of a future state of the world i (p_{hi}) one has to acknowledge that risk- (and certainty-) specific probabilities are not likely to be independent from each other. For example, a flood

[17] Note that in the case of s_{hk} the index i is left out since downside certainties with a probability of 100% occur in every relevant state of the world and are therefore independent from i.

might increase the risk of an illness. Also, the risk of death and other individual-related risks are mutually exclusive. That is, in the case of a state of the world, in which, for instance, two risks a and b take place and two others c and d do not, the correct way to define its probability would be

(10) $$p_{hi} = P(\gamma|\delta)$$

with $\gamma \cong P(risk_a \cap risk_b) = P(risk_a) \times P(risk_b|risk_a)$ and $\delta \cong P\big((1 - risk_c) \cap (1 - risk_d)\big) = P(1 - risk_c) \times P((1 - risk_d)|(1 - risk_c))$.[18] To obtain this probability is a very complex task since one has to estimate the covariance of risk probabilities, as well as to identify the causalities running between the risks in question. Because such an endeavor would go far beyond the scope of this paper independent risk- (and certainty-) specific probabilities will be assumed in its remainder.[19] Therefore, the probability that household h experiences state of the world i is given by equation 11.

(11) $$p_{hi} = \prod_{j=1}^{x_{hi}} p_{hij} \times \prod_{l=1}^{X_h, l\neq j} (1\text{-}\ p_{hil})$$

where $\prod_{j=1}^{x_{hi}} p_{hij}$ yields the probability that x risks will occur in state of the world i; and $\prod_{l=1}^{X_h, l\neq j} (1\text{-}\ p_{hil})$ represents the probability that all other risks do not take place in state of the world i.[20] For an exemplary application of formulas 7, 9, and 11 see appendix A.

4 Empirical Application of Perceived Vulnerability to Downside Risk

4.1 Data

The measure of perceived $vulnerability\ to\ downside\ risk$ is applied to data from the second wave of a household survey conducted within the context of the research project on “Vulnerability in South-East Asia” in 2008. Data was collected from some 4000 households in six rural provinces in Thailand and

[18] There would also be states of the world, in which the risks a and b take place and the other risks c and d do not, with a different probability than the one given in the text. If, for instance, risk b would occur prior to risk a (in the text it is implicitly assumed that it is the other way round), then $\gamma \cong P(risk_b \cap risk_a) = P(risk_b) \times P(risk_a|risk_b)$ which is different to $\gamma \cong P(risk_a \cap risk_b) = P(risk_a) \times P(risk_b|risk_a)$.

[19] Note that independent risk-specific probabilities are also assumed in Calvo and Dercon (2007), as well as in other vulnerability related articles. Furthermore, in the empirical application implemented in chapter 4 it was paid attention not to include mutually exclusive risks in the measure.

[20] Note that for the state of the world in which $x_{hi} = 0$, i.e. in which only certainties occur, the first part of the right hand side of equation 11 is equal to $\prod_{j=1}^{0} p_{hij}$ = 1 since the neutral element of a product is 1. Likewise, for the state of the world in which $x_{hi} = X_h$, i.e. in which all risks occur in addition to the certainties, the second part of the right hand side of equation 11 is equal to $\prod_{j=1}^{0} p_{hij}$ = 1

Vietnam; more precisely in the Thai provinces Buriram, Ubon Rachathani and Nakhon Phanom, as well as in the Vietnamese provinces Ha Tinh, Thua Thien-Hue and Dak Lak.

The sample of households was selected via a three-stage cluster-sampling procedure. The six provinces served as strata. From them sub-districts were selected with a probability proportional to the number of households they host. Special attention was paid to population density in order to ensure that densely, as well as less densely populated sub-districts were covered adequately. Within each sub-district two villages were chosen again with a probability proportional to size. In a last step ten households from each village were randomly incorporated into the sample.

The questionnaire used for the survey covered information about (i) household member characteristics such as demographics, education and health; (ii) shocks and risks; (iii) agriculture; (iv) off-farm and self-employment; (v) borrowing, lending, public transfers and insurance; (vi) expenditures; (vii) assets; and (viii) housing conditions. The empirical application presented here relies on information provided by the risk section of the questionnaire which covers numerous demographic, weather related, economic, and agricultural risks (cf. appendix B).This section was designed to shed light on, *inter alia*, the frequency, as well as the severity of the impact on income of downside risks a household faces during the upcoming five years. Since only negative future events were included the information obtained is appropriate for a measure of perceived $vulnerability\ to\ downside\ risk$. Also, the information originates from the present (t) and reflects expectations concerning the time after t. Therefore, it is well suited for an *ex-ante* assessment of vulnerability.

Concerning a future event's perceived impact on income the respondents had to state whether it would have a "high", "moderate", "low", or "no impact" if it occurred within the next twelve months.[21] Admittedly, the use of this information implies the stringent assumption that respondents are able to assess the severity of impacts across different future events without having some sort of a reference scale. The respondents' answers were transformed in a way that a value of 1 was assigned to a high severity, a value of 0.66 to a moderate severity, a value of 0.33 to a low severity, and a value of 0 to an event without any impact.

Perceived probabilities were obtained by asking the respondents about the expected frequency of occurrence of a certain event within the next 5 years. To a frequency of 0 (1, 2, 3, 4, 5 or more) a

[21] Therefore, in the remainder of this paper the terms severity and vulnerability refer to the dimension of income if not stated otherwise.

probability of 0% (20%, 40%, 60%, 80%, 100%) was assigned.[22] An event with a probability of 0% and 100%, respectively, can be interpreted as a perceived downside certainty k whereas an event with a probability of between 0% and 100% can be seen as a perceived downside risk j.

The information about the impact's severity on income and about the probability of occurrence was used to construct a vulnerability measure that incorporates all future events which are expected to take place (i.e. have a probability of more than 0%) by at least 5% of the surveyed households.[23] The necessary information about severities and probabilities for the 11 relevant risks which fulfill this requirement is available for 2070 Thai and 1805 Vietnamese households. According to equation 8 these households face between $\sum_{j=0}^{0}\frac{0!}{0!0!}=1$ (in the case of 11 certainties) and $\sum_{j=0}^{11}\frac{11!}{(11-j)!j!}=2048$ (in the case of 11 risks) possible states of the world depending on how many adverse events they expect to take place. Table 1 (cf. appendix D) provides summary statistics from the three demographic, four weather related, two agricultural, and two economic risks included in the measure.

The most frequent risk in both countries is an "illness of a household member" which is expected to occur by 76.5% of the Thai, as well as by 70.8% of the Vietnamese households. The importance of the only health related risk included in the measure is further underlined by its high expected probability and severity: The mean probability[24] in both countries exceeds 47% and thus constitutes the second highest probability of risks included in the measure in Thailand and Vietnam. Moreover, with a mean severity[25] of 0.53 (0.49) an illness is expected to be the (second) most severe risk in Thailand (Vietnam). This prominent role indicates that households in both countries neither have sophisticated prevention capacities against an illness (therefore the high probability) nor implement adequate mitigation strategies (therefore the high severity).

The other two demographic risks included in the analysis – "person leaves household" and "person joins household" – are perceived by 19.4% and 16.9%, respectively, of the Thai households which assign only

[22] The probability of 50% was explicitly excluded. According to Bruine de Bruin and Fischhoff (2000) respondents often confuse the phrase of "fifty-fifty", i.e. of having no idea, with the "actual" probability of 50%. Therefore, it is not certain whether a stated probability of 50% really indicates a probability or rather a "don't know".

[23] Although the two risks "money to be spent for ceremony in the household" and "house damage" are expected to occur by more than 5% of the surveyed households they are excluded from the measure due to data constraints.

[24] Households which do not expect the risk to take place enter the calculation of the mean probability with a probability of 0%. In this part of the text we present mean probabilities and severities which are, among others, influenced by households that do not perceive the risk in question to occur because from these numbers it can easily be deduced how strongly the respective risk impacts on the vulnerability measure. However, the mean probabilities and severities from whose calculation households are excluded which do not expect the risk to occur are additionally provided in table 1 (cf. appendix D).

