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Theoretical Underpinnings and Empirical Evidence for a New Approach to Vulnerability to Poverty

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Contents

Summary

The present research analyzes the debate on the link between risk and future welfare presenting the theoretical underpinning of a new sound empirical framework for measuring vulnerability to poverty.

It demonstrates that uninsured risk reduces household's well-being for the more exposed subsets of the population through its impact on the "ex-ante"household's behavior. Challenging the common view that looks at the coping and managing strategies as an optimal "ex-ante" behavior to reduce the potentially harmful consequences of risk, this work demonstrates (theoretically and empirically) that the risk-induced changing behavior actually has a cost in terms of welfare, especially for poor households in developing contexts. If it is the case, current monetary approaches to vulnerability to poverty lead to bias poverty prevention recommendations. The thesis is structured in three chapters.

Chapter 1. It reviews the key concepts concerning the links between risk, welfare and poverty and analyzes the existing monetary approaches to vulnerability. It highlights the strengths as well as the limits of current vulnerability analyses, suggesting new research perspectives.

The increasing number and quality of household-level data from developing countries in the last two decades allowed the researches to improve their assessments on a number of additional issues. In particular, the access to reliable data on the evo-

lution of the households' welfare allowed the researchers to shed more light on the dynamic nature of poverty and on the difference between its transitory and persistent components. Moreover, the economic literature had the chance to better understand and test more specific questions: How does risk affect individual welfare of poor households? How much do welfare losses caused by risk contribute to poverty? Is it possible to anticipate the negative effects of risk on future welfare and protect the vulnerable? Chapter 1 analyzes how the economic literature answered to these questions focusing most of its efforts on the last topic.

Scholars have extensively reported that economic, social, political and environmental risk realizations - i.e. shocks - constantly threaten the households welfare in developing countries and force them to adopt mitigating strategies to prevent their effects (e.g. Alderman and Paxson, 1994; Morduch, 1995, 1999; Townsend, 1995; Fafchamps, 1999; and Dercon, 2005). The interaction between the shocks and the households' behavioral responses determines the net impact of risk on welfare. Despite the notion of welfare is a quite extensive and its application is widely debated by the economic literature (e.g. Ravallion, 1996; Sen, 1985, 1987), the above effects are normally identified with some monetary measures (Deaton, 2003). In particular, this assessment aims at verifying if the household behavioral responses are able to offset the negative consequences of shocks on income and consumption. The common view is that uninsured risk reduces household's well-being and endangers the future possibilities of development for the more exposed subsets of the population. While most of the literature focuses its attention on the mitigating strategies exclusively as a mean to reduce the downside effects of risks, the welfare effect of this changing behavior linked to the ex-ante strategies still deserves additional investigation. So far, the existing theoretical and empirical analyses agree on the fact that risk usually influences consumption, saving and production decisions, moving the household toward investment with lower risk but also lower expected profits. Moreover, risk can push the household to deplete productive assets normally used for generating income or accumulate an excessive amount of precautionary saving. However, it is worth to focus more seriously on the sign and the magnitude of the net effect of the above process to determine if risk contributes or not to future poverty.

Current literature on transient and chronic poverty (e.g. Rosenzweig and Stark, 1989; Morduch, 1990; Rosenzweig and Wolpin, 1993; Rosenzweig and Binswanger, 1993; Morduch, 1995; Jalan and Ravallion, 1996 and 1999; Dercon and Krishnan, 2000; Giles and Yoo, 2007) share the conclusion that the presence of risk endangers the household living conditions and induces behavioral responses that may compromise the long-term life expectations (Dercon, 2006). The main limit of this body of literature is that the final evaluation on the impact of risk is done on ex-post measures of welfare such as the observed income and consumption, which are defined only after all uncertainty has been resolved. As consequence, the policy recommendations coming from these analyses are constrained to the ex-post measures of poverty alleviation while they don't provide any information on what ex-ante measures for prevention should be deployed.

During the last decade some development economists have tried to fill this gap moving their attention towards the impact of risk on future poverty, investigating what economic literature indicates with the term *vulnerability to poverty*. The term vulnerability means different things to different people (Hoddinott and Quisumbing, 2003) and it is used by a wide range of disciplines. In this research, the interest is focused on the monetary assessment of vulnerability, defined as the possibility of becoming or remaining materially poor in the future (Cafiero and Vakis, 2006). Even if poverty and vulnerability are obviously two related concepts they must be kept separated: the former limits its analysis to the static outcomes of a continuous process of risk and response while the latter is the forward-looking assessment of expected outcomes which only potentially may occur (Alwang et al, 2001). The economics literature developed several strategies to conceptualize vulnerability and each approach has its own definition and method to analyze it[1] . In the present research the attention is focused on the monetary approaches which make operative the vulnerability assessment through the proposition of quantitative techniques. In particular, this chapter examines three methodologies: Vulnerability to Expected Poverty (VEP), Vulnerability as Threats of future Poverty (VFP) and Vulnerability to Expected Utility (VEU). We focus on these techniques because they are the only that quantify future poverty using household-level data, providing a good opportunity to increase the effectiveness and efficiency of poverty prevention programs.

Despite the methodological differences, the three approaches evaluate how risk influences the fluctuation of household's welfare around its expected value retrieving monetary measures of future outcomes observing their past fluctuations. However, they suffer a major shortcoming: they do not consider if and how the future level of the household's welfare is affected by the behavioral responses put in place to mitigate risk. As a result, they lack of a solid micro-foundation which would be able to motivate the economic behavior of the household in a risky context. This weakness implies that it is impossible for the researcher to distinguish if the future welfare losses are due to the structural characteristics of the household, to the negative impact of risk realizations or to the risk-induced changing behavior. Wasting the information provided by the different components of vulnerability reduces the potential contribution of this literature in terms of policy recommendations. In the light of these considerations, several suggestions for the future research in the field of vulnerability raise. The most important would be developing a theoretical and empirical framework able to catch the ex-ante impact of household's changing behavior on its future welfare. Chapter 2 of the thesis focuses on the elaboration of a micro-founded monetary measure of vulnerability to poverty, while Chapter 3 performs the

[1]For a complete review of these *economic* approaches to vulnerability, see Alwang et al. (2001).

empirical strategy and provides a first test on VHLSS (Vietnam Household Living Standards Survey) panel data.

Chapter 2. It proposes a micro-founded measure of vulnerability to poverty based on the solution of the intertemporal optimization problem for a representative household in developing countries. In particular, the new measure separates the welfare cost generated by the risk-induced changing behavior (*ex-ante effect of risk*) from the impact of the shock realizations (*ex-post effect of risk*) and it is based on a model of precautionary saving adapted to the special features of the poor households in developing countries where households are assumed to be credit constrained with risky income and assets.

According to the standard theory proposed by the *life-cycle* (Modigliani and Brumberg, 1954) and the *permanent income* (Friedman, 1957) models, the households attempt to keep their consumption constant over time, saving in good times and depleting the accumulated resources during the bad times. These models lay most of the theoretical foundations for the household's saving behavior. However, they don't examine directly the role of risk in the household's choice. The extension to the uncertainty scenario of the life-cycle/permanent income models is the theory of precautionary saving where saving becomes an insurance mechanism to reduce the negative influence of risk (Lusardi, 1998). As demonstrated by several studies (Deaton, 1991; Jalan and Ravallion, 2001; Dercon, 2005; Giles and Yoo, 2007; Elbers and Gunning, 2007; Elbers et al., 2009; Gunning, 2010), the standard version of this model has been developed to describe saving choices in advanced economies while it is not able to explain why risk may induce forms of rational behavior which perpetuate poverty in developing countries. These authors modify some basic assumptions of the precautionary saving model, introducing the presence of liquidity constraints and risky assets. In the first case, households are not ensured from repeated negative shocks because they cannot accumulate enough assets to protect themselves (Deaton, 1991). In the second case, households are not able to fully smooth consumption using buffer stocks because risk reduces the effectiveness of the self-insurance scheme (Dercon, 2005; Elbers and Gunning, 2007; Karlan and Morduch, 2009). As consequence, risk may actually lead to a decreased saving with a direct impact on households' development process. In fact, even if the rate of saving doesn't influence the consumption growth in steady state, it matters during the movement towards it, which is highly relevant in a development scenario. A reduction in the rate of saving would slow down the transition process and increase the time to reach the long-run equilibrium (Gersovitz, 1988).

Following this body of literature, we use a discrete version of the dynamic and stochastic Ramsey model to simulate the transitional dynamics of saving for a household with liquidity constraints, risky income and risky assets. The model is solved using a numerical simulation based on the *value function iteration* technique. We first simulate the deterministic asset, consumption and welfare paths for a 50-year period under the assumption that the household lives in a risk-free context. Then we consider a stochastic environment, too. The difference - in terms of welfare - between the determinist case and the full-stochastic case determines the total cost of risk. In this specific analysis, the results show that risk tilts down the optimal lifetime consumption path with respect to its deterministic counterpart, forcing the household to pay a substantial cost in terms of future welfare. Subsequently, we re-simulate the model for a household which behaves as if shocks are expected to occur but they never hit the income or the asset processes, which means considering only the ex-ante impact of risk. Applying a decomposition method based on these three counterfactuals, the total welfare cost is divided between the impact due to the risk-induced changing behaviour (i.e. the difference between deterministic and ex-ante welfare counterfactuals) and the effect caused by risk realizations (i.e. the difference between the ex-ante and the full-stochastic counterfactuals). At the end of the 50-year period of simulation the deterministic consumption path is on average 20% higher than the consumption path in the full-stochastic case. The 80% of this difference depends on the ex-ante effect of risk while the remaining 20% depends on the ex-post risk realizations. These results indicate that the risk-induced changing behaviour can lead to an important welfare loss and - instead reducing the potential negative effects of risk realizations - it may actually exacerbates them. The results also suggest that public intervention should be aimed to improve the self-insurance mechanisms of the households in such a manner that the mitigating strategies would be an efficient instrument against the potential negative impact of shocks and not another cause of deprivation.

The results are in line with those presented by other authors such as Dercon (2005), Elbers and Gunning (2007), Carter and Ikegami (2009) and Elbers et al. (2009). However, these works don't consider the serial correlation of the income and asset shocks and calibrate their model using country-specific parameters. On the contrary, we propose a more generalized version with shock persistence and a baseline calibration based on parameters provided by the economic literature on developing countries. The introduction of the serial correlation in the model helps to better represent the idea that many behavioral responses have welfare implications not only in the present but they influence the household's welfare path over several future periods. Moreover, the choice of the parameters linked to the previous works on developing countries allows to sustain that the welfare cost of the risk-induced changing behaviour may be a potential problem which affects a larger proportion of poor households than originally thought by scholars. Then, the model has the merit to better represent the relationship between welfare and risk in developing countries, providing a dynamic and forward-looking analysis which can be easily exploited to propose for the first time a reliable solution to the major weaknesses presented by the current analysis on vulnerability to poverty.

At this purpose, using the results provided by the numerical simulation and following the most up-to-date debate on the aggregation over time of poverty indices, Chapter 2 builds up a monetary measure of vulnerability based on the above decomposition. This measure captures the different impacts of the risk components on future poverty and - in particular - it separates the contribution due to the characteristics of the household (poverty component) from the contribution of the changing behavior (ex-ante component) and the risk realizations (ex-post component). We quantify the relative weights of these components on the total vulnerability in terms of utils and it comes out that the 70% of future welfare losses are caused by the ex-ante component, i.e. the effect of the risk-induced behavioral choice of the households. We also show that the higher is household's risk aversion, the persistence of the shocks and the total amount of income and asset risks, the higher is the total level of vulnerability.

Unlike the previous approaches to vulnerability to poverty, the proposed measure has the advantage to exploit the relationship between risk and welfare as theoretical underpinning of a new micro-founded monetary measurement. In particular, the risk-induced behavioral choices are not considered just because of their contribution to the consumption fluctuations around its mean, but they are rigorously introduced as an active and direct component in the determination of the expected level of welfare. In fact, the micro-foundation allows to consider directly and autonomously the impact of the household's behavior on its own expected level of future welfare. Such a measure has the merit to prevent the researcher from wasting the information provided by the different components of vulnerability and increase the potential contribution of this literature in terms of policy recommendations.

Chapter 3. It presents the empirical strategy to make the micro-founded measure operative as well as an empirical test with the VHLSS household-level panel data on Vietnam.

The lack of a strong theoretical framework to model the household's behavior has negatively influenced the empirical estimation of the existing vulnerability measures. They regress consumption on a set of household's and village's characteristics and - where the design of the survey allows the researcher to collect enough information - on aggregate and idiosyncratic shocks. They usually rule out assets and the characteristics of the distribution of shocks, raising several econometric problems which may bias the vulnerability estimates and - as consequence - suggest wrong policy decisions. Chapter 3 addresses this issue proposing a method for estimating the micro-founded measure of vulnerability based on a three-stage strategy which allows to evaluate the influence of asset and income risks on the household's behavior and - at the same time - provides a valid instrument to construct the series of empirical consumption counterfactuals for measuring the different vulnerability components.

The first stage of the strategy proposes a method to individuate two workable proxies for income and asset risks which are exploited later to catch the overall impact of risk on the household's behavior. Following a method largely applied by the empirical literature on precautionary saving (Guiso et al. 1992, Carroll, 1994; Carroll and Samwick, 1997 and 1998; Jalan and Ravallion, 2001; Giles and Yoo, 2007), the two proxies are calculated as the variance of the innovations to the income and asset processes. The benefit of looking at the fluctuation of the income innovations is that it allows to consider only that part of income and asset variations which are not explained by the individual characteristics and then cannot be foreseen in advance by the households. The second stage of the procedure imposes a proper form to the consumption function based on the previous considerations on the household's saving behavior in developing countries. In particular, the function is modeled relying on the assumption that individual consumption in any period depends on multiple factors such as the household's tastes and composition, the expectations on future income, the current physical assets, the presence of risks and the relative ability to smooth consumption. Finally, the third stage exploits the results of the first two steps with the aim to build up the consumption counterfactuals for calculating the empirical version of the vulnerability measure proposed in Chapter 2.

We apply this three-stage procedure to the household-level data provided by VHLSS for three consecutive surveys (2002, 2004 and 2006). The empirical application sustains several considerations presented during this research and provide two main conclusions which may contribute to the debate on risk and future poverty. First of all, the analysis of the impact of risk on consumption behavior performed in the first two stages confirm that if the presence of risky income is coupled with the risky assets hypothesis, the net impact on saving is negative and this is coherent with the numerical simulation presented in Chapter 2. For Vietnamese households, an increase of 50% in the total amount of asset and income risks results in a net increase of consumption equal to 5%. Secondly, the estimation of the future consumption counterfactuals and the subsequent calculation of the empirical version of the micro-founded vulnerability measure reveal the relative importance of its main components. The results suggest that in Vietnam the vulnerability to poverty calculated on the basis of the available panel data mostly depends on the potential damages caused by uninsured shocks. For those households which report a positive level of vulnerability, the ex-post component accounts for the 57% of the total measure. At the same time, almost 30% of the future welfare losses are caused by the ex-ante component, confirming that forms of rational behavior such as precautionary motive may have a cost. Lastly, the poverty component which depends on the households' structural characteristics account only for the 13% of total vulnerability.

This results are in line with those provided by the numerical simulation in Chapter 2, even if the ex-ante component of vulnerability has reduced its importance in the determination of future poverty. In fact, this discrepancy can be motivated by the methodological approaches (representative agent vs. linear regression) and the choice of the temporal horizons (50-year period vs. 3 panel waves). However, both models supports the original intention to demonstrate that risk-induced changing behavior produces a welfare cost and contributes to the determination of the future level of poverty. The threat of being poor depends not only on the observable characteristics of the households or on the idiosyncratic and covariate shocks, but also on rational behavioral changes triggered by risk. In particular, despite the asset risk offsets the negative impact of income risk on the predicted consumption, the introduction of the two risk proxies in the estimation influences the other parameters of the model in such a manner that for the vulnerable households the resulting ex-ante consumption will be on average lower than the deterministic one, even though we are in a context where precautionary motive has a negative impact on saving. Finally, the results are also in line with the current situation of Vietnam characterized by a continuous reduction of poverty in the last two decades but also by an increasing presence of risk caused by the introduction in the economic system of new sources of uncertainty such as prices fluctuations, market deregulation and trade liberalization.

Concluding remarks and Policy implications

The proposed micro-founded measure is a key instrument for policymaking, too. Differently to previous monetary measures, it is able to distinguish among the different causes of future poverty. In particular, if the threat of future poverty comes from the structural components such as the households' characteristics or from the likely realizations of bad shocks, providing transfers through safety net could be seen as the most appropriate policy. On the contrary, if the most important cause of future poverty is the welfare cost caused by the changing behavior, the intervention should primarily support the households to better protect themselves against risk. It can be done in several ways: supporting self-insurance via savings (through micro-financial instruments), assisting income risk management by providing access to credit, sustaining community-based risk-sharing and pushing the public and private institutions to develop new products such as life and health insurance (Dercon, 2006). Going into details on the different instruments that could be deployed by policy-makers as well as providing selection criteria is largely beyond the scope of this work. It is worth noting, however, that the suggested new vulnerability measure represents a clear added value in the above debate because it contributes to sustain and facilitate an efficient allocation of resources between treatment and prevention of poverty. Moreover, it presents robust theoretical underpinnings linked to the most up-to-date discussion on the relationship between risk and welfare in poverty contexts. Finally, it can be transformed in a sound applied monetary measure of vulnerability easily applicable with available panel data in developing countries since its empirical strategy is flexible and adaptable to a wide range of possible datasets. In this sense, it permits to reach a more robust assessment of vulnerability to poverty in developing contexts without paying the cost of strong data requirements and high computational burden.

Introduction

Since the last two decades economic literature has broadly investigated how risk influences the daily life of poor households in developing countries. Farmers are exposed to harvest failure because of climatic agents such as drought, floods and frost as well as their cattle can be hit by illness or death. Urban areas are affected by economic and environmental risks like unemployment, business failure, excessive pollution while political and social problems such as civil war, crime and ethnic discrimination endanger the entire population. The households don't suffer the consequences of these risks without trying to protect themselves. They *manage* risk trying to reduce the chances to be hit by future adverse shocks as well as they *cope* with those already occurred. They decrease the pressure of risk by reducing the exposure of their investment portfolio and they decide to shield themselves accumulating savings or activating formal and informal risk-sharing mechanisms. Hence, risk plays a major role to determine the quality of life of the more exposed households and may generate potentially harmful consequences in terms of future living standards, contributing to exacerbate the statistics on poverty.

The increasing availability of longitudinal data allowed scholars to address more efficiently this issue. During the last two decades the economic literature had the chance to better understand and test more specific questions. In particular, some development economists focused their attention on *vulnerability to poverty*, i.e. the impact of risk on *future poverty*. However, the existing monetary approaches -

which measure vulnerability using household-level data - take into consideration only the direct effects of risk, attributing the entire future welfare costs triggered by the presence of uncertainty to the negative consequences of bad shocks. The risk-mitigating strategies put in place by the household are considered exclusively as a mean to reduce the downside effects of shocks and even if some authors started to recognize that risk-induced changing behavior may have a cost in terms of welfare, additional investigation is still needed.

In the light of these considerations, the main objective of the present research is contributing to the debate on the link between risk and future welfare presenting the theoretical underpinnings of a new sound empirical framework for measuring vulnerability to poverty. This general objective is mainly addressed through:

- the proposition of a new micro-founded measure of vulnerability able to disentangle the "ex-post" impact of shocks on the future households' welfare from the "ex-ante" risk-induced changing behavior effects;
- the elaboration of a sound empirical strategy for estimating and validating the new theoretical framework.

The thesis is structured in three different chapters. The first chapter reviews the theoretical debate on the role of risk both in poverty and vulnerability literatures and the relative consequences in terms of welfare for the poorest households. It comes up with the conclusion that current analyses underestimate risk-reducing mechanisms and overestimate the poverty component of vulnerability, leading to a biased political intervention. The second chapter proposes a new micro-funded measure of vulnerability which is able to capture the different impacts of risk on the future poverty, overcoming the main shortcomings of the current approaches. Performing a simulation of a *discrete-time stochastic Ramsey* model, it shows that the introduction of risk on poor household's income and asset - combined with persistent shocks - tilts down the optimal lifetime consumption path with respect to a risk free counterpart. The results of the simulation are exploited to separate the ex-ante impact of risk from its ex-post effect and to build up a new dynamic "risk sensitive" vulnerability measure based on a counterfactual decomposition of the household's welfare process. In particular, the proposed measure is able to disentangle 1) the contribution of poverty to vulnerability (due to the characteristics of the household); 2) the ex-ante impact of risk on the household's behavior; 3) the ex-post effect of realized shocks. Finally, the last chapter proposes a method to make the micro-founded measure operative and an empirical test applied to VHLSS household-level panel data on Vietnam in the period 2002-2006. The econometric method exploits the considerations on household's behavior in developing countries emerged in the previous chapters and combines them with an empirical strategy based on linear regression techniques. In particular, the method is based on a three-stage strategy which allows to evaluate the influence of different sources of risks (asset and income) on the household's behavior and - at the same time - provides a valid instrument to construct the series of empirical consumption counterfactuals for measuring the different vulnerability components.

The added value of the research can be fleshed out as follows:

- It reviews the theoretical underpinnings which characterize the link between risk and welfare, showing how the current measures of vulnerability to poverty are not able to properly evaluate the welfare cost of risk-induced changing behavior;

- It proposes a dynamic and stochastic simulation for testing the impact of risk on the welfare of a representative household with liquidity constraints and serially correlated shocks on asset and income. These assumptions allow to better represent the specific characteristics of developing contexts even if productive assets are not risk-free;

- It contributes to the micro-foundation of a new dynamic and risk-sensitive measure of vulnerability to poverty which captures the main determinants of the future poverty, included the ex-ante component linked to the risk-induced changing behavior;
- It elaborates an empirical strategy to make the proposed measure of vulnerability operative and workable with extremely short panel dataset and it assesses its performances using household-level data on the post "Doi-moi" Vietnam from 2002 to 2006.

Chapter 1

From Poverty to Vulnerability: the Role of Risk in Welfare Analysis

1.1 Introduction

Economic literature has broadly recognized that the presence of risk affects the daily behavior of poor households in developing countries. Economic, social, political and environmental risks constantly threaten their welfare and force them to adopt mitigating strategies to prevent the negative effects. Scholars started to deal concretely with these problems only in the last two decades because of the increasing availability of longitudinal data which allowed to detect the movement across time in and out poverty. In particular, the possibility to analyze panel data allowed the researchers to address precise questions: How does risk affect individual welfare in developing countries? How much do welfare losses caused by risk contribute to poverty? Is it possible to anticipate the negative effects of risk on future welfare and protect vulnerable households? The present Chapter analyzes how the economic literature answered to these questions and focuses most of its efforts on the last issue.

Farmers in developing countries are exposed to harvest failure because of climatic agents such as drought, floods and frost as well as their cattle can be hit by illness or death. Urban areas are affected by economic and environmental risks like unemployment, business failure and excessive pollution while political and social problems such as civil war, crime and ethnic discrimination endanger the entire population. The existence of substantial downside risk realizations i.e. shocks - for households in developing countries has been extensively reported by a large body of literature (e.g. Alderman and Paxson, 1994; Morduch, 1995, 1999; Townsend, 1995; Fafchamps, 1999; and Dercon, 2005). However, households don't suffer the consequences of risk without trying to protect themselves. They manage risk trying to reduce the chances to be hit by future adverse shocks as well as they cope with the shocks already occurred. For example, they can reduce the pressure of risk by reducing the exposure of their investment portfolio, as well as they can decide to protect themselves using accumulated saving or risk-sharing mechanisms as self-insurance instruments (Aldermann and Paxson, 1994). The interaction between risk realizations and the households' behavioral responses determines the net effect of risk on welfare. Despite the notion of welfare is a quite extensive and its application is widely debated by the economic literature (e.g. Ravallion, 1996; Sen, 1985, 1987), the need to quantify it usually lead the economists to identify welfare with some monetary measures like - for example - observed consumption and income (Deaton, 2003). Therefore, the impact of risk on welfare is usually assessed verifying if the household behavioral responses are able to offset the negative consequences of shocks on income and consumption.

The sign and the magnitude of this process determines if risk contributes or not to current and future poverty. Most of the literature focused its attention on the effect of risk on current poverty, distinguishing between transient and chronic poverty and trying to understand if transitory events had permanent effects on the household's welfare (e.g. Rosenzweig and Stark, 1989; Morduch, 1990; Rosenzweig and Wolpin, 1993; Rosenzweig and Binswanger, 1993; Morduch, 1995; Jalan and Ravallion, 1996 and 1999; Dercon and Krishnan, 2000; Giles and Yoo, 2007). Even if there are substantial differences related to the adopted methodologies, this strand of literature shares the conclusion that the presence of risk endangers the household living conditions and induces behavioral responses that may compromise the long-term life expectations (Dercon, 2006). However, they also share the limit to assess the influence of risk on welfare from an ex-post perspective, looking at the ex-post outcomes such as the observed consumption and income. They don't investigate from an ex-ante perspective what risk-induced effects might be in the future (Hoddinott and Quisumbing, 2003).

During the last decade some development economists try to fill this gap moving their attention towards the impact of risk on future poverty, investigating what economic literature indicates with the term *vulnerability to poverty*. The term vulnerability means different things to different people (Montalbano, 2011) and it is used by a wide range of disciplines. In this research, the interest is focused on the economic interpretation of vulnerability, defined as the possibility of becoming or remaining materially poor in the future (Cafiero and Vakis, 2006). Even if poverty and vulnerability are obviously two related concepts they must be kept separated: the former focuses on the static outcome of risk, i.e. the ex post movement into and out of the state of deprivation (Alwang et al, 2001) while the latter is an ex-ante condition that only potentially may lead to welfare looses (Montalbano, 2011). The economics literature developed several strategies to conceptualize vulnerability and each approach has its own definition and method to analyze it. In the present research the attention is focused on the monetary approaches which make operative the vulnerability assessment through the proposition of quantitative techniques. In particular, this Chapter examines three methodologies: Vulnerability to Expected Poverty (VEP), Vulnerability as Threats of future Poverty (VFP) and Vulnerability to Expected Utility (VEU). We focus on these techniques because they are the only that quantify future poverty using household-level data, providing a good opportunity to increase the effectiveness and efficiency of poverty prevention programs.

Despite the method, all three approaches evaluate how risk influences the fluctuation of household's welfare around its expected value retrieving monetary measures of future outcomes observing their past fluctuations. However, they suffer of a major shortcoming: they do not consider if and how the future level of the household's welfare is affected by the behavioral responses put in place to mitigate risk. The main cause of this problem is that monetary approaches to vulnerability lack of a solid micro-foundation which would be able to motivate the economic behavior of the household in the presence of risk. As consequence, it is impossible for the researcher to distinguish the welfare losses due to risk realizations from the impact of the risk-induced changing behavior. The Chapter proceeds as follows. Paragraph 1.2 provides a conceptual framework which clarifies how risk affects welfare and the relative consequences in terms of current and future poverty. Paragraph 1.3 describes the most important monetary approaches to the measurement of vulnerability. Lastly, Paragraph 1.4 provides a critique of the existing methodologies and defines the future perspectives to improve the existing literature.

1.2 The Role of Risk in Poverty and Vulnerability Analysis

In 1988, Ravallion still wondered why the fundamental question whether the presence of risk was good or bad for poverty wasn't yet been addressed by researchers. Morduch (1994) answered to that question with one practical and one conceptual reason. At a practical level, issues of risk had not been addressed for lack of longitudinal data on the income and consumption of poor households and the absence was particularly notable in low-income countries. The conceptual reason was that the analytical schemes used to analyze the link between risk and welfare came from studies in high-income countries which didn't consider the peculiarities of the poor households in developing countries. Nevertheless, several progresses have been done in the last two decades and the most important is that development economists are benefiting an increasing availability of longitudinal surveys. The access to reliable data on the evolution of the households' welfare allowed the researchers to shed more light on the stochastic nature of poverty. In particular, economic literature had the chance to better understand and test the multiple connections between risk and welfare as well as their relative consequences in terms of future poverty.

1.2.1 The Impact of Risk on Welfare

Defining the concept of risk is not straightforward, especially for its relationship with the notion of uncertainty. In his well-known attempt to differentiate between these two terms, Knight (1921) refers to *risk* when the decision-maker can assign mathematical probabilities to the randomness of the event he is facing, while with the term *uncertainty* he refers to the situation where the randomness of the event is unknown and it cannot be measured. For others, risk is the uncertainty that affects the individual's welfare and it is associated with adversity and loss (Harwood et al. 1999, Bodie and Merton, 1998). In this case the presence of uncertainty - a situation in which a person doesn't know for sure what will happen - is necessary for risk to occur, but uncertainty may not lead to a risky situation. Moreover, we can distinguish between objective and subjective risk. Objective risk is based on available information and data about the probability of an event while subjective risk is determined by the perception of the decision-maker (Holton, 2004). According to Siegel and Alwang (1999), current literature on development economics makes little distinction between risk and uncertainty because they both stress the stochastic

Table 1.1: Main Sources of Risk

	Micro **Idiosyncratic**	**Meso**	**Macro** **Covariate**
Natural		Rainfall Landslides Volcanic Eruption	Earthquakes Floods Drought Strong winds
Health	Illness Injury Disability		
Life-cycle	Birth Old Age Death		
Social	Crime Domestic violence	Terrorism Gangs	Civil strife War
Economic	Umemployment Harvest Failure Business failure	 Resettlement	Output collapse Balance of payment Financial/currency Terms of trade shocks
Political	Ethinic discrimination	Riots	Political default Coup d'tat
Environmental		Pollution Deforestation Nuclear Disaster	

nature of the events. In this research, the term risk indicates the uncertain events with either known or unknown probability distribution. This definition implies that the concepts of risk and uncertainty are used in a interchangeably manner even if we are aware of the distinction between the two terms.

The presence of risk materializes through its realizations (i.e. shocks). Holzmann and Jorgensen (2000) classifies these realizations by sources, correlation, frequency and intensity (see Table 1.1). The sources can be natural or related to the life-cycle as well as it can be the result of human activity; it can be uncorrelated (idiosyncratic) or correlated (covariant) among individuals and households over time or with other risks. Risks can have low frequency but severe welfare effects (catastrophic) or high frequency but low welfare effects (non-catastrophic). The degree of covariance can range from purely idiosyncratic (micro or individually specific), to regionally (meso) or nationwide (macro) covariant events. As pointed out by Dercon (2005), households don't suffer the consequences of risk realizations without putting in place self-protection mechanisms, but they respond using different strategies. Alderman and Paxson (1994) catalogue these possible strategies in two broad categories: *risk management* strategies and *risk-coping* strategies [1]. In the first case, households aim to reduce the variability of their welfare through ex-ante decisions such as income diversification, multiple occupations and strategic migration. These actions usually imply conservative choices which lower the expected value of income in exchange for lower variability [2]. In the second case, the households engage themselves in self-insurance practices (e.g. precautionary saving, asset smoothing, etc) or have recourse to grouped-based risk-sharing which enables to spread the effects of shocks across households (Dercon, 2005)[3]. Both management and coping strategies can operate through i) an informal channel, which includes personal, family and community arrangements; ii) a market-based channel, based on the opportunity provided by institutions such as banks, insurances or microfinance corporations; or iii) a public channel, which implies a series of welfare state interventions aimed to the protection of specific subsets of the population, e.g. against unemployment, old-age, work

[1] The Social Risk Management (SRM) framework provides another classification. Risk management can occur through a) prevention strategies, implemented before a risk event occur with the aim to reduce the probability of the bad realizations; b) mitigation strategies, implemented before as well but with the aim to reduce the impact of future risk; and coping strategies, designed to relieve the impact of risk (shocks) once it has occurred (Holzmann, 2001).

[2] The literature on income smoothing mainly focuses its interest on aspects related to farm production such as the intensity of inputs adoption (Bliss and Stern, 1981; Morduch, 1990; Dercon, 2010), the diversification of activities (Morduch, 1990, Reardon et al. 1994; Townsend, 1995, Dercon, 1996), the occupational choices (Rosenzweig and Stark, 1989; Kochar, 1999; Rose, 1995) and their net impact on the expected profit of the household (Rosenzweig and Binswanger, 1993)

[3] For more information on full and partial risk-sharing arrangements see Coate and Ravallion (1993), Udry (1994), Townsend (1994), Townsend (1995), Besley (1995) and Morduch (2002). This literature focuses its attention on the presence of systems of mutual assistance between family networks or communities living in the same economic environment.

injury, disability, widowhood and sickness.