[25] Households which do not expect the risk to take place enter the calculation of the mean severity with a severity of 0 (see also footnote 25). Severities range between zero (lowest) and 1 (highest).

very low probabilities (4.7% / 4.3%) and severities (0.06 / 0.06) to them. A similar picture holds true for Vietnam: Here, 23.4% (20.4%) of the households expect a person to leave (join) the household. The mean probability of these events is 6.6% and 5.2%, respectively. Their expected severity is higher than in Thailand but with 0.11 and 0.10 still fairly low. Since the severity component is exclusively focusing on the impact on income these low values seem to be plausible: For instance, persons who leave the household may migrate in order to find new income sources somewhere else. Also, persons joining the household may start to contribute to its income. In such cases the corresponding risks would even have a positive impact on the household's income.

Weather related risks are very serious hazards especially in Vietnam. More than half of the Vietnamese households perceive to be exposed to the risk of "floods" (52.5%), "droughts" (51.6%), and "storms" (57.1%); more than a third (33.7%) fears the threat of "unusually heavy rainfall". The expected probability of these events is high and rises from 22.6% in the case of rainfall, to 33.2% in the case of droughts, 41.0% in the case of floods, and 46.1% in the case of storms. Furthermore, the mean severity of floods, storms, and droughts is 0.43, 0.41, and 0.40, respectively. Only the impact of unusually heavy rainfall on income is expected to be rather low (0.24). These perceptions of Vietnamese households lead to the conclusion that efficient (covariate) risk management strategies have not yet been put in place although weather shocks are frequent events and impact severely on income generating activities in the country.

By contrast, in Thailand adverse weather events are perceived to be less frequent, less likely, and less severe – the only exception being droughts: They are expected to take place by 57% of the households, and have a mean probability of 36.1% as well as a mean severity of 0.45. When turning to floods, unusually heavy rainfall, and storms it is recorded that between 18.4% (rainfall) and 26.5% (storm) of Thai households are threatened by these risks. Their mean probability ranges between 10.2% (rainfall) and 15% (storm), their mean severity between 0.10 (rainfall) and 0.17 (flood). An explanation for the differences between Thai and Vietnamese households concerning their perception of weather risks is that the former households' income sources do not depend as much on weather conditions as the ones of the latter. This interpretation is supported by the fact that in Thailand more household members tend to have an off-farm employment – i.e. an employment in a sector which is not as much prone to weather shocks as the agricultural sector is – than in Vietnam (cf. table 5 in appendix D).

The same rationale is also applicable to the country-specific differences regarding agricultural risks: Vietnamese households which in comparison to their Thai counterparts are relatively dependent on agricultural income often perceive to be exposed to agricultural risks. Thus, 65.3% (47.8%) of them expect to be hit by "crop pests" ("livestock disease") in future – as opposed to 36.6% (13.7%) in the Thai case. Accordingly, the mean probabilities, as well as the mean severities of agricultural risks are higher in Vietnam than in Thailand (51.8% versus 27.7% in the case of crop pests; 0.50 versus 0.24 in the case of livestock disease).

With respect to economic risks, the last remaining group of risks which is included in the measure, Thai households seem to be more threatened by adverse events than the Vietnamese ones. While in both countries a "strong increase in interest rate on loan" is perceived to be neither frequent (12.5% of Thai and 15.9% of Vietnamese households), nor likely (6.5% in Thailand and 6.8% in Vietnam), nor severe (0.09 in Thailand and 0.13 in Vietnam), a "strong increase in prices for input" seems to be a much bigger hazard in Thailand. There, 57.8% of households expect this risk to occur – as opposed to 36.2% in Vietnam. Its mean probability is above 50% (versus 23.7% in Vietnam) and its mean severity equals 0.49 (versus 0.27 in Vietnam). Thus, a strong increase in prices for input is seen as the most likely, as well as the second most severe (after illness) risk in the country.

4.2 Vulnerability at an aggregated level

Before using the eleven risks to compute the vulnerability measure their degrees of severity have to be transformed in a way that the highest possible state-specific index of deprivation equals one (cf. equation 7). Therefore, the following risk-specific "degrees of severity" were established: $\frac{1}{11}$ (high impact), $\frac{0.66}{11}$ (moderate impact), $\frac{0.33}{11}$ (low impact), and $\frac{0}{11}$ (no impact).[26] Furthermore, in line with most of the literature on risk attitudes in developing countries (cf., for example, Binswanger, 1981) households are assumed to be risk averse – although, as explained above, the possibility of other risk attitudes cannot be discarded. That is, α from equation 7 is set equal to 2.

[26] By choosing $\frac{1}{11}$ as the highest possible impact it is ensured that d_{hi} from equation 7 cannot surpass the value of one since in the case of 11 risks the highest possible aggregate severity equals $\frac{1}{11} \times 11 = 1$.

Households in Vietnam are more vulnerable to perceived downside risk than households in Thailand (cf. table 2, appendix D). On average the vulnerability indices of the former (0.0529) is about 75% higher than the one of the latter (0.0302). In addition, the lower bound of the 95%-confidence interval of Vietnam's aggregate vulnerability (0.0499) is considerably above the upper bound of Thailand's corresponding interval (0.0319). Another finding is that households are much more heterogeneous in terms of vulnerability in Vietnam than in Thailand: Perceived vulnerability values in the former country range between 0 and 0.4298 (with a standard deviation of 0.0654) whereas they range between 0 and 0.3301 (with a standard deviation of 0.0388) in the latter country.

Given the "ingredients" of the measure, namely eleven risks which tend to threaten Vietnamese households more than Thai households, the difference between the two countries is not surprising. As indicated above households in both Thailand and Vietnam are similarly exposed to demographic risks whereas economic risks play a more important role in the former country. However, regarding adverse agricultural and weather related events which constitute more than half of the risks included in the measure (6 out of 11) Vietnam is far worse off.[27]

When taking a closer look at the vulnerability *within* both countries it is revealed that the heterogeneity at hand in Vietnam is driven by the relatively vulnerable provinces Ha Tinh and Thua Thien-Hue where vulnerability levels range between 0 and 0.4050 (with a standard deviation (mean) of 0.0692 (0.0568)) and 0 and 0.04298 (with a standard deviation (mean) of 0.0784 (0.0577)), respectively (cf. table 3, appendix D). On the contrary, a very homogeneous picture is provided by Dak Lak, the third and with a mean vulnerability of 0.0430 least vulnerable Vietnamese province in the sample, where the standard deviation is merely 0.0373. The highest degree of vulnerability in this province is but 0.1939 (cross-national the lowest maximum value of all provinces). About the reason for the difference between Dak Lak and the other two provinces can only be speculated. One possible explanation might be that Ha Tinh and Thua Thien-Hue are situated at the coast – while Dak Lak is inland – were adverse events, especially weather related ones, are common and heterogeneous depending on the households' location close to or further away from the sea. In Thailand province-specific standard deviations of aggregate vulnerability range between 0.0312 in Nakhon Phanom and 0.0434 in Buriram, i.e. they are much lower than in Ha Tinh and Thua Thien-Hue.

[27] Note that in a country case study the risks included in the measure would certainly differ between Thailand and Vietnam since their risk exposure is not the same. For the purpose of this study, however, the risks were selected in a way that allows for the comparison of the two countries.

4.3 Estimation method

After having identified and compared aggregate vulnerability at the country and province level we now turn to the analysis of the driving forces behind a household's degree of perceived $vulnerability\ to\ downside\ risk$. The variable to be explained in this context is an index bounded below (at 0) and above (at 1; cf. equation 7). When taking a closer look at this variable it becomes obvious that in neither country a household reaches a vulnerability of 1. By contrast, 143 (80) households are entirely non-vulnerable to downside risk in Thailand (Vietnam; cf. table 4, appendix D, and figure 1, appendix E) – at least with respect to the eleven different risks included in the measure. Certainly, measurement error may cause these numbers. However, a zero degree of perceived $vulnerability\ to\ downside\ risk$ seems plausible if, for instance, the households in question did not experience corresponding shocks in the past. In fact, such a relationship would be suggested by the heuristic of availability (cf. chapter 2). As shown in table 4 (cf. appendix D) 73.4% of the non-vulnerable households in Thailand did not report corresponding shocks for the time period between January 2007 and April 2008 which is in line with this interpretation. In Vietnam, however, where only 40% of the non-vulnerable households reported zero shocks for the same period the picture is not that clear.