The risk realizations, coupled with the household responses lead to an outcome, which is generally a measure of individual welfare (Heitzmann et al.,2002). Economic literature has broadly focused itself on looking for the right metric of the welfare indicator. Microeconomic theory generally refers to welfare as synonymous of *satisfaction*, *well-being* or *living standards* (Bryant, 1990; Deaton 2003) and assumes that the household acts to maximize it through the maximization of its utility function. Utility can be characterized by material (income and consumption) or immaterial goods (education, health, friendship, leisure, employment and others) and it is usually a one-dimensional quantity (Strengmann, 2000). In this research, the analysis of the impact of risk on welfare is limited to the economic definition of living standards because our analysis focuses on the monetary measures of poverty and vulnerability. The most applied monetary measurement of welfare is the money metric utility (Deaton, 2003) according to which the indifference curves representing the household's preferences are labeled by the amount of money at constant prices required to reach them[4] . The welfare is measured as the total money needed to sustain the maximum level of utility the household is able to achieve, given its budget constraint. Deaton and Muellbauer (1980) show that the money metric utility can formally be approximated by the consumption expenditure adjusted by prices (over time and space) and household demographics and this is the standard practice followed by most of economic literature [5] .

We then can understand the net impact of risk on welfare summing up the effects of risk realizations and behavioral responses on a monetary measurement of the consumption expenditure. Even if the shocks can reflect negative as well positive de-

[4]An alternative approach is the welfare ratio proposed by Blackorby and Donaldson (1987), where welfare is measured as multiples of a poverty line.

[5]The approach has been subject to several critiques. In particular Sen's works (1985, 1987) pointed out that the measuring welfare with the income metric is limitative because it should be refined with the inclusion of non-income indicators such as life expectancy, infant mortality and literacy (Ravallion, 1996).

viations from the expected welfare outcome, development economists are obviously more interested in understanding the impact of downside risk realizations. Therefore, their aim is actually to understand if the household responses to risk are able to offset the negative consequences of shocks. The extreme complexity of the issue led the economic literature to produce different methods. Each strand focuses its analysis combining sources of risk with different mitigating strategies and the conclusions as well as the policy implications vary together with the different approaches. Theoretically, in a world with symmetric information and complete markets all the potential negative impact of risk realizations should be addressed by the households through market-based solutions without any welfare consequences (Dercon 2005; Holzmann and Jorgensen 1999, 2000). However, in developing countries there are several aspects which prevent the households to fully ensure themselves against risk. Specific problems such as moral hazard, information asymmetries and incapability to enforce contracts may lead to incomplete or absent insurance markets (Alderman and Paxson, 1994). Moreover, the lack of access to credit prevents the household to absorb risk realizations through consumption smoothing with the consequences to observe large fluctuations in the welfare indicator (Eswaran and Kotwal, 1990). Despite poor households in developing countries are affected by all these problems, a large part of the literature agrees that households in developing countries are actually using a extensive range of mechanisms to at least limit the welfare losses caused by risk. While the specific characteristics of these mechanisms are deeply investigated in the following paragraphs, for now it is worth to note that the strategies to mitigate risk share a common feature: they have a cost in terms of welfare (Elbers and Gunning, 2007). Both the theoretical and the empirical literature which tried to understand the link between risk and welfare recognized that risk exposure is harmful for the households' living standards (Ravallion 1988; Morduch 1994; Dercon, 2005). Many empirical analyses also confirmed that trying to reduce the degree of risk which characterizes the future is a common behavior across all the economic agents (Cafiero and Vakis, 2006) and under specific circumstances these mitigating strategies may have the opposite effect to reduce welfare (Giles and Yoo, 2007; Jalan and Ravaillon, 2001). If the consequence of risk is to reduce the household's welfare because of the joint effect of shocks and risk-induced changing behavior, the next step is to understand if it matters or not in terms of poverty. It means to evaluate if the reduction of welfare triggered by the presence of risk is so important to push the households below some socially accepted poverty threshold.

1.2.2 The Link between Risk, Welfare and Poverty

According to Lipton and Ravallion (1995) poverty exists "*when one or more persons fall short of a level of economic welfare deemed to constitute a reasonable minimum, either in some absolute sense or by the standards of a specific society*". If the presence of risk has a negative impact on the households' welfare, we are then justified to think that risk increases poverty. One way to assess the impact on poverty is to differentiate between the effects of risk on transient and chronic poverty, referring to the literature on poverty dynamics. Morduch (1994) defines transitory poverty as the failure to find protection against stochastic elements in the economic environment and it is also called stochastic poverty. Understanding the link between risk and stochastic poverty is quite easy: the household may have a permanent income well above the poverty line but it can experience a negative shock which lowers the current consumption below the poverty line because the household is not able to borrow against future income. Economic literature provides a lot of examples of transitory poverty due to unexpected shocks on income and consumption (e.g. Jalan and Ravallion, 1996 and 1999; Gunning et al., 2000; Dercon and Krishnan, 2000). On the other hand, chronic poverty is characterized by a permanent income which constantly generates consumption streams below the poverty line. In this case, it seems more reasonable to think that risk has nothing to do with chronic poverty because it is that part of poverty which remains even when the inter-temporal variability in welfare has been smoothed out. Chronic poverty is strictly correlated with the lack of earning capacity of the households and with factors like occupation, education, and demographic characteristics of the individuals. However, literature recognizes that risk can have also persistent effects on poverty and this possibility is strictly connected with the mitigation strategies adopted by the households. As pointed out by Dercon (2006), there are at least three strands of development economics that recognize risk as factor influencing the chronic poverty in developing countries. According to the fertility literature, the risk that children won't survive beyond a certain age increases the fertility rate, jeopardizing the women's welfare as well as putting pressure on the environment and the well-being of others. A second strand of literature analyzes the impact of risky nutrition on long term welfare because short-term shocks may contribute to lower nutritional outcomes in the long-run, having persistent health effects. Finally, a third part of literature based on agricultural economics but also suitable for other contexts in developing countries, focuses on risk aversion and its impact on economic behavior. For example, some income strategies undertaken to reduce risk and fluctuation in income may lower the expected value of profits in exchange for lower variability. Morduch (1990) shows that households with lower and riskier level of consumption devote a greater share of land to safer, traditional varieties of rice than to riskier and high yielding varieties while several authors find evidence that members of the household facing more volatility in farm activity engage themselves in more stable non-agricultural employment with lower wage (Rosenzweig and Stark, 1989; Kochar, 1999 and Rose, 1994). Morduch (1995) highlights that mitigating risk through production choices may be costly because it generates lower expected profits and these costs exacerbated chronic poverty over time if risk averse households don't take advantage of new technologies and economic opportunities. Households can be also pushed to protect their consumption from risk by depleting their productive assets or withdrawing their children from school. As we will see deeply in Chapter 2, these mechanisms - which operate through the precautionary motive - can be harmful for the household's welfare and increase poverty. For example, Giles and Yoo (2007) sustain that - if we look at the composition of the consumption expenditure instead of its magnitude - the reduction in the early life consumption caused by precautionary motive may result in substitution away from productive investments (like health or education of family members) or lead to reductions in other consumption activity important for household welfare. This *excessive* and *unproductive* precautionary saving may have a particularly severe negative impact on the welfare of poorer households, exposing them to a situation of chronic poverty. These three literatures share the common feature to acknowledge that transitory events may have permanent effects. The presence of risk which endangers the household living conditions induces behavioral responses that may compromise the long-term life expectations. However, they also share the limit to assess the influence of risk on welfare from an ex-post perspective, only after uncertainty has been resolved. The poverty measures are defined using ex-post outcome variables such as the observed consumption and income. They don't investigate from an *ex-ante* perspective what risk-induced effects might be in the future. For example, when assessing the impact of a new transfer scheme after it has been introduced, data on its actual impact and the resulting poverty outcomes are observed. However, when deciding to commit resources to competing schemes ex-ante, evaluating which one will be more effective to reduce poverty will have to take into account potential outcomes in different states of the world (Dercon, 2005). It means that we cannot use anymore a static and risk-free poverty measure as benchmark, but we need to move towards the vulnerability to poverty analysis.

1.2.3 Moving from Poverty to Vulnerability Analysis

Beside the economic literature which tries to investigate the link between risk and poverty, during the last decade some development economists moved their attention towards the impact of risk on vulnerability to poverty. In its broader sense the term vulnerability refers to the condition of being at risk of any potential harmful event and it has been applied with different meanings by a wide range of disciplines such as economics, sociology/anthropology, disaster management, environmental and health/nutrition literatures (Alwang et al, 2001). Each discipline focuses the attention on its own sources of risk and outcomes [6]. The interest of this research is limited to that part of the economic literature which defines vulnerability as the possibility of becoming or remaining materially poor in the future (Cafiero and Vakis, 2006). This definition seems to liken the notion of vulnerability to the notion of poverty and sometimes they are confused even by expert scholars. However, poverty and vulnerability are two different concepts where the former focuses on the static outcome of risk, i.e. the ex post movement into and out of the state of deprivation (Alwang et al, 2001) while the latter is an ex-ante condition that only potentially may lead to welfare looses (Montalbano, 2011). It means that the sets of poor and vulnerable households don't necessarily match and even non-poor households are vulnerable to fall into poverty in the future. More precisely, vulnerability could be considered as a forward looking assessment of poverty. Calvo and Dercon (2005) refers to vulnerability to poverty as "*..the magnitude of the threat of poverty, measured ex-ante, before the veil of uncertainty has been lifted..*". This is a completely different measure from static poverty, which is defined by the same authors

[6] For example, sociologists use the term social vulnerability as an alternative to describe the dimensions of poverty which are not captured by the monetary measures used by economists. For the disaster management literature human vulnerability is defined with respect to natural disasters and people are vulnerable to damages. For environmentalists, the term relates to the vulnerability of species or ecosystems which are vulnerable to extinction while for nutrition literature vulnerability is the a probability of inadequate food intake needed to live a normal and active life. For a review of these literatures, see Alwang et al. (2001).

as "*..the magnitude of low welfare outcomes, as observed without uncertainty and whereby low welfare is defined as outcome levels below some accepted poverty line..*". The distinction between the two concepts also implies a distinction in the aspects which characterize the two phenomena. While static poverty analysis focuses on the observable characteristics of the households and the ex-post outcomes of risk, the dynamic perspective provided by the vulnerability analysis forces the researchers to consider other specific features such as the ex-ante probability distribution of welfare determined by the economic and social conditions as well as by the risk-mitigating ability of the household.

The desire to provide a forward-looking assessment of poverty combined with the necessity to include risk-induced behavioral responses in the analysis make clear that future household welfare cannot be fully understood just looking at the ex-post poverty measures. The main consequence to focus just on poverty outcomes is that efficiency and the effectiveness of the poverty reduction programs adopted by the public institutions are reduced, especially for what concern the resources devoted to prevention. In fact, an household with a permanent consumption well above the poverty line could be erroneously classified as poor just because it suffered a temporary negative shock, as well as a poor household with consumption below the poverty line could be included in the non-poor category after a positive shock. For having the right picture of the situation, the stochastic nature of consumption and income has to be analyzed in a more accurate way. It implies the development of a theoretical and empirical framework capable of estimating the distribution of the households' consumption and this is the point where the current vulnerability to poverty literature is mainly focusing its efforts.

Moreover, a reliable assessment of vulnerability to poverty should not be limited to evaluate the future household's chance of being poor but it should be able to catch which are its main determinants. It can be done only if we take account of all the components which determine welfare, included the risk management and coping strategies put in place by the household. We have seen that in the last two decades, practitioners broadly recognized that the response of agents to the perceived risk is by itself an important part of the explanation for poor economic performances in developing countries. The change in the activities caused by these mechanisms has a cost in term of welfare: in order to reduce the exposure to risk, the household could decrease the expected value of its income and consumption paths. It is generally accepted that the consequences of this particular behavior are lower level of future well-being (Elberg et al., 2007). As we will see in the following Paragraphs, vulnerability to poverty still misses a theoretical framework able to include the impact of risk management behavior on the possibility to be poor in the future and therefore justifies the development of a broader and more solid conceptualization of the phenomenon as well as the research of a new empirical strategy.

1.3 Existing Approaches to Vulnerability to Poverty

A first attempt to define a road map for the vulnerability to poverty analysis has been done by the World Bank "Social Risk Management" (SRM) approach (Heitzmann et al, 2001; Holzmann, 2001; Holzmann and Jorgensen, 2001). The SMR approach has the merit to individuate the most important components of the analysis: a) the definition of the characteristics of risk realizations; b) the evaluation of the resilience and responsiveness mechanisms available to the households and c) the individuation of a benchmark defined by some socially accepted minimum threshold[7] . Following the SRM approach, the literature tried to make this defini-

[7]Beside the SRM, another approach to vulnerability is the *Sustainable Livelihood Vulnerability* (SLV) framework adopted by the UNDP and by other development agencies. As reported by Montalbano (2011) the SLV approach considers vulnerability to poverty as the likelihood that people's living standards deteriorate over time and analyzes the dynamics and characteristics of the

tion *operative* developing a series of monetary analyses of vulnerability to poverty based on consumption as measure of individual welfare. The earliest efforts has been focused on understanding the impact of observable shocks on some measures of changes in consumption expenditure (Amin et al., 1999; Glewwe and Hall, 1998) while later approaches attempted to estimate vulnerability in terms of expected welfare (Ligon and Schechter, 2004). Following an acknowledged taxonomy (Hoddinott and Quisumbing, 2003; Montalbano, 2011), we can individuate three main monetary approaches to vulnerability to poverty: Vulnerability to Expected Poverty (VEP); Vulnerability as Threat of Future Poverty (VFP) and Vulnerability as Low Expected Utility (VEU). Each of these strands has to deal with the same two issues: 1) defining the vulnerability measure by identifying the elements which compose it and 2) individuating a sustainable empirical strategy to estimate it.

Defining a vulnerability measure implies to build up a model which a) predicts the future realization of the household's welfare; b) compares it to a benchmark indicator; and c) synthesize the information with a proper index (Hoddinott and Quisumbing, 2003). At first glance, the process seems to be quite similar to the poverty analysis even though the stochastic environment imposed by the prediction of a future indicator increases the issues to be faced by the researcher. Unsurprisingly, the choice of the individual welfare indicator and its benchmark is still strictly connected with the poverty literature. As already mentioned, the standard measures of economic welfare are consumption and income, even if the practitioners are still debating if and how these indicators should be supplemented with other aspects of well-being such as nutritional and health status, life expectancy and education (Deaton, 1997) [8]. In the framework of development economics, the choice between consumption and income has been resolved by a strong case in favor of the for-

population's reaction strategies in various political and social contexts.

[8] For more information on conceptual and measurement issues in poverty analysis see Thorbecke (2004).

mer. The standard theoretical argumentation is strictly connected with both the "life-cycle" model inspired by Modigliani and Brumberg (1954) and the "permanent income hypothesys" model developed by Friedman (1957) [9] . The rational agent smoothes his consumption along his life through savings and dissaving and - as consequence - it is more stable than current income and provides more information on the household's living standards. However, empirical evidence showed that in developing countries consumption tracks income quite closely which means that using either the PIH or the life-cycle explanation for preferring the former is not a strong motivation.

Beside the theoretical motivation, the practical considerations to use consumption over income appear more solid. While in richer countries it is easier to collect data on income because of the difficulty to gather information on households' expenditure, in poorer countries is the opposite. Considering the weakness of the wages system in the formal sector and that many households in rural areas consume what they produce without going through a market, consumption is more accurate to measure the actual living standards. At the same time, it is also true that households are more reluctant to share information about income and assets than about consumption, which means that they are more motivated to provide inaccurate answers to questions about their income (Deaton and Grosh, 1998). Since now, the econometric works on vulnerability use consumption expenditure as welfare indicator. This aspect is a common feature shared by all the approaches presented in this Chapter (VEP, VEU and VFP) and it will be also the key variable used in the vulnerability measure proposed in Chapter 2.

[9] In the life-cycle model consumption is determined by the value of lifetime resources while in the PIH model it is determined by permanent income, typically defined as average or expected income over a time horizon (Deaton, 1992). In both models consumption is constant over time, and it can be represented as a *martingale*, a stochastic process whose expected value is equal to its current value, i.e. $c_t = Ec_{t+1}$. However, the implications in terms of saving behavior are different as well as the empirical strategies to test them. These aspects will be examined more deeply in the first part of the Chapter II.