Another possible reason for being non-vulnerable to downside risk is that households have developed risk management strategies which very efficiently reduce the probability and/or severity of adverse events. This might be a viable explanation for households which either do not expect risks to take place in the first place (because of their prevention strategies) or do not expect risks to have a negative impact on income (because of their mitigation and prevention strategies). In the given sample 51.7% of the non-vulnerable households in Thailand and 51.2% of the ones in Vietnam do not expect any of the risks included in the measure to take place. The remaining households expect the risks to take place but perceive that they will not have an impact (cf. table 4, appendix D).

Even if there is good reason to believe that a large part of the seemingly non-vulnerable households really does not perceive to be prone to downside risks the question remains whether at least some of these households actually are exposed to a *negative* degree of vulnerability. If a household exhibited such a negative degree it would be facing upside instead of downside risks – a situation which, due to the re-interpreted focus axiom, cannot be reflected by the measure of perceived $vulnerability\ to\ downside\ risk$. With regard to the risks underlying the vulnerability measure presented here it is plausible that some of them impact positively on income. Take, for instance, the risks "person leaves the household" and "person joins the household". As aforementioned, persons who leave the household may migrate in order to find new income sources somewhere else. Also, persons joining the household may start to contribute to its income. In the case of both risks large shares of households which expect them to take place, i.e. assign to them a probability of more than 0%, do not think that they will impact negatively on their income (cf. figures 2 and 3, appendix E). It is absolutely possible that these "none impacts" cover at least some positive impacts which could not be reported as such due to the questionnaire's design.

Consequently, the dependent variable is assumed to be left censored. Variables are said to be censored if there are observations which cannot cross a certain threshold although they would do so in the absence of boundaries. Left (right) censored variables are bounded below (above). Because of this property of the dependent variable we use a Tobit model (cf. Tobin, 1958) – which takes into account that the dependent variable is not observed beyond a certain threshold – to estimate the determinants of perceived $vulnerability\ to\ downside\ risk$. Assuming μ_i to be an independently, normally distributed error term with zero mean and constant variance σ^2 we specify the equation to be estimated as follows:

(12) $$V_h = \beta X_h + \mu_i \quad \text{if} \quad V_h^* > 0$$

$$V_h = 0 \quad \text{if} \quad V_h^* \leq 0$$

V_h represents the perceived $vulnerability\ to\ downside\ risk$ of household h and V_h^* the household's actual, in case of a negative value unobserved vulnerability. X_h is a vector of explaining variables which can broadly be grouped in information about the (i) household, its (ii) head and (iii) wealth, as well as its (iv) shock exposure in the past and its (v) location. Summary statistics of the explaining variables are provided in table 5 (cf. appendix D). Three specifications of Tobit regressions are estimated for each country. The first specification does not include past shocks as explanatory variables whereas specifications two and three differ from each other with respect to the shock variables they comprise. On the one hand, the number of self-reported shocks between January 2006 and April 2008 is included.[28] On the other hand, the number of self-reported shocks from which the household had not yet recovered when reporting them in May 2007 (applies to shocks between January 2006 and April 2007) and in May 2008 (applies to shocks between May 2007 and April 2008), respectively, is used as predictor. Thus, the

[28] Respondents reported shocks they experienced in 2006 and between January and April 2007 in May 2007, as well as shocks they experienced between May 2007 and April 2008 in May 2008.

second specification merely considers the frequency of shocks whereas the latter also introduces a notion of their severity. The shocks included in the analysis precisely match the eleven risks underlying the vulnerability measure.

In order to determine how well the model fits the data a modified pseudo R^2 is calculated in addition to McFadden's pseudo-R2 which is also provided. The latter can adopt negative values (as it does in all specifications) and its interpretation is not straightforward. Instead, the former reflects the squared correlation between the actually observed degrees of perceived $vulnerability\ to\ downside\ risk$ and the ones predicted by the model. Thus, similarly to the R^2 in ordinary least squares regressions it can be interpreted as the proportion of the dependent variable's variance which is explained by the independent variables.

4.4 Results

The regression results for Thailand and Vietnam are presented in table 6 (cf. appendix D). Determinants of perceived $vulnerability\ to\ downside\ risk$ differ between the two countries. Also, in both countries there are slight differences in the coefficients of the explaining variables when switching specifications.

All Thailand-specific regressions indicate that the share of household members employed in agriculture has a strongly significant (at the 1 percent level) and positive impact on vulnerability. However, the magnitude of this variable's effect on perceived vulnerability is not as high as it appears to be at first glance. More precisely, an increase of the share by one percentage point triggers the degree of vulnerability to rise by between 0.000226 and 0.000297 depending on the specification.[29] As already stated, given the adverse events underlying the dependent variable, namely, *inter alia*, two agricultural and four weather related risks, this result was to be expected. The fact that the shares of household members with off-farm or self employment do not impact significantly on vulnerability implies that other than agricultural income sources are certainly not as risky as the latter but do not have a vulnerability decreasing effect, either. In Vietnam a higher share of agriculturally employed household members leads to an increase in perceived $vulnerability\ to\ downside\ risk$, as well. This correlation is significant at the

[29] Recall that in both countries the mean (median) vulnerability ranges between 0.0302 (0.0166; Thailand) and 0.0529 (0.0305; Vietnam). Therefore, the marginal effects presented in this section are – in relation to the households' vulnerability indices – not as small as they might seem.

1 percent level across specifications. With marginal effects ranging from 0.00032 to 0.00036 depending on the specifications its scale is slightly larger than in Thailand. Households which diversify their income sources and engage in off-farm or self employment not just escape the threat of future harm associated with agricultural employment, they even decrease their degree of vulnerability. In the case of off-farm employment this relation is significant at the 1 percent level, regarding self employment at the 5 (specification excluding shocks) and at the 10 (specifications including shocks) percent level. The absolute quantitative impact of these variables on perceived vulnerability is lower than in the case of agricultural employment.

The age of the household members only plays a significant role in Thailand: the mean age of household members is negatively correlated with vulnerability and statistically significant at the 1 (first and third specification) and at the 5 percent level (second specification). The same holds true for the age of the household head (significant at the 1 (first specification) and at the 5 (second and third specifications) percent level). However, the latter relation is not linear since the head's squared age impacts significantly negative on perceived vulnerability. Regarding marginal effects an increase of the mean age of a household (the age of the household's head) by one year leads to a decrease in its vulnerability index by between 0.0003 and 0.0004 (about 0.001) depending on the specification. While the Thai case is plausible – increasing age is likely to be associated with increasing (risk management) capacities, employment opportunities and income – it is not apparent why it does not seem to be the same in Vietnam.

In order to explore the relationship between the wealth of households and their vulnerability the explanatory variables lagged income, an index which proxies the endowment with assets, and land holdings are introduced in the analysis. The option to use current income is discarded due to the problem of endogeneity this might cause.[30] In Vietnam the income richer a household is the less it suffers from perceived vulnerability. In Thailand the same relation is not statistically significant. This is surprising since higher income levels should enable households to, among others, access credit and insurance markets more easily and therefore be able to manage risk more efficiently by, for example, contracting insurances.

Both countries also differ in terms of the impact of land holdings on vulnerability. Similarly to income land holdings are expected to decrease vulnerability because they facilitate the households' access to

[30] Recall that – at least in theory – economic behavior of households and therefore their current income is influenced by risk expectations.

credit markets when being used as collateral. On the other hand, more land leads to a higher degree of perceived $vulnerability\ to\ downside\ risk$ if it increases the risk exposure of households. In Vietnam, where weak empirical evidence suggests that households perceive to be less vulnerable to downside risk the more land they hold, the former effect seems to outweigh the latter. This correlation is significant at the 10 percent level in two out of three specifications and its scale implies that an additional hectare of land lowers vulnerability by 0.0034. By contrast, in Thailand it is the other way round and households' degrees of vulnerability increase – significantly at the 10 percent level in the first, at the 5 percent level in the second and at the 1 percent level in the third specification, as well as with a magnitude of about 0.001 across specifications – with each additional hectare of land holdings. However, since the square of land holdings impacts significantly negative on vulnerability this relationship is not linear. The Thai case is probably caused by the threat of droughts which in terms of frequency, probability, and severity is perceived to be the third most influential component in the vulnerability measure (cf. table 1, appendix D).

The only proxy for wealth which is associated with a decrease in vulnerability of Thai households is the asset index. This, however, holds only true in the second specification at a significance level of 10 percent. As another dimensions of wealth assets should enable households to better manage their risks which does not seem to be the case in Vietnam. In Thailand assets have a small vulnerability decreasing effect in the specification which accounts for the number of self-reported shocks but no effect if shocks are not accounted for or the frequency of severe shocks is considered.

With respect to self-reported shocks it is revealed that they play a crucial role in determining the $vulnerability\ to\ downside\ risk$ of a household. In other words, households tend to perceive the shocks they experienced in the past as threats to which they will also be exposed in future. This strong evidence for the heuristic of availability can be found throughout all specifications which include shock-related explanatory variables. Concerning the magnitude of their impact significant coefficients related to shocks from 2007 and 2008 exhibit very large marginal effects in their respective specifications. For example, an additional severe shock experienced in 2008 would increase the perceived vulnerability of a Thai (Vietnamese) household on average by 0.0156 (0.0187). Only the provincial dummies for Buriram in Thailand and Thua Thien-Hue in Vietnam affect the degree of vulnerability in a comparable or more pronounced manner.

In addition, the positive impact of the number of (severe) shocks on vulnerability decreases the longer ago these shocks took place. Thus, in Thailand (severe) shocks experienced in 2006 are only significant at the 10 percent level and have marginal effects of around 0.004 whereas later shocks are significant at the 1 percent level and have marginal effects of 0.0074 or more. In Vietnam (severe) shocks from 2006 do not significantly impact on perceived vulnerability while the ones from 2007 and 2008 significantly do so at the 1 percent level and with marginal effects of 0.0081 or more.

When comparing the difference between the impact of the two types of shock variables it becomes obvious that not only the number of shocks but also their severity considerably matters for predicting degrees of vulnerability. While the shock-related coefficients do not differ with respect to their significance levels between the two specifications for each country their magnitude is larger in the case of the number of severe shocks. For instance, with every additional shock a Thai household experienced in 2007 (2008) its perceived vulnerability rises on average by 0.0074 (0.0109). The marginal effect of the number of severe shocks experienced in the same year equals on average 0.0093 (0.0156) and is thus more than 25% (43%) larger. The situation in Vietnam where the marginal effects of severe shocks are about 38% (2007) and 29% (2008), respectively, higher than the ones of the number of shocks is very similar. That is, when perceiving risks households from both countries seem to take into account particularly rather recent and severe shocks.

The coefficient of the household size variable is only significant in two Thai specifications, namely in the one excluding shocks and in the one including the number of severe shocks, respectively. The fact that the household size does not statistically matter if the number of self-reported shocks is considered suggests that – unsurprisingly – larger households are hit by more shocks. This finding in combination with the significant coefficients from the other specifications implies that in Thailand the size of a household is positively correlated to both risk perception and shock exposure. Consequently, this household characteristic seems to be well suited for guiding – at least partially – policy targeting.

The same rationale holds true for the coefficient of the minority dummy in the Vietnamese specifications. Being insignificant if it is accounted for the number of shocks but significantly positive at the 5 (without shocks) and at the 10 (with the number of severe shocks) percent level in the other specifications this coefficient implies that Vietnamese households headed by a member of an ethnic minority tend to more exposed to shocks and risks than the ones whose head belongs to the majority.

Surprisingly, the other household head-related variables – with the exception of age in Thailand -, i.e. the female dummy and years of school enrollment, do not show a significant or only a very weak correlation with perceived vulnerability. The fact that female headed households are not more vulnerable than their male headed counterparts can possibly be explained by remittances. Remittances probably improve the households' risk management capacities because they stem from an income source subject to other risks than the ones "at home" and may vary in scale depending on the households' needs to cope with adverse events. Female headed households in Vietnam (Thailand) receive on average about 55% (17%) more remittances per household member who stayed in the household for at least 180 days during the past year than their male headed counterparts.

The lack of predictive power of the proxy for education might be caused by two contrary effects: On the one hand, households with better educated heads perceive to be less threatened by risks because they can deal with them more efficiently. On the other hand, better educated individuals probably assess future risks more adequately in terms of their probability and severity than less educated ones wherefore their risk perception may seem to be relatively pronounced. Since the household head was also the respondent in about 54% of the Thai and 65% of the Vietnamese cases this latter effect is likely to be present in the given data. In fact, it would explain the significantly positive coefficient (at the 10 percent level) in the first Vietnamese specification.

Finally, the provincial dummies in the Thai regressions are significantly positive at the 1 percent (Buriram) and at the 5 to 10 percent level (Ubon Rachathani), respectively. Especially the difference in terms of perceived vulnerability between being a household in Buriram and being a household in Nakhon Phanom is enormous. Households in the former region exhibit on average a vulnerability level which exceeds the one of households in the latter region by between 0.0252 and 0.0219 depending on the specification. With respect to Vietnam, the degree of perceived $vulnerability\ to\ downside\ risk$ does not differ significantly between Ha Tinh and Dak Lak if shock related explanatory variables are included in the regression. In other words, households in the former province are more exposed to shocks, wherefore their risk perception is higher, than households in the latter. Instead, vulnerability is significantly (at the 1 percent level) lower in Dak Lak than in Thua Thien-Hue even if shocks experienced in the past are taken into consideration.

The specified Tobit model fits the data better in Thailand than in Vietnam. According to the modified pseudo R^2 the squared correlation between the observed and predicted degrees of perceived

$vulnerability\ to\ downside\ risk$ equals, depending on the specification, 0.0789, 0.1448 and 0.1549. This suggests that the independent variables explain between 8% (without shock variables) and 15% (with shock variables) of the variability of the dependent variable. The corresponding Vietnamese values range between 6.81% when shocks are excluded and 9.25% and 10.5%, respectively, when shocks are included.

5 Conclusion

With this paper we aim to contribute to the search for an appropriate concept and measure of vulnerability. Vulnerability is a forward-looking concept and always refers to something negative that may or may not occur in future. That is, vulnerability is concerned with downside risks faced by households.

Vulnerability matters to economist due to its negative effect on wellbeing and its impact on behavior of households. Current concepts of vulnerability tend to rely on information from the past in order to estimate vulnerability although this approach comes at the cost of stringent assumptions. Therefore, we argue that subjectively perceived risk may contribute to the measurement of vulnerability: First, it can reveal probabilities of future events in a straightforward manner. Second, it enables researchers to calculate current and not past levels of vulnerability.

However, there are some caveats to the use of perceived risk as source of information for a quantification of vulnerability such as the heuristics of probability. We cannot rule out the possibility that the *de facto* perceived risks are partially obscured by the heuristic of representativeness. Nonetheless, it seems to be worthwhile to use perceived risk in the context of vulnerability since its underlying assumptions (e.g. that the heuristic of representativeness is either not present or does not change the results significantly) do not seem to be more stringent than the ones of other approaches. Moreover, not the actual risk but rather the subjective assessment of risk determines the welfare decreasing impact of risk and its effect on behavior.

After having discussed the possible merits of perceived risk as data source we propose a measure of perceive $vulnerability\ to\ downside\ risk$ which belongs to “the class of measures where vulnerability is a probability weighted average of state-specific ‘deprivation indices’...” (cf. Calvo and Dercon, 2005).