For what concern the issues related to the empirical strategy, vulnerability analysis has the peculiarity that it cannot rely on observable data but it has to predict what consumption might be in the future using only past observations (Ligon and Schechter, 2004). It forces the researcher to choose between different assumptions before the vulnerability measure is calculated and that choice is strictly correlated with the characteristics of the available data. The first characteristic to consider is the time-horizon of the surveys. On the one hand, we can have a cross-sectional household survey, a one-time observation designed to obtain a snapshot of a representative group of households at a given moment in time. On the other hand, we can gather longitudinal or panel surveys, which track households over time and collect multiple observations on the same household. The latter seems to be more attractive, considering that it allows to study the dynamics of living standards. However, panel surveys are relatively rare with respect to cross-sectional surveys and the problem becomes more marked for developing countries.

Directly linked to the type of available surveys, there is the evolution of the probability distribution of consumption that we need to map past outcomes into predictions about the future (Ligon and Schechter,, 2004). If we assume that the consumption distribution remains the same across time, we are operating in a stationary environment and we can estimate the probability of the different realizations in a specific period. This would be a scenario where consumption is not allowed to grow over time. However, we can partially correct this assumption allowing the consumption process to fluctuate around a deterministic trend and controlling for it with appropriate time variables. In this case, we can still operate in a stationary environment even if consumption is growing over time because of the trend-stationary process assumption. If we abandon this framework and we assume consumption growth, the probability distribution will vary over time and it's no longer possible to estimate the distribution using cross section data. In this case we can assume that the probability distribution of changes in consumption is fixed across periods which means that we are operating in a difference stationary environment.

Empirical literature on vulnerability adopted three different strategies which are a combination of these possible hypotheses on stationarity and availability of data. The first two scenarios operate in a stationary environment, but one with cross-sectional data and the other with panel surveys. In the first case we are in a "stationary cross-section" (Ligon and Schechter, 2004) environment and it means that we are extracting information about the consumption distribution from a one-time observation. In other words, the inter-household distribution of consumption at any point in time should represent the future distribution of consumption across states of nature for each household. We are not just ruling out consumption growth but we are also imposing that the probability distribution is the same for all the households in the sample. The other option is to operate in "stationary time-series" environment where - for any household - the probability distribution of consumption in one period is identical to the distribution in any other period. We are still excluding consumption growth but at least we are not imposing a single distribution for the entire sample. The first approach is more common for the VEP literature while the second one is more used by VEU and VFP empirical works. The last option is called "difference stationary time series": it includes consumption growth in the analysis and works with panel data. In this case, stationarity is weaker and we assume that consumption growth is a stationary process with zero mean over time. As pointed out by Ligon and Schechter (2004), this scenario is admitted only if consumption follows a random walk, but it's not suitable in a world with deterministic trend. This approach is the less common in the vulnerability literature and it's applied only by Prichett et al. (2000) and Chauduri and Datt (2001) in their VEP framework.

1.3.1 Vulnerability to Expected Poverty

Vulnerability to expected poverty is defined as the probability that a household will fall into poverty in the future. This approach is the most common measure of vulnerability and it is directly linked to the poverty index developed by Foster-Greere-Thorbecke (FGT) (Foster et al. 1984). This part of literature is inspired by Ravallion (1988), while Pritchett et al. (2000), Christiaensen and Subbarao (2001), Chaudhuri et al. (2002, 2003) and Kamanou and Morduch (2004) are the most precious contributions. They adapted a standard poverty measure to a stochastic environment by estimating an expected value of the FGT index. The approach foresees the choice of a focal variable, usually the consumption per capita, and the estimate of its ex-ante probability distribution (Christiaensen and Boisvert, 2000). Assuming as focal variable the consumption per capita c_h and as poverty line z, the vulnerability of a household h at time t with respect to time $t+1$ is measured by:

$$V_{ht} = \int_0^z \varphi(c_{h,t+1}, z) f_t(c_{h,t+1}) dc_{h,t+1} \tag{1.1}$$

with $c_{t+1} \in [0, \infty)$ and $\varphi(c_{h,t+1}, z)$ non-increasing in c_{t+1} and non-decreasing in z if the consumption is below the poverty line, and zero otherwise. Now we assume as functional form of $\varphi(c_{h,t+1}, z)$ the poverty index developed by Foster et al. (1984):

$$\varphi(c_{h,t+1}, z) = \left(max \left\{ 0, \frac{z - c_{h,t}}{z} \right\} \right)^{\alpha} \tag{1.2}$$

Where α is a parameter capturing the aversion to inequality. Substituting (1.2) into (1.1) and multiplying everything by $F(z)/F(z)$, we have the following vulnerability measure:

$$V_{\alpha,ht} = F(z) \int_0^z \left(max \left\{ 0, \frac{z - c_{h,t+1}}{z} \right\} \right)^{\alpha} \frac{f(c_{h,t+1})}{F(z)} dc_{h,t+1} \tag{1.3}$$

where $F(.)$ and $f(.)$ indicate, respectively, the cumulative distribution and the density function of the per capita consumption at time t+1. Equation (1.3) measures the probability of falling below the poverty line $z(F(z))$, multiplied by a conditional probability-weighted function of the shortfall below this poverty line (Christiaensen and Boisvert, 2000). Note that when we apply $\alpha = 0$, $V = F(z)$: the vulnerability measure reduces to the probability that the household will experience poverty, i.e. $c < z$ [10]. The distribution F is taken as given and reflects both the households' exposure to shocks (idiosyncratic or covariant) and its ability to cope with them.

Following Pritchett et al. (2000), we can extend the definition of vulnerability beyond the one-period horizon $(t + 1)$ and defining it as the probability of observing at least one episode of poverty in the next n periods, which is equal to one minus the probability of no episodes of poverty:

$$V(h, n, z) = 1 - [(1 - Pr(c_{h,t+1} < z)) * ... * (1 - Pr(c_{h,t+n} < z))] \tag{1.4}$$

Since this measure is expressed in terms of probability points and the future is, by definition, uncertain, the magnitude of vulnerability rises with the time horizon n. In other words, assuming that the probability to fall below the poverty line in each period is constant, the higher is n the higher is the chance to be poor at least once.

As pointed out by Pritchett et al. (2000), since expenditures at time t are known, it is known whether a household in poor or not. In the future, however, many poor households will escape from poverty in the next n-periods, so the future vulnerability of the poor is less than one. At the same time, since the probability to be poor is

[10] Several authors (Christiaensen and Boisvert, 2000; Pritchett et al., 2000; Chaudhuri, 2001; Chaudhuri et al., 2002) prefer to consider only the headcount measure of poverty ($\alpha = 0$), while others paid attention to the depth of the poverty and the spread of its distribution by using $\alpha = 2$ (Ravallion, 1988). However, the most applied version is the first one, while the second approach had a limited space in literature.

usually different from zero even for the richer households, literature prefers to count the number of *vulnerable*, instead looking at the vulnerability index itself. In other words, a household is defined as vulnerable if the risk to be poor in n periods is greater than a threshold probability level p:

$$V(h, n, z, t) = I[V(h, n, z, t) > p] \tag{1.5}$$

where $I[.]$ is an indicator function equal to one if the vulnerability index is higher than the probability thereshold p and zero otherwise. So, while vulnerability is a risk and is expressed in degrees - between zero and one - being vulnerable is a state, either zero or one. (Pritchett et al. 2000). The most common value of the probability threshold is 0.5, which means that a household is vulnerable if the probability of being poor in the next period is higher than the probability of being non-poor (see, for example, Chaudhuri and Datt, 2001; Chaudhuri et al., 2002; Christiaensen and Subbarao, 2005; Azam and Imai 2009; Jha and Dang 2009; Jha, Dang and Tashrifov 2010). For what concerns the time horizon n, literature seems to be more confused. The less ambiguous approach is Chaudhuri (2003) who proposes two different alternatives: a time horizon of one year (short term) and a time horizon of three years (medium term).

In order to estimate 1.3, the first issue to solve is to assume a consumption generating process. Household's consumption is affected by some factors as wealth, current income, expectations of future income, uncertainty on future income and ability to smooth consumption (Chaudhuri, 2003). These factors are, in turn, influenced by the characteristics of the household as well as by the surrounding macroeconomic environment. Then, the consumption process can be written as:

$$c_{ht} = c(X_h, \beta_t, \lambda_h, e_{ht}) \tag{1.6}$$

where X is a set of observable household characteristics, β is the corresponding vector of parameters at time t, and λ and e represent, respectively, unobservable household-specific effects and idiosyncratic shocks. The introduction of the observable characteristics in the analysis of the consumption process is fundamental for differentiating vulnerability from poverty. In order to understand better the role of the vector X, we may provide two extreme examples. First, we assume that our covariates perfectly predict the level of future consumption and these characteristics don't change over time. In this case, the vulnerability index will be equal to the level of poverty for each household, because we are removing risk from the picture. On the other side, we assume that the characteristics included in the vector X are not able to influence at all the level of consumption but change over time. In this case, the consumption follows a random walk process and the vulnerability index is the same for all the households. VEP approach lies between these two extreme scenarios and, specifically, the vulnerability index can be re-written as:

$$V_{\alpha,ht} = E[P_{\alpha,h,t+1}(c_{h,t+1})|F(c_{h,t+1}|X_h, \beta_t, \lambda_h, e_{ht})] \tag{1.7}$$

It is clear from Equation (1.7) that vulnerability is mainly influenced by the stochastic properties of the inter-temporal consumption streams and these, in turn, depend on the household's characteristics (Chaudhuri, 2003). In order to have an empirical estimate of Equation (1.7), we need to find an explicit functional form of the consumption process. Chaudhuri et al. (2002) adopted the following simple form:

$$lnc_h = X_h\beta + e_h \tag{1.8}$$

Despite its simplicity, the functional form expressed in Equation (1.8) has several implications. First, the idiosyncratic shocks to consumption are identically and independently distributed over time for each household, ruling out unobservable sources of persistence. Secondly, Equation (1.8) doesn't consider aggregate shocks, overlooking that part of uncertainty that arises from the macroeconomic environment. Third, Equation (1.8) neither distinguishes the relative impact of different sources of risk nor introduces direct information on the distribution of shocks. It means that we are not able to understand if future welfare losses will depend on unforeseen idiosyncratic and covariate shocks or risk-induced behavioral changes.

The second step to estimate the consumption distribution is to calculate its higher moments. The easier starting point is to assume that consumption is log-normally distributed and, as consequence, the log of consumption has a normal distribution, limiting the number of needed moments to two (mean and variance). VEP analysis directly models the variance of the consumption with the same technique used for estimating its mean, exploiting the set of covariates in the vector X, i.e.:

$$\sigma_{e,h}^2 = X_h \theta \tag{1.9}$$

This specification allows to account directly for heteroskedasticity, which is likely to affect household-level surveys. However, the reason why the VEP approach is interested in estimating consumption volatility is not only to solve an econometric problem. In this particular framework, assuming homoskedasticity would imply that the inter-temporal variance of log consumption is common to all households, excluding the possibility that two households with the same mean level may face different consumption volatilities and experience different exposure to risk. Therefore, the homoskedasticity assumption is largely unsatisfactory even from an economic point of view. Moreover, while failing to account for heteroskedasticity in the poverty analyses results only with a loss of efficiency, in the VEP approach it leads to a biased estimate of the measure because the variance of consumption enters directly in the index (see Equation (1.14)).

In order to have robust estimates in Equations (1.8) and (1.9), the VEP approach uses a particular econometric procedure suggested by Amemiya (1977), called three-step Feasible Generalized Least Squares (FGLS). At first, we estimate Equation (1.8) using an ordinary least squares (OLS) procedure. Then we estimate the residuals from the Equation (1.8) and run the following:

$$\hat{e}^2_{OLS,h} = X_h\theta + \eta_h \tag{1.10}$$

The prediction of Equation (1.8) are used to weight the previous Equation, obtaining the transformed version:

$$\frac{\hat{e}^2_{OLS,h}}{X_h\hat{\theta}_{OLS}} = \left(\frac{X_h}{X_h\hat{\theta}_{OLS}}\right)\theta + \frac{\eta_h}{X_h\hat{\theta}_{OLS}} \tag{1.11}$$

As reported by Chaudhuri (2003), the estimation of Equation (1.11) using an OLS gives us back an asymptotically efficient FGLS estimate, θ_{FGLS} and then, $X_h\theta_{FGLS}$ is a consistent estimate of $\sigma^2_{e,h}$, i.e. the variance of the idiosyncratic component of the household consumption. Once we obtain an efficient estimate of the variance we can finally take the square root of it and transform Equation (1.8) as follow:

$$\frac{lnc_{h,t}}{\hat{\sigma}_{e,h}} = \left(\frac{X_h}{\hat{\sigma}_{e,h}}\right)\beta + \frac{e_h}{\hat{\sigma}_{e,h}} \tag{1.12}$$

An OLS estimation of Equation (1.12) gives a consistent and asymptotically efficient estimate of β. Once we have the estimates of β and θ, it is possible to estimate the expected log consumption and its variance:

$$\begin{aligned}\hat{E}[lnc_h|X_h] &= X_h\hat{\beta}\\ \hat{Var}[lnc_h|X_h] &= \sigma^2_{e,h} = X_h\hat{\theta}\end{aligned} \tag{1.13}$$

Recalling the previous assumption that the consumption is log normally distributed and hence that the log-consumption is normally distributed, we can estimate the probability that household h with the characteristics X_h will be poor, i.e. its vulnerability to poverty. Indicating with $\Phi(.)$ the cumulative function of the standard normal, the estimate of the vulnerability index will be as follow:

$$\hat{V_h} = Pr[lnc_h < lnz|X_h] = \Phi\left(\frac{lnz - X_h\hat{\beta}}{\sqrt{X_h\hat{\theta}}}\right) \tag{1.14}$$

Where $\hat{V_h}$ lies between zero and one. The most common way to interpret VEP index is to impose a probability threshold which separates vulnerable from non-vulnerable households. Usually the threshold is 0.5, which means that a household is vulnerable if the probability of being poor in the next period is higher than the probability of being non-poor (see, for example, Chaudhuri and Datt, 2001; Chaudhuri et al., 2002; Christiaensen and Subbarao, 2005; Azam and Imai 2009; Jha and Dang 2009; Jha, Dang and Tashrifov 2010)[11].

The main benefit in using VEP is given by its simplicity: the vulnerability measure is directly linked to the households' wealth as well as to the experienced idiosyncratic and aggregate shocks (Ligon and Schechter, 2004). At the same time, it produces a figure analogous to the measure of the poverty incidence and, as noted by Hoddinott et al (2003), it could be very useful for policymaking interpretation. For example, where poverty incidence is low but a substantial proportion of households have consumption just above the poverty line, governments could assume that poverty is not an issue to be targeted. But if the households lying just above the arbitrary line are vulnerable to shocks, VEP index will be much higher, indicating that public intervention is still needed. Moreover, looking at the observed expen-

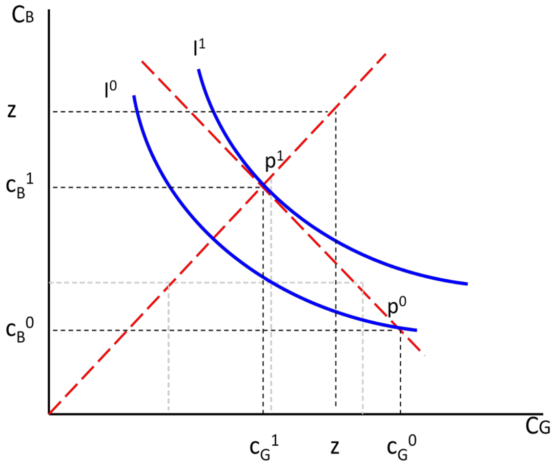
[11] Gunther et al. (2009) modify this approach by integrating the multilevel modeling in the VEP analysis. The multilevel analysis allows to assess the relative impact of idiosyncratic and covariate shocks on future household's well-being and on the VEP vulnerability measure.

ditures of the households we are incorporating the existence and the use of coping mechanisms. As noted by Prichett et al (2000), it reflects both income risk and the utilization of consumption smoothing instruments. However, it doesn't allow to understand if the observed expenditure is due either to high income volatility coupled with a good capacity to cope with it or to the absence of risk.

The simplicity of the VEP approach raises also several problems, some connected to its common origin with the static and risk-free FGT measures of poverty while the others to the nature of the empirical analysis. From a theoretical point of view, the VEP index - as well as the FGT measure - has not a solid theoretical background and its headcount ratio measure of poverty creates some apparent contradictions in the choice of the household in a risky context. In particular, the VEP measure is not able to represent households risk attitudes. To better understand this consideration, we can recall and expand an example made by Hoddinot (2003). Assume we have two possible scenarios. In the first one, a risk averse household is certain that its expected consumption in the next period will be below the poverty line so that the vulnerability is equal to one. In the second scenario, we introduce a small mean preserving spread such that the expected consumption is the same as the previous scenario but now the household will be below the poverty line with probability 0.5 and above it with the same probability. If the household is risk averse and presents a classical von Neumann-Morgenstern utility function, moving from the first to the second situation will make it worse off.

In Figure 1.1 the risky prospect is p^0 on the indifference curve I^0. In the bad state the consumption falls to C_B^0 while in the good state it is equal to C_G^0, above the poverty line z. If we offer to the household an actuarially fair insurance, it will prefer to consume its expected consumption with certainty instead facing the risky prospect, i.e. the household will choose p^1 on the indifference curve I^1. However, in p^1 the vulnerability index is equal to one, while in p^0 is equal to 0.5. In other words,

Figure 1.1



a risk averse rational agent would choice the option which makes him more vulnerable. Finally, as noted by several authors (Thorbecke, 2004, Ligon and Schechter 2003, Hoddinott 2003), the use of the vulnerability aversion approach may not be appropriate as it implies increasing absolute risk aversion [i.e. $(\alpha - 1)z/(z - c)$] with increasing consumption below the poverty line, which is contrary to empirical evidence on the risk preferences.

Besides the theoretical aspects related to the household's behavior in a risky environment, the VEP approach suffers several limits which depend on its empirical strategy. In particular, it relies on the strong assumption of stationary time series and assumes further that the distribution of shocks to consumption is independent normal (Montalbano, 2011). Using the stationary cross-section assumption the practitioners are allowed to build up a consumption distribution and a vulnerability measure with a single round of data[12]. This is an important aspect considering the chronic lack of reliable panel data in developing countries but it is possible only if we assume that observed inter-household distribution of consumption at a point

[12] As Elber (2003) pointed out, practitioners used other two ways for estimating the distribution $F(.)$. Firstly, if panel data are available, then F can be estimated as the distribution of consumption across time, for a particular household while a third method is to regress changes in consumption on households characteristics using bootstrapping to generate a distribution of shocks from the regression residuals.

in time represents the future distribution of consumption across states of nature for each household. The price we have to pay in terms of reality is quite high, first of all because we are not able to understand which unobserved household characteristics influence the current and the future consumption distribution. For example, it might be that being non-poor in the current period is a strong help for being non-poor in the following periods as well as being chronically poor might be caused by lack of ability or unobserved entrepreneurial skills. Without observing these aspects, our estimates might be biased. Another benefit of this methodological approach is that it allows to differentiate between poverty and vulnerability influencing factors. In other words, using the already existing poverty analyses, we can compare if the vulnerable and poor households share common characteristics or, more interesting, they are influenced by different set of covariates.

1.3.2 Vulnerability as Threat of Future Poverty

The second way for analyzing vulnerability is to consider it as a measure of the Threat of Future Poverty (TFP). In particular, Calvo and Dercon (2005, 2007) defined vulnerability as *the magnitude of the threat of future poverty*. The concept of magnitude of the threat relates to the likelihood of suffering poverty in the future and to the *severity* of poverty in such a case. We cannot consider vulnerability just as low expected welfare, neither just as exposure to risk. The term vulnerability is more related to the concepts of *dangers* and *threats* than to uncertainties in general. The authors introduced their vulnerability index describing its desirable properties through a set of axioms and assuming that the vulnerability is measured by $V^* = V(z, \bar{y}, \bar{p})$, where z is the poverty line, $\bar{y}$ is a vector of outcomes across n states of the world (usually consumption), and a vector $\bar{p}$ of corresponding probabilities.

The first axiom is called *symmetry*. It implies that the measure is not sensitive to permutations of the states of the world and the only difference between two states is in the outcome they produce. The second property of the VFP index is called *focus* axiom. Define $\tilde{y}_i = Min(y_i, z)$ and $\tilde{y}$ the relative vector where outcomes beyond the poverty line are equated to the poverty line itself. V^* satisfies the focus axiom if for every $(z, \bar{y}, \bar{p})$:

$$V(z, \bar{y}, \bar{p}) = V(z, \tilde{y}, \bar{p}) \tag{1.15}$$

which means that changes in the outcomes above the poverty line do not make individuals more or less vulnerable. The reason is quite clear and related to the definition of vulnerability provided by the authors: the ex-ante possibility to be better off in some states of the world is not enough to compensate the burden caused by the threat of future poverty. This axiom implies that outcomes are assumed to be non-transferable across states of the world and, more important, that no insurance mechanism exists. In other words, the household is not allowed to smooth consumption in order to reduce uncertainty and redistribute its wealth across states. The third axiom is defined as the *probability-dependent effect* of outcomes. It foresees that if the outcome in one state of the world improves, the consequent effect on vulnerability must be sensitive only to the likelihood of that particular state and not on the outcomes or probabilities of other states. Again, the vulnerability focuses only on how threatening poverty episodes are, and not on a weighted average of them. The forth property is called the *probability transfer* axiom. It says that the vulnerability index satisfies this axiom if for every $(z, \bar{y}, \bar{p})$ and $p_1 \geq e > 0$:

$$\begin{aligned} V(z, \bar{y}, (p_1, p_2, ..., p_n)) \begin{Bmatrix} \geq \\ = \\ \leq \end{Bmatrix} V(z, \bar{y}, (p_1 - e, p_2 + e, ..., p_n)) \\ \text{if and only if } y_1 \begin{Bmatrix} \geq \\ = \\ \leq \end{Bmatrix} y_2 \end{aligned} \tag{1.16}$$

which means that if we transfer probability from outcome 1 to outcome 2 and the former is greater than the latter, the vulnerability index cannot increase, and vice versa. This point has two implications: the vulnerability measures will be linear in the probabilities and, as long as outcomes are below the poverty line, the vulnerability index is monotonically decreasing in outcomes. The fifth axiom is called *risk sensitivity* and it implies that vulnerability would be lower if uncertainty were removed by making the final outcome independent of the state of the world realization. In other words, the existence of risk influences directly the well-being and implies that unless outcomes below the poverty line remain unchanged, vulnerability should be sensitive to an increase in risk. Lastly, the sixth axiom is *scale invariance* and it says that equal proportional changes in the poverty line and the outcomes leave the individual as vulnerable as before, i.e. the index has to be homogenous of degree zero [13]. In this case the vulnerability depends only on the relative distance from the poverty line and not on the unit of measure. Before explaining the other three axioms presented by the authors, we can formalize the first six axioms. If V^* satisfies Axioms 1-6, then:

$$V^* = \sum_{i=1}^{n} p_i v(x_i) \tag{1.17}$$

where $x_i = \frac{\tilde{y}_i}{z}$ and $v(.)$ is monotonically decreasing and convex. x_i can be seen as a deprivation index which lies in the interval $[0, 1]$. It assumes value of one when the outcome exceeds or equals the poverty line, which means that the individual reached his minimal needs. This explains why the function $v(.)$ has to be monotonically decreasing. In order to limit the set of the available measures which satisfy equation (1.17) and simplify the analysis, Calvo and Dercon (2005) introduced other three axioms. The seventh axiom is called *normalization.* Given the poverty line and the vector of probability distribution, state-specific outcomes y_i can change and alter the level of vulnerability. So, normalizing the vector of the outcomes has the benefit of bounding the vulnerability index by the interval $[0, 1]$, making easier the interpretation of the measure. Furthermore, the eighth and ninth axioms close this

[13] In other words, it means that $V(z, \bar{y}, \bar{p}) = V(\lambda z, \lambda \bar{y}, \bar{p})$ for any $\lambda > 0$

set by recalling that the vulnerability index has to show either *constant absolute* or *relative risk sensitivity* which imply that risk sensitivity remains constant if all state specific outcomes increase, respectively, in an absolute or proportional way. If V^* satisfies the first seven axioms and the constant relative risk sensitivity assumption, then we can indicate as measure of vulnerability:

$$V_\alpha^* = 1 - E\left[x_i^\alpha\right], \text{ where } 0 < \alpha < 1 \tag{1.18}$$

The parameter α can be used to determine the degree of risk sensitivity. In particular, the closer is α to one, the higher is the impact of an increase in risk exposure on the vulnerability index. The condition $0 < \alpha < 1$ reinforces the risk sensitivity axiom, treating uncertainty as forms of hardship (Calvo, 2008). Instead, if V^* satisfies the first seven axioms and the constant absolute risk sensitivity assumption, the vulnerability index can be indicated with:

$$V_\beta^* = E\left[\frac{e^{\beta(1-x_i)} - 1}{e^\beta - 1}\right], \text{where } \beta > 0 \tag{1.19}$$

In order to interpret this measure, it is worth to note that the denominator is equal to the numerator if and only if the x is equal to zero, which means that in the worst possible scenario the index is equal to 1. Among the main features of both V_α^* and V_β^*, Calvo and Dercon underline two interesting properties. First of all, coherently with the definition of vulnerability provided by VFP approach, people who are certain of being poor are highly vulnerable. If vulnerability is about threats, certainty of being poor is dominant threat. Secondly, the VFP vulnerability index is usually lower than the probability of being poor and they are the same only if consumption is bound to be zero in every state of the world where the individual is poor.

A different version of the VFP approach has been proposed by Calvo (2008).

Inspired by the well-known Sen's (1977, 1984) work on capabilities and the measurement issues raised by Atkinson and Bourguignon (1982), Calvo moves from the unidimensional analysis of poverty to a multidimensional space. Starting from the assumption that consumption is not enough to capture the household's well-being, the multidimensional analysis includes other relevant dimensions as health and education. The main VFP intuition still holds - individuals will be wary of the threat of hardship in any one dimension - but the measure is modified. Assume J is the number of dimensions, while y_{ij} and z_j are the outcome and the *poverty line* in the j^{th} dimension. The multidimensional VFP measure can be written as:

$$VM_i = 1 - E\left[\left(\sum_{j=1}^{J} \gamma_j x_{ij}^{\rho}\right)^{\frac{\alpha}{\rho}}\right] \tag{1.20}$$

$$\text{with } 0 < \alpha < 1,\ 0 \leq \rho \leq 1, \text{ and } \sum_{j=1}^{J} \gamma_j = 1$$

As previously done in Bourguignon and Chakravarty (2003) and Deutsch and Silber (2005), Calvo (2008) adopts a CES-function with weights γ and elasticity of substitution equal to $1/1-\rho$, introducing for the first time the expected value operator. In the same spirit of the original analysis, poverty episodes in one dimension are not allowed to be relieved by high performance in some other dimensions. In other words,richness possibilities compensate for hardship neither across states of the world, nor across the dimensions within a given state of the world (Calvo, 2008).

The empirical strategy to estimate Equation (1.18) followed by Calvo and Dercon (2006) and Calvo (2008) exploits the time dimension of the panel to extract information on the future distribution of shocks. In particular, they estimate Equation (1.18) using a random effects model with an autoregressive structure of the consumption function in order to obtain a time-specific shocks for N units and T periods available in their panel data set. The resulting set of T shocks are used to infer the household h distribution of random idiosyncratic shocks for the future. For example, Calvo (2008) uses a five years panel to retrieve the time-specific shocks and, consequently, it assumes that the distribution of the idiosyncratic shocks follows a discrete uniform distribution which stays stable over time. This kind of distribution allows the author to consider each realization as it was one of the five possible values the shock can take also in the future. Based on this strong and quite unrealistic assumption, it is possible to calculate the expected value of the second term in Equation (1.18), taking the average of the resulting possible five estimated consumption counterfactuals.

While the theoretical foundation based on the axiomatic approach provided by Calvo and Dercon (2005) seems to be a more elegant way to present a measure for vulnerability, it leaves some problems opened. In particular, as sustained by Montalbano (2011), the axiomatic approach to vulnerability needs to be coupled with a robust empirical analyses in order to create an effective improvement with respect to the previous methods. The measure proposed by Calvo and Dercon (2005) requires the availability of a large set of data able to gather information on all the possible states of the world and this could turn out to be a problem especially for developing states. Moreover, even if we have a panel data, VFP empirical approach doesn't fully exploit its potential. All the information on the evolution of consumption and the other observable variables over time are used to estimate the expected value of the household's well-being, obtaining a static measure of vulnerability. The VFP method considers the different T periods as if they were possible states of the world the household is going to face in the near future. However, it is quite likely that the evolution of consumption is determined by what happened before and periods cannot be treated as independent realizations. Moreover, they ignore serial correlation. Operating with panel data without considering autocorrelation, especially with variables like consumption and income, leads to unbiased but inefficient estimates. In terms of vulnerability it means that we may include in our estimation of the consumption function independent variables which are actually not explaining the household's welfare, with the consequence that we may deduce wrong policy suggestions. Even worse, if the model specification includes a lagged dependent variable, as for example in Calvo and Dercon (2007) analysis, in the presence of autocorrelation the estimates will be both biased and inconsistent. In this case we have again wrong policy suggestion but also a distorted index of vulnerability which may either underestimate or overestimate the problem of future poverty.

1.3.3 Vulnerability as Low Expected Utility

Another way to look at vulnerability is through an utilitarian approach. Ligon and Schechter (2003, 2004) developed a different theoretical framework in order to overcome the shortcomings presented by the VEP approach and provide a measure of vulnerability with a more solid theoretical background[14]. The authors assume that n households have a c_h distribution of consumption expenditure which depends on the state of the world $\omega \in \Omega$, i.e. $c_h(\omega)$. The level of consumption expenditure is the only argument of a strictly increasing and weakly concave utility function U_h , i.e. $U_h(c_h)$. The vulnerability of the household h is defined by the following function:

$$V_h = U_h(z) - EU_h(c_h) \tag{1.21}$$

where z is some certainty-equivalent consumption such that if household h had certain consumption greater than or equal to this number, the household is not vulnerable. In order to detect not only the mean of a household's consumption but

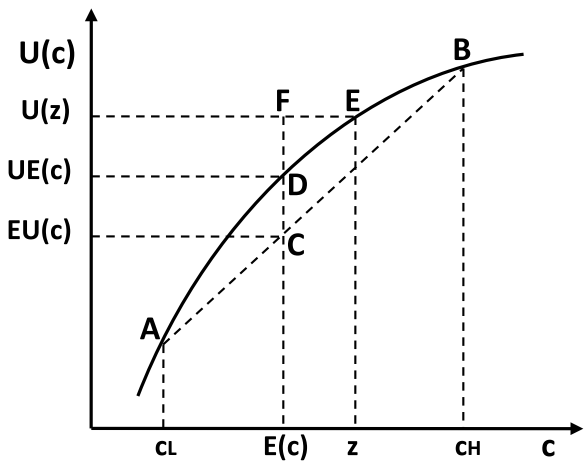
[14] The presentation of the VEU approach will follow strictly the two papers developed by the authors.

also its variation, we can decompose equation (1.21) into two distinct components reflecting poverty and risk:

$$V_h = [U_h(z) - U_h(Ec_h)] + [U_h(Ec_h) - EU_h(c_h)] \tag{1.22}$$

where the first bracketed term is a measure of poverty and involves no random variables. This is the difference between a concave function evaluated at the poverty line and at household h's expected consumption expenditure. The second bracketed term of equation (1.22) represents the risk faced by household h and it is measured by the *"risk premium"* expressed in terms of units of utility, i.e. utils. The risk premium is given by the amount of consumption expenditure the household would be prepared to give up rather than face the risky prospect, while the bracketed term expresses the same amount evaluating it on the utility function.