However, it differs from other approaches to vulnerability in its choice of the relevant benchmark. Instead of relying on a pre-determined threshold such as the poverty line it takes a household's current status of wellbeing as reference point. Due to the newly chosen reference point the proposed measure of vulnerability interprets the focus axiom differently as has been done so far: Only possible future states of the world which imply a lower level of wellbeing than the current one affect the vulnerability of a household.

We opt for this benchmark since it is reasonable to assume that households evaluate changes in wellbeing in comparison to their current status and not to an imposed benchmark they may not even know. Also, we think that households above the poverty line should be labeled as being vulnerable if they face possible shortfalls in their wellbeing. Certainly, the measure does not facilitate policy targeting of households threatened by poverty. However, also the targeting of "not expected to be poor" households which are vulnerable to downside risk may add to poverty reduction if it enables these households to redirect resources from risk management strategies to investment. Finally, the choice of this benchmark helps to send a clear policy message since households identified by a measure to downside risk are unambiguously in need of policies which strengthen their risk management capacities. By contrast, currently poor households which are vulnerable to poverty not necessarily face downside risk wherefore it might not be apparent what policies are best suited for them.

We apply the proposed measure to information about perceived risks obtained from household survey data from Thailand and Vietnam. Descriptive statistics suggest that Vietnam is more prone to perceived $vulnerability\ to\ downside\ risk$ than Thailand. This result is driven by the "ingredients" of the measure which by the majority incorporates risks that tend to be more likely and severe in Vietnam.

In order to explore and compare the country-specific determinants of perceived vulnerability we use a Tobit model which accounts for the left censoring of the dependent variable. The results of the multivariate analyses suggest that in Thailand and Vietnam the share of household members employed in agriculture has a significantly positive impact on vulnerability. Vietnamese households reduce their vulnerability by engaging in off-farm and self-employment while their Thai counterparts do not. That is, in both countries policy interventions to lower levels of vulnerability should target, among others, households depending to a high degree on agriculture. Furthermore, especially in Vietnam the support of income diversification measures at the expense of agricultural income sources is advisable.

The correlation between household wealth and perceived $vulnerability\ to\ downside\ risk$ is very different between the two countries. In Vietnam income richer households suffer less from vulnerability whereas in Thailand a statistically weak but significant and negative relation exists between the households' endowment with assets and their vulnerability. In the latter country larger land holdings are associated with higher degrees of vulnerability – probably because at the same time land holdings are positively correlated with the exposure to weather related risks which constitute an essential part of the applied measure. In Vietnam where households perceive to be less vulnerable the more land they hold this effect seems to be outweighed by the access to credit markets which is facilitated by land holdings.

With regard to shocks it is revealed that in both countries past exposure to adverse events has a highly significant and highly positive impact on vulnerability pointing at the presence of the heuristic of availability. When it is also accounted for the severity of shocks – as opposed to merely their number – the predictive power of the estimation rises.

Moreover, in Vietnam households whose head belongs to an ethnic minority seem to experience more shocks, and consequently perceive more risks, than households headed by a member of the majority. Similarly, large households in Thailand exhibit a higher shock and risk exposure than small households. These findings suggests that in Vietnam (Thailand) particularly ethnic minorities (large households) should be targeted by policies aiming at improving risk management capacities of households.

Other explaining variables expected to affect perceived $vulnerability\ to\ downside\ risk$ do not impact significantly – neither in Thailand nor in Vietnam. Thus, female headed households are not more vulnerable than their male counterparts, probably because they benefit more from remittances which increase the risk management capacities of households. In most specifications the correlation between vulnerability and the education of the household head is not statistically significant, either. This result might be due to the fact that better educated households (as presented by their heads) are more capable to manage risks, on the one hand, and report their risk exposure more accurately, on the other.

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Appendix A - Exemplary Application of the Measure of Vulnerability to Downside Risk:

For an exemplary application of formulas 1, 3, and 4 imagine again a household h that faces 1 certainty a and 3 risks b, c, and d (i.e. $C_h = 1$ and $X_h = 3$). Let the severity of a be high, i.e. equal to $\frac{s_{hk}}{C_h+X_h} = \frac{1}{4}$, and the risk severities vary between $\frac{s_{hj}}{C_h+X_h} = \frac{0.66}{4}$ for b, $\frac{0.33}{4}$ for c, and $\frac{0}{4}$ for d.[31] The probabilities of a, b, c and d are $1, 0.2, 0.4$, and 0.6, respectively. Since there are $\sum_{j=0}^{3} \frac{3!}{(3-j)!j!} = 8$ possible states of the world household h's degree of vulnerability is calculated as follows:

State of the world	Events occurring	State-specific severity	State-specific probability	State-specific vulnerability
1	a	$d_{h1} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{0} s_{hij} \cong \frac{1}{4} + 0 = \frac{1}{4}$	$p_{h1} \cong \prod_{j=1}^{0} p_{hij} \times \prod_{l=1}^{3-0} (1\text{-} p_{hil}) \cong 1 \times (1-0.2) \times (1-0.4) \times (1-0.6) = 0.192$	$d_{h1} \times p_{h1} = 0.048$
2	$a \; and \; b$	$d_{h2} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{1} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.66}{4} = \frac{1.66}{4}$	$p_{h2} \cong \prod_{j=1}^{1} p_{hij} \times \prod_{l=1}^{3-1} (1\text{-} p_{hil}) \cong 0.2 \times (1-0.4) \times (1-0.6) = 0.048$	$d_{h2} \times p_{h2} = 0.020$
3	$a \; and \; c$	$d_{h3} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{1} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.33}{4} = \frac{1.33}{4}$	$p_{h3} \cong \prod_{j=1}^{1} p_{hij} \times \prod_{l=1}^{3-1} (1\text{-} p_{hil}) \cong 0.4 \times (1-0.2) \times (1-0.6) = 0.128$	$d_{h3} \times p_{h3} = 0.043$
4	$a \; and \; d$	$d_{h4} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{1} s_{hij} \cong \frac{1}{4} + 0 + \frac{0}{4} = \frac{1}{4}$	$p_{h4} \cong \prod_{j=1}^{1} p_{hij} \times \prod_{l=1}^{3-1} (1\text{-} p_{hil}) \cong 0.6 \times (1-0.2) \times (1-0.4) = 0.288$	$d_{h4} \times p_{h4} = 0.072$
5	$a, b, and \; c$	$d_{h5} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{2} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.66}{4} + \frac{0.33}{4} = \frac{1.99}{4}$	$p_{h5} \cong \prod_{j=1}^{2} p_{hij} \times \prod_{l=1}^{3-2} (1\text{-} p_{hil}) \cong 0.2 \times 0.4 \times (1-0.6) = 0.032$	$d_{h5} \times p_{h5} = 0.016$
6	$a, b \; and \; d$	$d_{h6} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{2} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.66}{4} + \frac{0}{4} = \frac{1.66}{4}$	$p_{h6} \cong \prod_{j=1}^{2} p_{hij} \times \prod_{l=1}^{3-2} (1\text{-} p_{hil}) \cong 0.2 \times 0.6 \times (1-0.4) = 0.072$	$d_{h6} \times p_{h6} = 0.030$
7	$a, c \; and \; d$	$d_{h7} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{2} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.33}{4} + \frac{0}{4} = \frac{1.33}{4}$	$p_{h7} \cong \prod_{j=1}^{2} p_{hij} \times \prod_{l=1}^{3-2} (1\text{-} p_{hil}) \cong 0.4 \times 0.6 \times (1-0.2) = 0.192$	$d_{h7} \times p_{h7} = 0.064$
8	$a, b, c, and \; d$	$d_{h8} \cong \sum_{k=1}^{1} s_{hk} + \sum_{j=0}^{3} s_{hij} \cong \frac{1}{4} + 0 + \frac{0.66}{4} + \frac{0.33}{4} + \frac{0}{4} = \frac{1.99}{4}$	$p_{h8} \cong \prod_{j=1}^{3} p_{hij} \times \prod_{l=1}^{3-3} (1\text{-} p_{hil}) \cong 0.2 \times 0.4 \times 0.6 \times 1 = 0.048$	$d_{h8} \times p_{h8} = 0.024$
Total			1	$\sum_{i=1}^{8} (d_{hi} \times p_{hi}) = 0.317$

That is, the degree of vulnerability of household h is equal to 0.317.