Figure 1.2



As suggested by Thorbecke (2004), we can further clarify the VEU methodology using Figure 1.2. Under uncertainty the expected consumption of household h is $E(c_h)$, yielding an expected utility $EU(c_h)$ at point C. The household faces two states of nature - a low consumption one, c_L, and a high consumption one, c_H -

with expected consumption being the average of the two. However, if the household could have a level $E(c)$ with certainty the utility of expected consumption $UE(c_h)$ would be higher at point D. Given the poverty line z and utility $U(z)$, VEU defines vulnerability as equal to the distance FC and break it down into two different parts: poverty (FD) and risk (DC). This *"vulnerability to risk"* term could be further decomposed into its aggregate and idiosyncratic component. Indicating with $E(c_h|X_t)$ the expected value of consumption, conditional on a vector of covariant variables X_t , we can rewrite equation (1.22) as follow:

$$\begin{aligned} V_h &= [U_h(z) - U_h(Ec_h)] && \text{(Poverty)} \\ &+ \{U_h(Ec_h) - EU_h[E(c_h|X)]\} && \text{(Aggregate Risk)} \\ &+ \{EU_h[E(c_h|X)] - EU_h(c_h)\} && \text{(Idiosyncratic Risk)} \end{aligned} \tag{1.23}$$

The first step to estimate this measure is to impose a functional form to the utility U_h. Among all possible choices provided by the literature, the class of von Neumann-Morgenstern expected utility functions seems to be the best way to detect the impact of risk on household welfare for two reasons: they have been designed to capture risk preferences and they are widely used in empirical applications. In particular, Ligon and Schechter (2003) adopt the CRRA utility function which takes the following form:

$$U_h(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{1.24}$$

with the parameter $\gamma > 0$ measuring the household's coefficient of the relative risk aversion. The higher is the value of γ, the higher is the sensitiveness of the utility function to risk[15] . The authors normalize c to let the average consumption

[15] As already discussed in the second chapter, existing empirical literature proposes a lot of different values for . In this case, the authors choose the value of 2 because in their opinion it seems to be the best approximation for this measure.

over all households in all periods be equal to 1 ($\bar{c} = 1$). The normalization has the aim to reinforce an important concept: if there is no inequality and no uncertainty, then there is no vulnerability (Ligon and Schechter, 2004).

The second step is estimating the conditional and unconditional expectations which appear in the vulnerability measure. As already noted, the main assumption for operating with the stationary time-series hypothesis is that we need to estimate a probability distribution of consumption for each unit of observation. It means that if we observe one consumption realization in one period, it must have the same chance to occur again in any other period. In a panel data with T periods and N households, we can compute the main VEU measure as:

$$\hat{V_h} = U(\bar{c}) - \frac{1}{T}\sum_{t=1}^{T} U(c_{ht}) \tag{1.25}$$

If stationarity holds, as T grows large we can invoke the law of large numbers for sustaining that the second term of Equation 1.25 converges to the expected value of consumption. Despite its simplicity this approach wouldn't take into consideration two aspects. Equation 1.25 doesn't provide any information on risk and it doesn't consider measurement error. While the first problem is not influencing the vulnerability measure, even if it is reducing the information provided by the analysis, the second point could lead to biased estimates.

Ligon and Schechter (2003) solve these problems further refining their method. In order to estimate risk and differentiate between the impact of idiosyncratic and covariate shocks, they rely on variation over time. Denoting with x_{ht} time varying household's idiosyncratic variables and with X_t aggregate variables, the authors assume the conditional expected value of the consumption as follow:

$$E(c_{ht}|x_{ht}, X_t) = \alpha_h + \eta_t + x_{ht}\beta \tag{1.26}$$

with $\theta = (\alpha_h, \eta_t, \beta)$ an unknown vector to be estimated. However, without an assumption on the measurement error process we cannot still estimate an unbiased and efficient vector θ. At this purpose, the authors adopt a technique similar to instrumental variables. They assume that $\tilde{c}_{ht} = c_{ht}e^{\epsilon_{ht}}$, where ϵ_{ht} is a measurement error process such that $E(\epsilon_{ht}x_{ht}) = E(\epsilon_{ht}logc_{ht}) = 0$. In a sort of first stage, they estimate the following form of the expected consumption:

$$log\tilde{c}_{ht} = \alpha_h + \eta_t + x_{ht}\beta + u_{ht} \tag{1.27}$$

Where α_h are household's fixed effects, η_t are time-effects which capture aggregate shock, x_{ht} are deviations from the household mean and u_{ht} residuals. Only after a restricted estimation of Equation (1.27) they can use an empirical version of the decomposition of Equation (1.23), obtaining:

$$\begin{aligned}
V_h = {} & [U_h(1) - U_h(\hat{E}c_{ht})] && \text{(Poverty)}\\
& + \left\{ U_h(\hat{E}c_{ht}) - \frac{1}{T}\sum_{t=1}^{T} U[\hat{E}(c_{ht}|X_t)] \right\} && \text{(Aggregate Risk)}\\
& + \left\{ \frac{1}{T}\sum_{t=1}^{T} U[\hat{E}(c_{ht}|X_t)] - \frac{1}{T}\sum_{t=1}^{T} U[\hat{E}(c_{ht}|X_t, x_{ht})] \right\} && \text{(Idiosyncratic Risk)}\\
& + \left\{ \frac{1}{T}\sum_{t=1}^{T} U[\hat{E}(c_{ht}|X_t, x_{ht})] - \frac{1}{T}\sum_{t=1}^{T} U[c_{ht}] \right\} && \text{(Unexplained Risk)}
\end{aligned} \tag{1.28}$$

In the last row we can see the contribution of measurement error which, unfortunately, cannot be differentiated from the contribution of the unobservable variables. Equation (1.28) produces a measure of vulnerability expressed in utility units and it allows to regress each component (Poverty, Aggregate Risk, Idiosyncratic Risk, Unexplained Risk Measurement Error) on household characteristics for determining which factors are more influent. As noted by Hoddinott and Quisumbing (2003), considering the lack of information available to policymakers, VEU is an effective method for understanding if vulnerability reflects low asset levels, unfavorable settings or poor returns to assets - captured by the poverty term in Equation (1.28) - or if it reflects shocks and the inability to cope with shocks, either covariate (the second term) or idiosyncratic (the third term).

However, the VEU approach raises several concerns mainly because the measure obtained applying this method is directly linked to the choice of the functional form of the utility function. As consequence, we can have two different problems. First of all, the functional form influences the magnitude of the index and its relative interpretation. Secondly, the units of measurement in Equation (1.11) are units of utility. While it is a clear concept for expert economists, policymakers may find difficult interpreting and designing programs based on this measurement. Lastly, Calvo and Dercon (2005) sustained that if vulnerability depends on expected utility it has not to be sensitive to the likelihood and the magnitude of outcomes above the poverty line. In other words, even if a positive outcome is one possible scenario, a household should be considered as vulnerable even if other scenarios are promising enough to compensate for the fear of starvation.

1.4 A Critique of current Vulnerability Analysis

Besides model-specific problems, current vulnerability to poverty analysis shares several issues which are independent from the framework we consider. As already mentioned, the vulnerability to poverty analysis should have the main objective to evaluate the possibility of becoming or remaining materially poor in the future. The term possibility makes clear that we are operating in a risky environment where the risk-free poverty assessment is not longer valid. We need a theoretical and empirical framework which would be able to consider two different aspects of risk. On the one hand, vulnerability to poverty has to evaluate how risk influences the fluctuation of household's welfare around its expected value in order to have a probability distribution of future outcome. On the other hand, we need to know if and how the household's welfare fluctuation influences its expected value through the behavioral responses put in place to mitigate risk. The VEP, VEU and VFP approaches don't take into consideration directly the latter aspect, focusing their efforts to understand how to retrieve the consumption and income distribution observing their past fluctuations. The main cause of this shortcoming is given by the fact that vulnerability analyses lack of a solid micro-foundation which would be able to motivate the economic behavior of the household in the presence of risk and provide more flexibility to the analysis.

1.4.1 The Lack of Micro-Foundation and the Role of Household's Behavior

We have already seen that risk can have a permanent effect on poverty because of the household's responses triggered by management and coping strategies. Therefore, measuring vulnerability should mean evaluating the net effect of three different processes: the non-stochastic poverty determinants, the household's exposure to shocks and, lastly, the risk-induced changing behavior. If we ignore the last aspect, we can overestimate the incidence of structural determinants on poverty, misclassify households and provide wrong policy recommendations. As suggested by Elbers and Gunning (2003), using current approaches to vulnerability would register a household which adopted complete self-insurance mechanisms at the cost of a lower mean welfare as a household which is unaffected by risk but with a low level of welfare because of its structural conditions (e.g. occupation, education, health, etc). In other words, current approaches show the impossibility to distinguish the impact of risk due to the realizations of shocks (ex-post effect of risk) from the welfare cost of the risk-induced changing behavior (ex-ante effect of risk)[16]. As we briefly examined in Paragraph 1.2, part of the literature on poverty dynamics has already focused its attention on the risk-mitigation strategies and their impact on the household's well-being. Dercon (2005) pointed out that there is increasing evidence that uninsured risk reduces household's welfare, through behavioral responses affecting activities, assets and technology choices, as well as through persistent and possibly permanent effects of transitory shocks. Surprisingly, current vulnerability analyses are not considering the ex-ante impact of risk on the household's welfare and this problem cannot be corrected until this part of literature doesn't introduce a solid micro-foundation in the picture. In fact, the best way to differentiate between ex-ante and ex-post effects of risk is only through a micro-founded model which is able to take into considerations the household's optimal behavior in a risky context.

Wasting the information provided by the different components of vulnerability may reduce or invalidate at all the potential contribution of this literature in terms of policy recommendations. In fact, the main advantage of vulnerability over poverty is that the former allows to move from treatment to prevention interventions[17] . If we are not able to disentangle the relative weight of the structural components of poverty from the negative contribution of the ex-ante and ex-post effects of risk, our poverty prevention policies could be biased and reinforce the hardship of the poor households. Therefore, designing suitable programs for anticipating the possible negative consequences of risk means individuating its main cause and adopting the

[16]The terms ex-ante and ex-post have nothing to do with the ex-ante and ex-post strategies to mitigate risk we mentioned before. In that case we referred to ex-ante and ex-post household behavior (risk management and risk coping strategies) while in this case we are referring to the ex-ante and ex-post effects of risk on welfare.

[17]Chaudhuri (2003) provides an interesting example for clarifying the difference between treatment and prevention intervention. Assume we have information on both the incidence of a disease in different areas and the relative risk of contracting it. Funds for treatment should be clearly directed to areas where the incidence of the disease is highest, while prevention should be done where the fraction of population at risk is largest. In other words, the allocation of resources for the treatment of poverty must be allocated on the basis of the incidence of poverty, while any other program aimed to the prevention of poverty should be addressed considering the incidence of vulnerability

best measure to address it. For example, if the structural components of poverty are still the most important part in explaining future poverty, we should focus our prevention intervention to guarantee that poor households would benefit of direct money transfer, free access to education and better medical services. On the other hand, if the potential welfare loss comes from the ex-ante effect of risk, the prevention policy should be focused on other specific measures aimed to reduce the perception of risk, to support self-insurance via savings and to assist income risk management providing access to credit.

1.4.2 The Empirical Consequences

The lack of a strong theoretical framework to model the household's behavior has also negatively influenced the empirical estimation of the existing vulnerability measures. In Paragraph 1.2 we have already seen some strengths but also a series of weaknesses which are associated to the underlying assumptions on the consumption distribution and the data availability. Nevertheless, VEP, VEU and VFP also share some other limits which are common to all the econometric strategies and they are connected to the structure of the consumption function and to the choice of the independent variables used to explain the household's welfare. As pointed out by Elbers and Gunning (2003), theory demonstrated that a robust consumption function should be a mapping from assets (k), shocks (s), productivity determinants (x) and characteristics of the distribution of shocks (σ) to the level of consumption (c):

$$c_{ht} = f(k_{ht}, s_{ht}, x_{ht}, \sigma_{ht}) \tag{1.29}$$

Existing vulnerability analyses regress consumption on a set of household's and village's characteristics and - where the design of the survey allows the researcher to collect enough information - on aggregate and idiosyncratic shocks. However, they usually rule out assets and the characteristics of the distribution of shocks, raising several theoretical and econometric issues which may bias the vulnerability estimates and - as consequence - suggest wrong policy decisions.

Assets are fundamental in the determination of household's living standards and its behavioral responses to risks. Especially for poor households in developing contexts, decisions on stored crops, livestock, land and machines used in the production process are strictly linked to the strategies for smoothing consumption and reducing risk. Assets can be used to buffer consumption in bad times, as well as they can be employed to increase the seasonal harvest or even as collateral for borrowing. It means that assets are one of the most important determinants of the household's well-being because they influence both the level of consumption and they synthesize the ex-ante and ex-post risk coping strategies. It seems obvious that excluding assets from the vulnerability analysis provide biased estimates and it doesn't allow to understand how the agents are responding to the surrounding economic environment. Consequently, the econometric estimates of vulnerability which don't include assets in the consumption function are obviously suffering from omitted variable bias. The estimated consumption could be biased either downward or upward as well as the relative index which is calculated on the basis of these counterfactual estimates.

Besides the lack of assets in the consumption function, current empirical approaches to vulnerability are not even considering the role played by the characteristics of the distributions of shocks. We have already explained that risk affects welfare in two different ways: it directly hits the level of well-being through the realization of shocks and indirectly determines the household's economic strategies put in place to deal with the perceived uncertainty. The monetary measurements are not able to distinguish between these two components, overlooking the effect of a change in the parameters of the distribution of shocks. For example, a mean-preserving increase in the variance of a normally distributed income shock influences both the ex-ante and the ex-post household's behavior because - in the first case - it changes the lifetime optimization process and its optimal policy function while - in the second case - it modifies the support from where shocks are drawn. Therefore, it seems more reasonable to estimate the consumption function including also information on the ex-ante impact of risk (usually the higher moments of the distribution of income shocks), following the approach used by economic literature to test - for example - the presence of precautionary saving motive. As we will see in Chapter 3, the contribution of this strategy will be twofold: on the one hand it improves the quality and the accuracy of the econometric estimates while on the other hand it allows us to build up a series of consumption counterfactuals to be used to compute the vulnerability measure.

Including a proxy for income uncertainty is not enough because household's lifetime welfare is not influenced only by income risk but also by asset fluctuations. Asset risk is an autonomous source of uncertainty which interacts with income uncertainty and influences saving decisions. The frequency and the intensity of crop pests, livestock death and diseases, land problems such as governmental reforms, asset losses caused by natural (flood, hurricane, earthquake, etc) and man-made (war, civil disorders, crime, fire, etc) disasters are not just influencing the total amount of accumulated asset but they are also modifying the household's perception of risk[18]. The two sources of risk may have different and opposite effects on the economic decisions and, as consequence, we cannot determine in advance which is the final impact on household's behavior. In other words, including asset and income uncertainty in the empirical estimates of vulnerability is not just an exercise to increase the efficiency of the regression, but is also a valid instrument for testing the impact of the risk-induced changing behavior on households' well-being.

[18] The dynamic stochastic simulation of chapter II will show that if the asset accumulation process is risky, the standard results of precautionary saving fall apart and the same result is also confirmed by Hahn (1970), Dercon (2005), Elbers et al. (2009), Gunning (2010).

Finally, the last problem is related to the restriction we have to impose on our functional form. The consumption function and the consequent vulnerability index is usually estimated using a linear specification which is a highly restrictive hypothesis. For example, performing the regression without introducing any interaction terms among risk proxies and the other covariates makes the effect of the shocks on the consumption independent of the household's characteristics. It is not difficult to sustain that this assumption is quite restrictive and that the impact of risk on the welfare is household-specific and depends also on the instruments available to the economic agent to contrast any potential harmful consequences.

1.5 Conclusion and Future Perspectives

In this Chapter we went through the current status of the economic literature on future poverty and risk. We have seen that in the last two decades practitioners incorporated risk in the framework of poverty dynamics analysis, assessing its cost in terms of welfare for the poor households in developing countries. The common view is that uninsured risk reduces household's well-being and endanger the future possibilities of development for the more exposed subset of the population. There are several causes which explain the link between risk and welfare loss. The most interesting is the impact of risk on household's behavior through the coping and managing strategies. Both theoretical and empirical analyses agree on the fact that risk usually influences production and consumption decisions, moving the household toward investment with lower risk but also lower expected profits. Moreover, risk can push the household to accumulate an excessive amount of precautionary saving as well as to deplete productive assets normally used for generating income. The main limit of this strand of literature is that the final evaluation of the welfare loss is done on ex-post poverty measures which are defined only after all uncertainty has been resolved. As consequence, the policy recommendations coming from this analysis are constrained to ex-post measures of poverty alleviation while we don't have any information on what ex-ante measures for poverty prevention we should deploy. To partially overcome this problem, we have seen that in the last ten years a little number of practitioners tried to move the attention of poverty analysis from an ex-post framework toward a forward-looking approach in order to evaluate the possibility of becoming or remaining materially poor in the future. This part of the literature is called vulnerability to poverty. The most important approaches acknowledged by the researchers are Vulnerability to Expected Poverty, Vulnerability as thread of Future Poverty and Vulnerability as low Expected Utility. We discussed the theoretical and empirical framework proposed by each approach and detected the main shortcomings. The most surprising limit shared by all these analyses on vulnerability is that they are not able to catch the ex-ante impact of risk on household's behavior. The consequence is that poverty prevention recommendation may be biased and unable to reduce the potentially harmful effects of risk on poor household's future welfare. In the light of these considerations, several suggestions for the future research in the field of vulnerability raise. The most important step is to develop a theoretical framework which would be able to catch the ex-ante impact of household's changing behavior on its future welfare. This objective can be achieved only proposing a measure of vulnerability based on a solid micro-foundation and a first effort to move towards this direction has been done by Elbers and Gunning (2003). In their work, the authors fully understand the limits of the current vulnerability analysis and underline that the problem can be solved only relying on a dynamic and stochastic model which would be able to incorporate the risk mitigating strategies of the household. In particular, Elbers and Gunning (2003) propose to estimate vulnerability using simulation-based econometric techniques and panel data. They calibrate a life cycle optimization problem using empirical data on household-level income and asset shocks and search econometrically for the values of parameters that maximized the model's ability to fit some measured feature of the empirical data. Elbers and Gunning (2003) model inspires the theoretical model proposed in the present research and it is analyzed more deeply in the Chapter 2. However, even if their work shows some important progresses with respect to the previous vulnerability analyses, it presents several shortcomings which justify a further investigation on the theme. First of all, the authors never came up with the proposition a new measure of vulnerability able to disentangle the impact of household's changing behavior on its welfare, leaving unsolved the main problem faced by current approaches. Secondly, their numerical simulation is calibrated on the specific case of Zimbabwe while we generalize our model to poor households in developing countries using the parameters provided by the literature. Third, even if the numerical simulation of the dynamics and stochastic model is an elegant way to test the theoretical prediction, it pays a high price in terms of reality and loss of information. At this purpose, we prefer to go further in Chapter 3 and testing empirically the model relying on regression techniques which allows the data to speak in a much less filtered way than the structural estimation approach [19]. Hence, the two following chapters of the research will focus their efforts to propose 1) a micro-founded vulnerability measure and 2) a robust empirical methodology to evaluate the performance of the new index.

[19] See Carroll (2007) for a brief review on the empirical techniques to estimate the consumption function in the framework of precautionary saving theory.

Chapter 2

A Micro-Founded Approach to Vulnerability to Poverty

2.1 Introduction

In Chapter 1 we focused on monetary measures of vulnerability to poverty based on consumption expenditure as indicator of individual welfare. The incapability to catch the impact of the risk-induced changing behavior is the main shortcoming of these approaches and it reduces the potential contribution of this literature in terms of policy recommendations. In fact, households which adopted complete self-insurance mechanisms at the cost of a lower mean welfare would be registered as households unaffected by risk but with a low level of welfare because of their structural conditions (i.e. demographics, education, occupation). In this Chapter we address this problem proposing a micro-founded measure of vulnerability to properly consider the impact of risk on future poverty and - in particular - to separate the welfare cost generated by the risk-induced changing behavior (ex-ante effect of risk) from the impact of the shocks realizations (ex-post effect of risk).

We start looking at the literature on consumption and saving behavior to better understand how the households deal with risk. According to the standard theory proposed by the *life-cycle* (Modigliani and Brumberg, 1954) and the *permanent income* (Friedman, 1957) models, the households attempt to keep their consumption constant over time, saving in good times and depleting the accumulated resources during the bad times. These models lay most of the theoretical foundations for the household's saving behavior even though they don't examine directly the role of risk in the household's choice. More appropriate to our aim is the precautionary saving theory which can be considered an extension to the life-cycle/permanent income models where saving is not just an instrument to spread consumption over life but also an insurance mechanism to reduce the negative influence of risk (Lusardi, 1998). The standard version of this model is more suitable for describing behavior in advanced economies while it is not able to explain why risk may induce forms of rational behavior that reduce welfare and perpetuate poverty in developing countries, as demonstrated by several recent studies (Jalan and Ravallion, 2001, Dercon, 2005; Giles and Yoo, 2007; Elbers and Gunning, 2007; Elbers et al., 2009; Gunning, 2010). These authors prove that precautionary saving produces costs: if we assume that the households lack access to credit and assets are risky, the household could reduce current saving, endangering its potential consumption growth and reducing expected welfare.

Following this approach, we use a dynamic and stochastic Ramsey Model to simulate the optimal saving behaviour for a household with liquidity constraints, risky income and risky assets. We show that adding risks on asset and income tilts down the optimal lifetime consumption path with respect to its risk free counterpart, forcing the household to pay a cost in terms of welfare. Using a decomposition method based on a series of consumption counterfactuals we show that the welfare cost of risk can be divided between the impact due to the household's exposure and the impact due to the risk-induced changing behaviour. In particular, at the end of a 50-year period of simulation the consumption path in the deterministic case is on average 20% higher than the consumption path in the stochastic case, and the 80% of this difference depends on the household's changing behaviour. Moreover, using the results provided by a numerical simulation and following the most up-to-date debate on the aggregation over time of poverty indices, we build up a *dynamic risk sensitive* vulnerability measure based on a counterfactual decomposition of the household's future welfare. The measure distinguish three different components of vulnerability: the structural component due to the characteristics of the household (*poverty component*); the impact of the risk-induced changing behaviour (*ex-ante component*); and the impact of the household's exposure to risk (*ex-post component*). Applying the new measure of vulnerability to the simulation results we show that almost 70% of the future welfare cost triggered by the presence of risk is due to the ex-ante component.

The contribution of this Chapter is twofold. On the one hand it has the merit to bridge the gap between the monetary approaches to vulnerability and one of the most recent debate in the field of development economics, i.e. the welfare costs of risk-induced changing behavior. On the other hand, it provides a solid microeconomic basis to the monetary measurement of vulnerability and new implications in terms of poverty alleviation policies. The Chapter proceeds as follow. Paragraph 2.2 describes the most important theories on saving and consumption behavior, focusing on those versions more suitable to the poor households in developing countries. Paragraph 2.3 performs a dynamic and stochastic simulation to model the risk-induced changing behavior while Paragraph 2.4 proposes a micro-founded measure of vulnerability to poverty.

2.2 Saving and Consumption Behavior in Developing Countries

As recognized by Deaton (1997), poor individuals close to subsistence use to free consumption from income in order to avoid their welfare to fall below a poverty threshold because of temporary low earnings. They save a fraction of their wealth during the good times and deplete it during the bad times. However, this consumption smoothing mechanism can take different forms which are based on the saving behavior of the households and they can produce a cost in terms of welfare. In this Paragraph we look at the literature on consumption and saving behavior to better understand how households deal with risk and then we analyze some specific features which characterize these behavioral responses in developing countries.

2.2.1 Standard Models of Saving and Consumption

In the past decades the economic literature on intertemporal allocation of money between present and future consumption has been subject to a series of important theoretical developments. Standard theory mostly relied on both the *life-cycle* model inspired by Modigliani and Brumberg (1954) and the *permanent income* model developed by Friedman (1957). As briefly mentioned in Chapter 1, in the life-cycle model consumption is determined by the value of lifetime resources while in the second case consumption is determined by the permanent income, typically defined as average or expected income (Deaton, 1992). Even if the two approaches appear to be similar they must not be confused because they coincide only if the permanent income is calculated as the average of the lifetime income and Friedman (1957) has never committed his theory to this hypothesis. The central idea of these two theories is that the rational forward looking agents attempt to keep their marginal utility of consumption constant over time and this principle applies both in the short run (high frequency) and the long run (low frequency) allocation. Browning and Lusardi (1996) recognize that both the life-cycle model and the permanent income hypothesis (PIH) share some basic assumptions: the agents have intertemporally additive utility functions and they face perfect capital markets; either there is perfect certainty or agents maximize expected utility, they form rational expectations and have quadratic utility functions. As shown by Deaton (1997), these assumptions applied to a basic intertemporal optimization problem give us back the formal justification for model in which planned consumption is constant, such as in the life-cycle model and PIH. Let assume that the agent maximizes the following standard intertemporal utility problem:

$$\begin{aligned} \max_{x} \quad & U = E_t \sum_{t=1}^{T} (1+\delta)^{-t} u_t(c_t) \\ \text{s.t.} \quad & k_{t+1} = (1+r_{t+1})(k_t + y_t - c_t) \end{aligned} \tag{2.1}$$

where c_t is the consumption at time t, u_t is the instantaneous utility function, T is the finite time-horizon, E_t the expectation operator, k_t the real value of asset and y_t the income. δ_t and r_t are respectively the rate of time preference and the interest rate. The result of this problem is the well-known Euler Equation which is in this case:

$$u'_t(c_t) = \frac{(1+r)}{(1+\delta)} E_t[u'_{t+1}(c_{t+1})] \tag{2.2}$$

If we further assume that 1) the rate of time preference is equal to the interest rate; 2) the instantaneous utility functions don't change over time and 3) the unique utility function is quadratic, we can rewritten Equation (2.2) as:

$$c_t = E_t(c_{t+1}) \tag{2.3}$$

Equation (2.3) tells us that the consumption is a martingale, which means that it is a stochastic process whose expected future value is equal to its current value and it can be used to both interpret the consumption behavior predicted by the life-cycle model and the PIH (Deaton, 1997). In the first case, the consumption is constant over the entire lifetime while saving are accumulated during the working age and depleted during retirement, when labor income falls to zero. In the case of PIH, the consumption is equal to the permanent income, which can be defined over different and shorter time horizons.

Despite the importance of the life-cycle and the permanent income models for the theoretical literature on the intertemporal choice, the two models are based on quite restrictive assumptions which can be relaxed introducing two fundamental aspects in the analysis: the non-linearity of the marginal utility of consumption and the presence of future random income rather than determinate (Leland, 1968). The introduction of these two elements generates a *precautionary demand* for saving where saving is not just an instrument to spread consumption over the entire life but also an insurance mechanism to reduce the negative impact of risk (Lusardi, 1998). Precautionary saving has been widely studied by the economic literature since the well-known works of Leland (1968) and Sandmo (1970)[1] . They show that in the context of a two-period, partial-equilibrium model in which there is income risk in the second period and a single risk-free asset, household will save more with respect a deterministic framework if the marginal utility function is convex, which means a positive third derivative of the utility function. In particular, the first stage of the literature on precautionary savings assume that the second-period income y_2 is random and drawn from a distribution with parameter θ. The household maximizes an expected utility function $E[U(c_1) + U(c_2)]$ by choosing the amount of the asset k to save for the second-period consumption. The Euler Equation of the problem is

[1]The same theoretical framework has been used by other influential works on precautionary saving as Mirman (1971), Rothschild and Stiglitz (1971), Drze and Modigliani (1972) and Diamond and Stiglitz (1974).

given by:

$$U'(k_1 + y_1 - k_2) = E[U'(k_2 + \tilde{y_2})] \tag{2.4}$$

The main intuition is that with a convex marginal utility, increases in income uncertainty increase the expected future marginal utility of consumption for any fixed level of asset k_2 carried to the second period (Huggett and Ospina, 2001)[2] . Kimball (1990) labels the convexity of the marginal utility as *prudence*, defining the measure of absolute prudence as $-U'''(w)/U''(w)$ and the relative prudence as $-wU'''(w)/U''(w)$, where w indicates household's wealth. Examining the comparative statics of the two-period precautionary saving problem, Kimball (1990) explores the links and differences between the Arrow-Pratt concept of risk-aversion and the definition of prudence. Risk-aversion is controlled by the degree of concavity of the utility function, but the degree of precaution is the degree of convexity of the marginal utility function. While risk-aversion depends on the second derivative of the utility function, precaution depends on the third derivative. The former measures how much one would eliminate uncertainty if possible, while the latter represents the intensity of the precautionary saving motive. As pointed out by Deaton (1992), it is only for very special cases that one can be inferred from the other. For example, with iso-elastic utility function, risk-aversion and precautionary saving are controlled by the same parameter, i.e. the coefficient of relative risk aversion; the higher is risk aversion, the greater will be the curvature of the marginal utility function.

The same results of this first strand of literature has been later generalized to multi-period models with time separable utility function [3], confirming the theoretical intuition of the two-period model. Following Huggett (2004), we can further divide this subsequent literature in two main groups. The first one presents parametric

[2]In this framework the increase in risk is meant as a mean preserving spread of the second-period income distribution.

[3]See, for example, Miller (1974,1976), Sibley (1975), Schechtman (1976) and Mendelson and Amihud (1982).

decision models having closed-form solutions. Let assume that the consumer still maximizes the problem in Equation (2.1) where the subjective discount rate is equal to the riskless interest rate and they are both equal to zero. Assume also that income is a random walk $y_t = y_{t-1} + \epsilon_t$ with a normally distributed innovation $\epsilon_t \sim N(0, \sigma^2)$ and that the instantaneous utility function is a negative exponential $[U(c) = -(1/\alpha)e^{\alpha c}]$ with constant absolute risk aversion (CARA). Blanchard and Fisher (1989) show that the optimal consumption satisfies $c_{t+1} = c_t + \alpha\sigma^2/2 + \epsilon_t$ and the level of consumption is given by [4]:

$$c_t = \frac{k_t}{T+1-t} + y_t - \frac{\alpha(T-t)\sigma^2}{4} \tag{2.5}$$

The first two terms of the Equation (2.5) represent the household's consumption predicted by the permanent income hypothesis while the last term indicates the precautionary motive generated by the presence of income risk. It is clear from 2.5 that risk postpones consumption and accelerates growth, tilting down the optimal path during the first years of life. Deaton (1992) and Weil (1993) emphasize some limitations of this result. In particular, if the negative exponential is helpful for finding a closed form to the model, it doesn't rule out negative consumption, especially if initial assets are low or income innovation highly volatile.

The second strand of the literature, since Skinner (1988), Zeldes (1989), Deaton (1991) and Carroll (1997), analyses precautionary saving using a Constant Relative Risk Aversion (CRRA) utility function. These models lack of a closed form as in the case of the negative exponential utility function and they are forced to solve the decision problem of the household through computational methods [5]. With CRRA

[4] Equation 2.5 is derived combining the first-order condition $e^{-\alpha c_t} = Ee^{-\alpha c_{t+1}}$ with the fact that if x is normally distributed with mean $E(x)$ and variance σ_x^2, $E[exp(x)] = exp(E(x) + \sigma_x^2/2)$ and then using the intertemporal budget constraints to solve for the level of consumption.

[5] More details on the technical aspects of computational methods and numerical simulations will be presented in the following Paragraphs.

adding risk makes consumption more sensitive to wealth. In other words, when a small amount of risk is added, the consumption function becomes more steeply sloped implying a greater sensitivity of consumption to transitory income than under certainty equivalence (Zeldes, 1989). Even if there are substantial differences and particular cases, the standard result of precautionary saving analysis seems to be confirmed also by this group of scholars: households tend to accumulate more asset than would be in a risk-free framework. However, this last part of literature highlighted also other consequences of precautionary saving. For example, it explains why the older save more than how much predicted by the life-cycle and the permanent income models: uncertainty makes older people extremely cautious about consuming their assets (Deaton, 1992).

Finally, Carroll (1992) exploits precautionary motive to explain some puzzles in households' lifetime choice over saving and consumption. In particular, the author shows that with a positive probability that income will be zero and without a positive floor to income, households will never borrow even if there are not market constraints. Moreover, Carroll(1992) also shows that precautionary saving motive can explain the reason why consumption *tracks* so closely income over the life cycle. Assuming impatience [6], he demonstrates that the household faces, on the one hand, the need to save in order to ensure themselves from future bad shocks and, on the other hand, the aversion to postpone consumption opportunities. The final compromise seems to be that a few assets are held in the earlier years of life, just as buffer stock against income shocks, and only later we have significant savings.