[31] By choosing $\frac{1}{4}$ as the highest possible impact it is ensured that d_{hi} from equation 1 cannot surpass the value of one since in the case of a total of 4 risks and certainties the highest possible aggregate severity equals $\frac{1}{4} \times 4 = 1$.

Appendix B – Part of the Second Questionnaire's Risk Section of the Research Project on Vulnerability in Southeast Asia:

Section 3.2: Risks

Now, please consider the following possible future events:

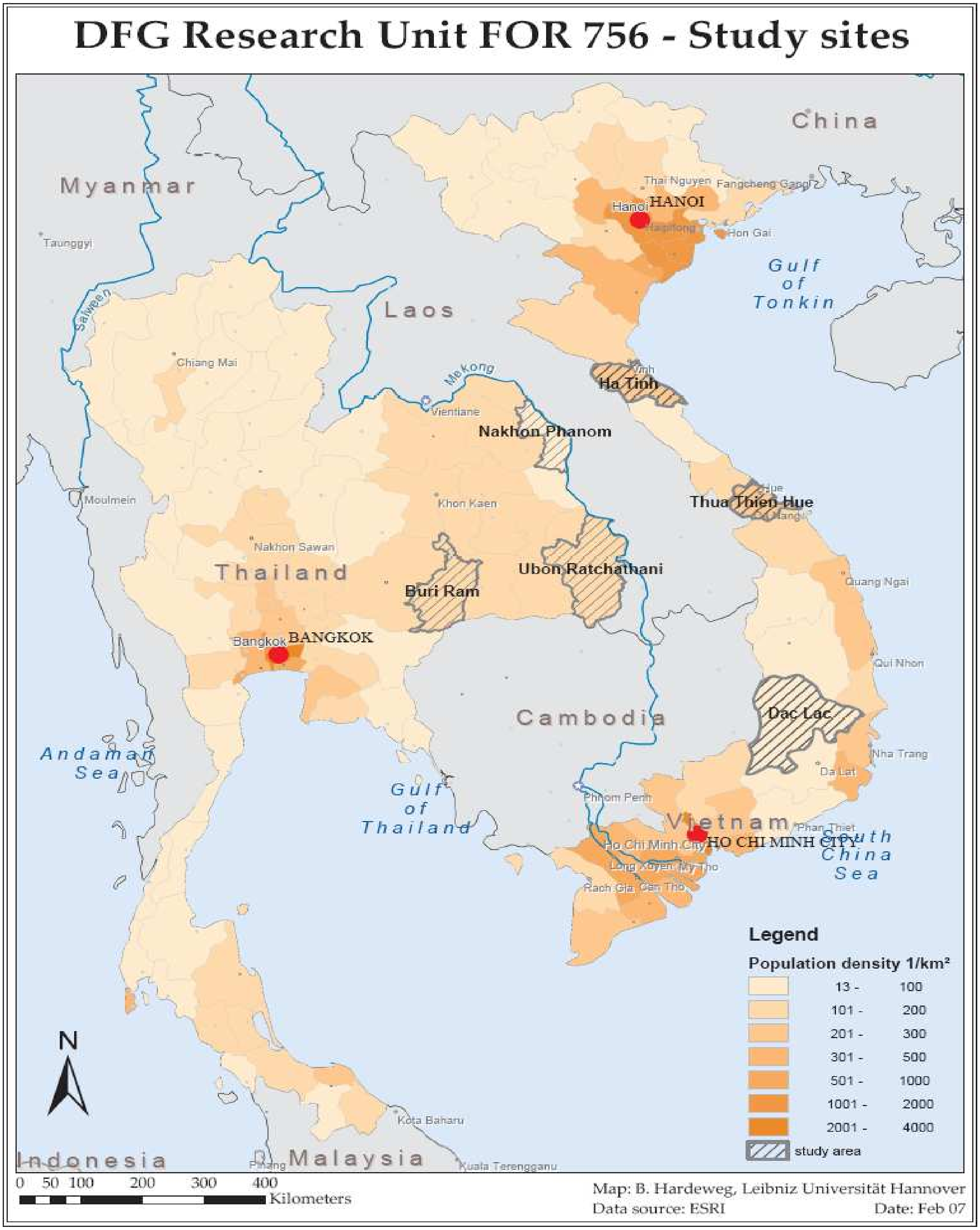
1	2	4	3	3a
Type of event	Do you think that ... will occur in the next 5 years? *If "No" go to Q13*	How often, do you think, will ... occur in next 5 years?	If ... occured within the next 12 months, what would be the impact on your household? Income	assets
	A	B	C	C
1 Illness of household member				
3 Household member left the household				
4 Person joined the household				
5 Money spent for ceremony in the household				
24 Accident				
38 Law suit				
6 House damage				
7 Theft				
8 Conflict with neighbours in the village				
9 Relatives/Friends stopped sending remittances				
10 Flooding of agricultural land				
11 Drought				
12 Unusually heavy Rainfall				
13 Crop pests				
14 Storage pests (including rats)				
15 Livestock Disease				
16 Landslide, Erosion				
55 Storm				
46 Was cheated				
60 Job loss (agricultural)				
61 Job loss (non-agricultural)				
18 Collapse of business				
20 Strong increase of interest rate on loans				
21 Strong decrease of prices for Output				
22 Strong increase of prices for input				
23 Change in market regulations				
57 snow / ice rain (VN)				

Code A
1 yes
2 no
98 no answer

Code B
1 1 in 5 years
2 2 in 5 years
3 3 in 5 years
4 4 in 5 years
5 5 in 5 years
6 more than 5 in 5 years
98 no answer

Code C
1 High
2 Moderate
3 Low
4 No impact
98 no answer

Appendix C – Map of study area:



Appendix D – Tables:

Table 1: Downside risks included in the vulnerability to downside risk measure

Risk		Stated by number (%) of households		Mean probability (including all households)		Mean severity (including all households)		Mean probability (excluding households which do not expect respective risk to occur)		Mean severity (excluding households which do not expect respective risk to occur)	
		Thailand (n=2070)	Vietnam (n=1805)	Thailand	Vietnam	Thailand	Vietnam	Thailand	Vietnam	Thailand	Vietnam
demographic	illness	1583 (76.5)	1278 (70.8)	0.4766	0.4722	0.5286	0.4867	0.6232	0.6670	0.6912	0.6874
	person leaves the household	402 (19.4)	423 (23.4)	0.047	0.0655	0.0643	0.1119	0.2418	0.2794	0.3313	0.4774
	person joins the household	351 (16.9)	369 (20.4)	0.0431	0.0517	0.0626	0.0952	0.2541	0.2531	0.3689	0.4658
weather	flooding	462 (22.3)	948 (52.5)	0.1453	0.4104	0.169	0.4253	0.6511	0.7814	0.7572	0.8097
	drought	1180 (57.0)	932 (51.6)	0.3611	0.3317	0.4459	0.3952	0.6334	0.6425	0.7822	0.7655
	unusually heavy rainfall	381 (18.4)	607 (33.7)	0.1015	0.2275	0.1025	0.2429	0.5517	0.6764	0.5566	0.7222
	storm	549 (26.5)	1030 (57.1)	0.1495	0.4608	0.157	0.4143	0.5636	0.8076	0.5921	0.7260
agricultural	crop pests	758 (36.6)	1179 (65.3)	0.2769	0.5175	0.2395	0.4985	0.7562	0.7922	0.6541	0.7632
	livestock disease	281 (13.7)	864 (47.8)	0.0866	0.291	0.0789	0.3467	0.6377	0.6079	0.5810	0.7243
economic	strong increase in interest rate on loans	257 (12.5)	287 (15.9)	0.0653	0.068	0.09	0.1261	0.5261	0.4279	0.7252	0.7934
	strong increase of prices for input	1196 (57.8)	654 (36.2)	0.5056	0.2372	0.4906	0.2697	0.8751	0.6547	0.8490	0.7443

Source: Author's own calculations.
Notes: Values for probability and severity of a risk range between 0 (lowest) and 1 (highest).

Table 2: Perceived vulnerability to downside risk by country (α=2)						
	min	median	mean	max	standard deviation	95% confidence interval
Vietnam (1805 obs.)	0	0.0305	0.0529	0.4298	0.0654	0.0499 0.0559
Thailand (2070 obs.)	0	0.0166	0.0302	0.3301	0.0388	0.0286 0.0319
Total (3875 obs.)	0	0.0223	0.0408	0.4298	0.0540	0.0391 0.0425

Source: Author's own calculations.

Table 3: Perceived vulnerability to downside risk by province (α=2)							
	provinces	min	median	mean	max	standard deviation	95% confidence interval
Vietnam	Ha Tinh (612 obs.)	0	0.0331	0.0568	0.4050	0.0692	0.0513 0.0623
	Thua Thien-Hue (640 obs.)	0	0.0256	0.0577	0.4298	0.0784	0.0516 0.0638
	Dak Lak (553 obs.)	0	0.0307	0.0430	0.1939	0.0373	0.0398 0.0461
Thailand	Buriram (778 obs.)	0	0.0293	0.0408	0.2975	0.0434	0.0378 0.0439
	Ubon Rachathani (914 obs.)	0	0.0120	0.0247	0.3301	0.0354	0.0224 0.0270
	Nakhon Phanom (378 obs.)	0	0.0090	0.0219	0.2298	0.0312	0.0187 0.0250

Source: Author's own calculations.

Table 4: Non-vulnerable households					
Thailand (n=143)			Vietnam (n=80)		
number of non-vulnerable households		%	number of non-vulnerable households		%
…reporting zero shocks in the past	105	73.4	…reporting zero shocks in the past	32	40.00
…not expecting any risk to take place	74	51.7	…not expecting any risk to take place	41	51.2
…expecting risks to take place with no impact	69	48.3	…expecting risks to take place with no impact	39	48.8

Source: DFG FOR 756 database.

Note: The time period for reported shocks ranges from January 2007 to April 2008.

Table 5: Summary statistics of independent variables

	abbreviation	description	Vietnam					Thailand				
			min	median	mean	max	standard deviation	min	median	mean	max	standard deviation
household	hhsize	size of household	1	4	4.35	14	1.79	1	4	4.03	16	1.72
	offempl	share of household members with off-farm employment	0	0.20	0.22	1	0.21	0	0.33	0.34	1	0.26
	selfempl	share of household members with self employment	0	0	0.07	1	0.14	0	0	0.08	1	0.15
	agrempl	share of household members mainly employed in agriculture	0	0.36	0.37	1	0.25	0	0.35	0.36	1	0.26
	mage	mean age of household members	11.4	28.5	31.61	98	13.62	13	32.6	34.73	85	10.91
household head	age	age of household head	22	47	49.18	96	13.85	24	55	55.84	105	13.27
	age2	age squared of household head	484	2209	2610.40	9216	1491.99	576	3025	3294.56	11025	1552.94
	female	self-reported female-headship (0=no/1=yes)	yes: 294 (16.29%) households					yes: 548 (26.47%) households				
	minor	household head belongs to ethnic minority (0=no/1=yes)	yes: 345 (19.11%) households					yes: 137 (6.62%) households				
	enroll	years of school enrollment of household head	0	7	6.56	17	4.05	0	4	4.85	19	2.95
	enroll2	squared years of school enrollment of household head	0	49	59.41	289	56.29	0	16	32.23	361	47.04
wealth	llaginc	log of lagged annual per capita income of household (THB/1000VND)	0.4502	8.2467	8.1215	11.8225	1.2892	4.5747	9.9365	9.8803	13.7296	1.2144
	ai	asset index of household	-2.1083	0.0049	0.0000	3.4770	1	-2.7211	-0.0892	0.0000	4.6661	1
	totland	land area hold by household (in ha)	0	0.47	0.88	30.38	1.49	0	2.36	3.23	64.32	3.54
	totland2	square of land area hold by household (in ha)	0	0.22	3.00	922.94	31.51	0	5.57	22.98	4137.06	120.59
shocks	shock_num06	number of self-reported shocks household experienced in 2006	0	0	0.56	4	0.66	0	0	0.24	4	0.49
	shock_num07	number of self-reported shocks household experienced in 2007	0	1	0.76	6	0.90	0	0	0.60	6	0.87
	shock_num08	number of self-reported shocks household experienced between January and April 2008	0	0	0.37	3	0.61	0	0	0.33	5	0.60
	shock_exp06	number of self-reported shocks which led to reduction of expenditures by household in 2006	0	0	0.46	4	0.63	0	0	0.13	4	0.38
	shock_exp07	number of self-reported shocks which led to reduction of expenditures by household in 2007	0	0	0.58	4	0.79	0	0	0.22	5	0.56
	shock_exp08	number of self-reported shocks which led to reduction of expenditures by household between January and April 2008	0	0	0.27	3	0.54	0	0	0.12	4	0.36
location	buriram	household lives in Thai province Buriram (0=no/1=yes)						yes: 778 (37.58%) households				
	ubon	household lives in Thai province Ubon Rachathani (0=no/1=yes)						yes: 914 (44.15%) households				
	ha_tinh	household lives in Vietnamese province Ha Tinh (0=no/1=yes)	yes: 612 (33.91%) households									
	hue	household lives in Vietnamese province Hue (0=no/1=yes)	yes: 640 (35.46%) households									

Table 6: Tobit regression results

dependent variable: vulnerability to downside risk (α=2)

independent variables	Thailand I		Thailand II		Thailand III		Vietnam I		Vietnam II		Vietnam III	
hhsize	0.0014**	(0.0006)	0.001	(-0.0006)	0.0013**	(-0.0006)	0.0008	(0.0012)	0.0008	(-0.0012)	0.0005	(-0.0011)
offempl	0.0032	(0.0037)	0.0038	(-0.0036)	0.0042	(-0.0036)	-0.0219***	(0.0079)	-0.0213***	(-0.0078)	-0.0206***	(-0.0077)
selfempl	-0.0011	(0.0064)	0.0006	(-0.0062)	-0.0027	(-0.0063)	-0.0273**	(0.0125)	-0.0224*	(-0.0123)	-0.0221*	(-0.0123)
agrempl	0.0297***	(0.0039)	0.0226***	(-0.0038)	0.0253***	(-0.0038)	0.0362***	(0.0075)	0.0319***	(-0.0074)	0.0325***	(-0.0074)
mage	-0.0004***	(0.0001)	-0.0003**	(-0.0001)	-0.0003***	(-0.0001)	0.0000	(0.0002)	0.0001	(-0.0002)	0.0001	(-0.0002)
age	-0.0009*	(0.0005)	-0.0010**	(-0.0005)	-0.0010**	(-0.0005)	0.0011	(0.0008)	0.001	(-0.0008)	0.0009	(-0.0008)
age2	0.0000**	(0.0000)	0.0000**	(0.0000)	0.0000**	(0.0000)	-0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0000)
female	-0.0023	(0.0021)	-0.0019	(-0.002)	-0.0013	(-0.002)	0.0013	(0.0047)	-0.0002	(-0.0046)	0.0001	(-0.0046)
minor	0.0010	(0.0042)	0.0014	(-0.004)	-0.0001	(-0.0041)	0.0120**	(0.0051)	0.0081	(-0.0051)	0.0084*	(-0.005)
enroll	0.0014	(0.0010)	0.0014	(-0.001)	0.0014	(-0.001)	0.0023*	(0.0013)	0.002	(-0.0012)	0.002	(-0.0012)
enroll2	-0.0001	(0.0001)	-0.0001	(-0.0001)	-0.0001	(-0.0001)	-0.0001	(0.0001)	-0.0001	(-0.0001)	-0.0001	(-0.0001)
llaginc	-0.0009	(0.0008)	-0.0006	(-0.0008)	-0.0009	(-0.0008)	-0.0042***	(0.0014)	-0.0037***	(-0.0014)	-0.0035**	(-0.0014)
ai	-0.0017	(0.0011)	-0.0020*	(-0.001)	-0.0014	(-0.001)	-0.0017	(0.0021)	-0.0004	(-0.0021)	0.0006	(-0.0021)
totland	0.0012*	(0.0007)	0.0010**	(-0.0004)	0.0012***	(-0.0004)	-0.0023	(0.0020)	-0.0034*	(-0.0019)	-0.0034*	(-0.0019)
totland2	-0.0001*	(0.0000)	-0.0000**	(0.0000)	-0.0000**	(0.0000)	0.0000	(0.0001)	0.0001	(-0.0001)	0.0001	(-0.0001)
buriram	0.0242***	(0.0029)	0.0252***	(-0.0029)	0.0219***	(-0.0029)						
ubon	0.0065**	(0.0029)	0.0047*	(-0.0028)	0.0047*	(-0.0028)						
ha_tinh							0.0106**	(0.0048)	0.0009	(-0.005)	0.0038	(-0.0048)
hue							0.0186***	(0.0042)	0.0130***	(-0.0043)	0.0134***	(-0.0042)
shock_num06			0.0035*	(-0.0018)					0.0031	(-0.0026)		
shock_num07			0.0074***	(-0.001)					0.0081***	(-0.0019)		
shock_num08			0.0109***	(-0.0014)					0.0145***	(-0.0028)		
shock_exp06					0.0044*	(-0.0023)					0.0035	(-0.0027)
shock_exp07					0.0093***	(-0.0015)					0.0112***	(-0.0021)
shock_exp08					0.0156***	(-0.0024)					0.0187***	(-0.003)
Constant	0.0337**	(0.0169)	0.0280*	(-0.0163)	0.0345**	(-0.0164)	0.0363	(0.0241)	0.0278	(-0.0238)	0.0279	(-0.0237)
standard error of estimate	0.0388		0.0375		0.0373		0.0645		0.0637		0.0632	
log-likelihood	3296.9618		3363.6082		3374.5621		2071.3597		2094.8584		2108.0552	
chi-squared	221.90		355.19		377.1		119.30		166.3		192.69	
pseudo R^2	-0.0348		-0.0557		-0.0592		-0.0297		-0.0413		-0.0479	
modified pseudo R^2	0.0789		0.1448		0.1549		0.0681		0.0925		0.1048	
linktest	ok		ok		ok		ok		ok		ok	
Observations	2008		2008		2008		1701		1701		1701	

Source: Author's own calculation.

Notes: standard errors in parentheses; asterisks denote significance at the 1%- (***); 5%- (**); 10%-(*) level; left out provincial dummy are Nakhon Phanom in Thailand and Dak Lak in Vietnam; “linktest” refers to a STATA command which is used to detect specification errors (all specifications pass this test indicating that they are not misspecified).

Appendix E – Figures:

Figure 1: Country-specific kernel density estimate of vulnerability to downside risk

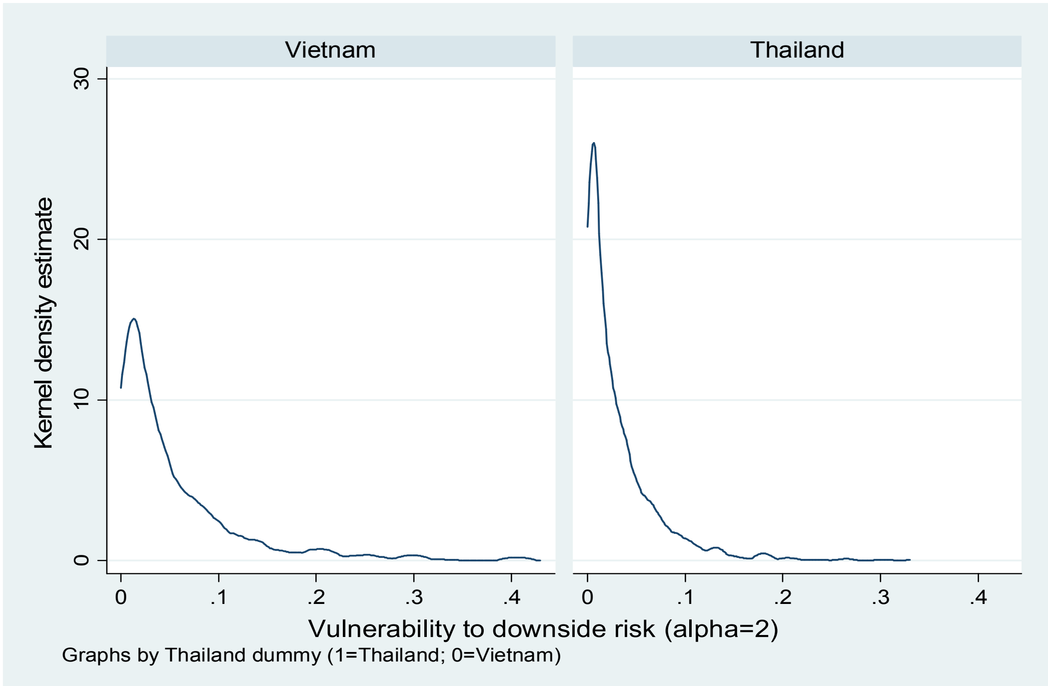


Figure 2: Country-specific severity distribution of risk – person leaves the household

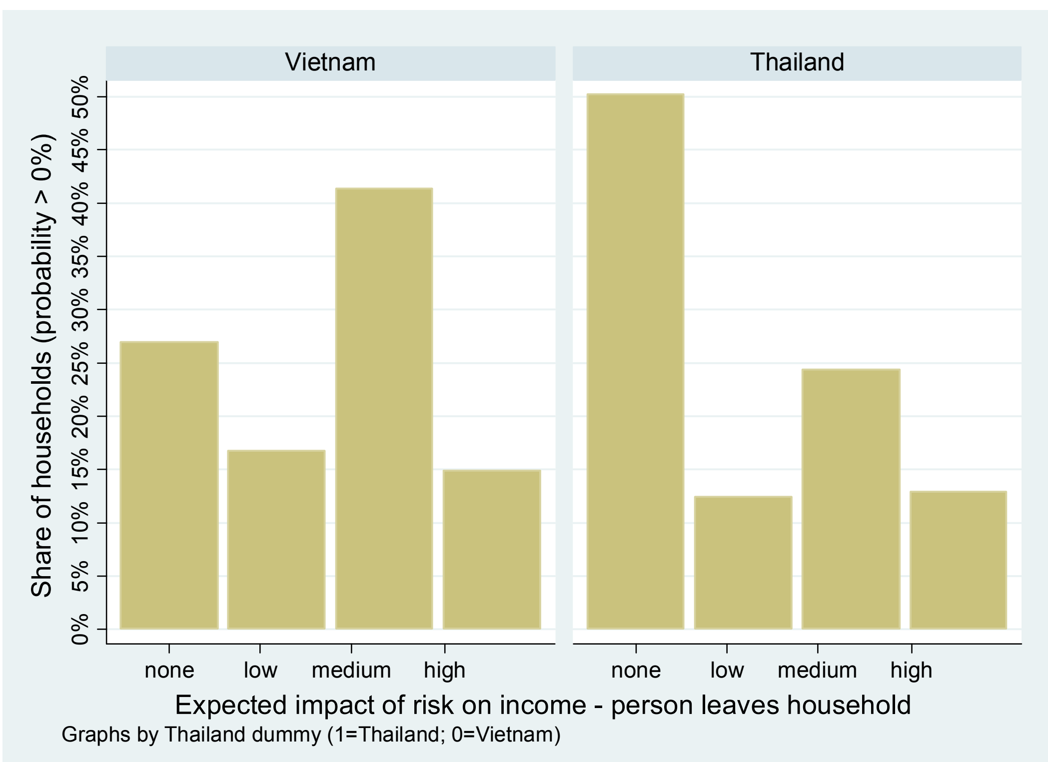


Figure 3: Country-specific severity distribution of risk – person joins the household