2.2.2 What Happens in Developing Countries?

In the previous section we analyzed three different models of saving and consumption which - in their standard versions - are more suitable for describing behavior in ad-

[6] The intertemporal discount rate is higher than the interest rate

vanced economies while they overlook some specific features of the poor households in developing countries. Especially for the life cycle/permanent income model, the empirical tests conducted on household-level data in developing countries showed significant inconsistencies between the basic theoretical predictions and the actual behavior of the poor households. Deaton (1992) underlines that the life-cycle model overstates the degree to which consumption is detached from income. In the poorest economies only a small fraction of old people live alone, while the majority lives with their families. The widespread existence of extended families reduces the need for life-cycle saving and then this mechanism is always of doubtful relevance in developing economies (Deaton, 2010). At this purpose, most of the empirical evidence showed that actually consumption tracks income quite closely as well as there is little evidence of dissaving among the older (e.g. Paxson, 1996; Deaton, 1997; Deaton and Paxson, 2000). Other authors tried to test the permanent income hypothesis verifying if the households are able to smooth consumption in response to short-term income fluctuations. The simplest method adopted by this part of literature usually estimate the consumption as function of permanent and transitory income, together with other control variables related to the demographic structure of the households. If the PIH is true, the coefficient of permanent income should be equal to one (the household consumes the entire permanent income) and the coefficient of transitory income should be equal to zero (the household saves the transitory income). Examples from data on developing countries have been provided by several researchers (e.g. Musgrove 1978, 1979; Bhalla 1979, 1980; Wolpin 1982; Paxson 1992, 1993; Deaton 1997) and the results are quite similar: the coefficient on permanent income is positive but less than unity and the coefficient on transitory income is different from zero but smaller than the coefficient on permanent income. These results suggest that the households are not completely following the theoretical prediction of the PIH model but at least there is a certain degree of consumption smoothing, indicating that the households save in good times. For this reason, Deaton (1992) suggests that PIH could be preferred to the life-cycle model to explain consumption and saving behavior in developing countries.

More recent empirical works indicate actually that poor households may held a significant amounts of extra-saving used to smooth consumption as response to risk[7]. This extra-saving usually takes the form of grain stocks, cash holdings, jewelry and livestock and often yield negative or low positive returns (Park, 2006; Lee and Sawada, 2010). The presence of a precautionary motive has been extensively tested by practitioners and the results are quite ambiguous[8] . For example, Jalan and Ravallion (2001) find that wealth in China is held in unproductive liquid forms to protect against idiosyncratic income risk but the effect is economically insignificant. At the same time, Park (2006) and Giles (2007) find out, respectively, that Chinese households prefer to keep a significant share of their wealth in grain stock and that almost 10% of their saving can be attributed to precautionary motive. Lee and Sawada (2010) provide strong evidence of the presence of precautionary saving in Pakistan, even if the effect is important only for the liquidity-constrained households with a limited credit access. At the same time, Elbers et al. (2007) find out that for rural households in Zimbabwe risk decreases the expected long-run saving stock by almost 50% once we introduce risky asset in the analysis.

Most of the difference in these results depends on the assumptions regarding the households' capabilities to access reliable saving opportunities and on the characteristics of risk. Standard theory assumes that savings can occur in a safe form and

[7]See for example, Paxson, 1992; Rosenzweig and Binswanger, 1993; Rosenzweig and Wolpin 1993; Alderman 1996; Dercon 1998; and Fafchamps et al. 1998, Jalan and Ravallion, 2001; Park, 2006; Giles and Yoo, 2007; Elbers et al, 2007;Lee and Sawada, 2010.

[8]The same consideration can be done for the analyses on developed economies. A series of studies on U.S and other OECD countries find no or little evidence of precautionary motive (Skinner, 1988; Dynan, 1993; Merrigan and Normandin, 1996; Guiso, et al., 1992; Kazarosian, 1997; Lusardi, 1998) while others - conducting analyses on the same countries - suggest that precautionary saving may explain a significant part of wealth accumulation, in the range of 20-50 percent of total wealth (Carroll and Samwick, 1998; Irvine and Wang, 2001; Gourinchas and Parker, 2001; Parker and Preston, 2005).

access to the credit market is granted for everyone. Both assumptions are quite unlikely for poor households living in countries without integrated asset markets (Dercon, 2005). While in developed economies households may have many products available to help them saving and building assets (savings accounts, automatic transfers, savings bonds, certificates of deposit), poor in developing countries face a much more limited menu of options (Karlan and Morduch, 2009). As consequence, risk can promote forms of rational portfolio behavior that reinforce poverty because a) the credit markets are imperfect and b) saving cannot occur in a safe and productive form (Jalan and Ravallion, 2001).

The first issue has been faced by Deaton (1991) who provides a theoretical scheme for analyzing precautionary saving in developing contexts describing the implications of self-insurance through savings when credit markets are imperfect. The hypothesis of liquidity constraints in developing countries seems to be largely accepted by literature and sustained by empirical evidence[9] . Deaton (1991) assumes that consumers are impatient (i.e. they prefer to consume today rather than tomorrow - interest rate are lower than time preference) as well as liquidity constrained, which means that households cannot borrow in bad times but they can consume only what they previously accumulated. Deaton (1992) sustains that the precautionary motive is actually strengthened by the existence of liquidity constraints and the ability to borrow in bad times is an insurance device for at least some households. However, bad time are not easily insured because a series of negative income shocks can still lower consumption. It happens because negative shocks can be offset by assets only if there are assets to run down, but if they have been depleted during previous bad times, nothing can be done and consumption falls. Deaton (1991) also shows that if income innovations are persistent over time, the difficulties to cope with risk increase and the smoothing strategies partially fail because consumption is more volatile and

[9] See, for example, Ogaki et al. (1996), Rossi (1988), Haque and Montiel (1989), Vaidyanathan (1993).

tracks closely income (Dercon, 2002). Deaton (1991) sustains that his results predict some of the empirical findings in developing countries as occasional low consumption, low asset holdings and high frequencies of asset transactions. However, Dercon (2005) highlights that this result is driven mainly by the impatience of household: without this assumption it would be possible to build-up enough assets stock to deal with future negative shocks.

The second problem regards the possibility to accumulate saving in safe and productive forms. Standard models of saving and consumption assume that only labor income is risky even if we know this is not possible in developing countries because extra-saving such as grain stocks and livestock are exposed to downside risks like pests, death, diseases and natural disasters. In case of risky assets, some authors argue that risk could actually reduce savings (Hahn, 1970; Dercon, 2005; Elbers et al., 2009; Gunning, 2010). Hahn (1970) is the first to show that a mean-preserving increase in risk could lead to a reduction of saving if risk affects the whole household's wealth rather than income and if the degree of relative risk aversion is less than one. However, this last assumption is quite limitative considering that usually the parameter of the CRRA utility function has been proved to be more than one, especially for poorer households. (see Paragraph 2.3.3). Instead, Gunning (2010) shows that if we assume i) only asset and not income risk, ii) positive exogenous income and iii) a linear capital income function, then the sign of the impact on saving depends on the sign of $(\gamma - 1)$ where γ is coefficient of relative risk aversion. In particular, when γ is equal or less than unity, the household will decrease its saving while if γ is more than one the final effect is not clear. These two theoretical works seems to be more suitable for modeling the impact of risk on saving and consumption in developing countries because those who are able to save are often forced to invest in risky assets or to use informal savings instruments (Karlan and Morduch, 2009). The household cannot fully smooth its consumption using buffer stocks (e.g. livestock) because risk reduces the effectiveness of the self-insurance scheme. The consequence is that the households' development process can be endangered because even if the rate of saving doesn't influence the consumption growth in steady state, it is still important during the movement towards it. A reduction in the rate of saving would slow down the transition process and increase the time to reach the long-run equilibrium (Gersovitz, 1988).

Starting from this consideration, a more comprehensive analysis on the impact of risk with both risky income and asset is provided by Dercon (2005) and Elbers et al. (2007). On the one hand, Dercon (2005) extends Deaton's model assuming that assets have risky return[10] and calculates a risk premium in order to evaluate the impact of risk in terms of welfare. He finds out that the amount of consumption the household is willing to give up in the first year of life to have the risk-free path is almost 20% even if once he allows for the possibility to save but not to borrow, the risk premium shrinks to less than 10%. The author sustains that the largest effect stem not from risk per se, but from the covariance between asset and income. The explanation is that when a common negative shock occurs on both asset and income, incomes are low and returns to different assets are also low, often even negative. As a consequence, just when assets are needed, net stocks could be low as well. In the Elbers et al. (2007) model the household's economic decisions on savings are affected by risk in two ways: through the household's experience of shocks and through its perception of the distribution of the shocks it faces. They find, by applying a simulation-based econometric methodology to panel data for rural households in Zimbabwe, that risk substantially reduces growth: for a household with median productivity the expected capital stock converges to a mean which is about 50% lower than what it would be in a risk-free context. They demonstrate: firstly, poorer households experience a reduction of lifetime asset accumulation (saving)

[10] He also assume that there is a terms of trade between asset and consumption and it is risky too.

and a cost in terms of welfare caused by the presence of risk[11] ; secondly, the effect of risk on savings depends not only quantitatively but also qualitatively on how productive households are. Thirdly, the welfare cost of risk is substantial: the median household would be willing to pay about 10% of its annual consumption for actuarially fair insurance. However, the explanation which links the lower level of saving to a decrease of the lifetime expected utility remains quite cloudy and it is ambiguously solved in the numerical simulation process.

For the sake of completeness, it is worth to remember that consumption smoothing mechanisms don't complete the set of possible behavioral responses to risk in developing countries. We have already seen in Chapter 1 that the households might engage themselves in other *coping* strategies such as risk-sharing arrangements or they might carry on *management* strategies such as income smoothing. Even if these behavioral responses to risk are able to explain an important part of the story on poor household's choices in risky environment, we prefer to keep them outside the analysis and focus just on consumption smoothing mechanisms. There are two reasons to justify this choice. First of all, these different approaches to behavioral responses have their autonomous theoretical and empirical framework which are difficult to integrate simultaneously in just one model. As consequence, the researcher is forced to choose one strand over the others and we prefer to look at consumption smoothing because it evaluate directly the impact of risk on the individual welfare indicator chosen by the vulnerability analysis, i.e. consumption. In fact, the others approaches are more focused on the direct impact of risk on income, production and transfers across households while they evaluate only indirectly the consequences in terms of individual consumption. Secondly, focusing on consumption and saving

[11] Elbers et al. (2007) measure the welfare cost of risk as *compensating variation*, calculated as the transfer received a $t = 1$ under risk which would increase the level of expected utility to the level of welfare in the risk free case. Dercon (2005) evaluates the consequences of different risks calculating a risk premium, which is defined as the consumption the household is willing to give up in the first year to obtain the optimal path of consumption without liquidity constraints.

behavior still allows the researcher to catch the other risk mitigating mechanisms impacts on the household's welfare because they are implicitly embedded in the consumption choice even if we are not able to distinguish which one is operating. Nevertheless, it is not true the opposite because the choices over production and risk-insurance arrangements are not able to fully reveal which is the consumption and saving behavior of the households and, as consequence, its level of future welfare we need to calculate the vulnerability measure.

2.3 Modeling the Welfare Cost of Changing Behavior

The analysis of the consumption responses to risk highlighted that the welfare costs suffered by poor households may be substantial and generate potentially harmful consequences. These costs are not only linked to the impact of negative shocks on income and assets but they also depends indirectly on the risk-induced changing behavior put in place by the households. To understand how to separate these different effects of risk on welfare, we use a modified version of the standard precautionary saving model in developing countries based on the works of Elbers et al (2007), Carter and Ikegami (2009) and Elbers (2009). The solution of the model will help us to build up a new vulnerability measure based on the considerations emerged in the Chapter 1.

2.3.1 The Model

The welfare cost of changing behavior will be modeled using a modified version of the discrete-time stochastic Ramsey model where – instead of a planning authority – decisions are taken by a single household which uses a single good for consumption, store of value and productive asset. Following Elbers et al. (2007), we assume that financial assets can be neglected and informal risk-sharing doesn't take place while the only investment the household performs is accumulating its own asset. Moreover, the household can save but cannot borrow, coherently with the Deaton's model (1991). These assumptions are suitable mostly for low-income countries based on agricultural activities where behavioral responses are restricted to consumption and saving choices. In the standard precautionary saving model there is no motive for saving in the deterministic case while the Ramsey model displays conditional convergence and incentive to save even if risk is absent (Elbers et al., 2007). It allows us to build up a counterfactual risk-free growth process which can be compared with the growth process under risk. Nevertheless, we have seen in Paragraph 2.2 that standard literature assumes access to safe assets even for poor households, which is a quite unrealistic assumption. We remove this hypothesis allowing risk to affect both asset and income where asset is used as the only input of the production function. As demonstrated by Gunning (2010), it implies that we cannot say anything on the final impact of risk on saving decisions and the final sign on welfare will depend exclusively on the parameters of the model. The household maximizes the discounted utility from consumption over an infinite horizon[12] :

$$\underset{\{c_t,k_{t+1}\}_{t=0}^{\infty}}{\mathrm{Max}} E_0 \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{2.6}$$

subject to

$$e^{A_t^y} f(k_t) + e^{A_t^k}(1-\delta)k_t \geq c_t + k_{t+1} \tag{2.7}$$

$$A_t^y = \rho A_{t-1}^y + \epsilon_t^y \tag{2.8}$$

$$A_t^k = \rho A_{t-1}^k + \epsilon_t^k \tag{2.9}$$

[12] As pointed out by Makame (2006), in lower income countries households are more complex because they are multigenerational agglomerates. It is more likely to see households that combine grandparents, parents, and grandchildren living in the same house. As consequence, the intergenerational households looks like a single, infinitely lived household.

$$c_t \geq 0$$

$$k_t \geq 0$$

$$\forall \text{ t} = 0...\infty \text{ and } k_0 \text{ given}$$

where c_t indicates the consumption at time t, k_t the asset corrected by the labor endowment[13], u the instantaneous utility function, β the discount factor, δ the depreciation rate and f the production function. $k_t \geq 0$ introduces the simplest form of borrowing constraints[14] .

The household faces two different sources of risk: both the production function and the asset accumulation process are exposed to an AR(1) shock. Equation (2.8) and Equation (2.9) specify the structure of these processes, where ρ indicates the persistence of the previous period shock[15] while ϵ_t^y and ϵ_t^k are two normally independently and identically (i.i.d.) distributed errors with mean zero and standard deviation $\sigma^2_{\epsilon^y}$ and $\sigma^2_{\epsilon^k}$. The unconditional mean of the two processes is zero as well while their variances are, respectively $\sigma^2_{A^y}$ and $\sigma^2_{A^k}$[16]. In this work we rely on the Carter and Ikegami (2009) assumption that income and asset shocks are statistically independent from each other. This simplifies the numerical simulation of the model[17] and allows us to focus just on the serial correlation and the relative persistence. Dercon (2005) shows the eventual assumption of correlation between the two shocks doesn't change significantly the conclusion of his model, with the unique result to exacerbate the negative impact of risk on welfare [18]. The pres-

[13]Variables are expressed in terms of labor endowment in order to reduce the dimensionality of the problem and limit the number of the state variable.

[14] Another way to introduce borrowing constraints is to fix a negative limit for assets.

[15] For simplicity, we assume that persistence is the same for both asset and income shocks.

[16]It is worth to remember that the two variances are calculated as $\sigma^2_{A^y} = \sigma^2_{\epsilon^y}/(1-\rho^2)$ and $\sigma^2_{A^k} = \sigma^2_{\epsilon^k}/(1-\rho^2)$

[17]Accounting for both cross and serial correlation in this framework would force us to convert a Vector Autoregressive (VAR) representation of the two shocks into a multivariate Markov process. It would be a time-consuming routine which doesn't influence significantly our results.

[18]In particular, the model shows that passing from the statistical independence (covariance equal to 0) to the perfect correlation (covariance equal to 1) increase the risk premium as percentage of

ence of persistence in the income and asset innovations in developing countries has been provided by numerous studies (Jalan and Ravallion, 2001; Loshkin and Ravallion, 2004, Fields et al. , 2003; Newhouse, 2005; and Attanasio, 2009)[19] and its introduction in the model helps to better represent the idea that many behavioral responses have welfare implications not only in the present period but they influence the consumption and savings path over several future periods, as confirmed also by Deaton (1991). We further assume that future shocks are unknown, but the household knows the unconditional mean of the processes as well as the distribution of the i.i.d components.

As in the Ramsey's original formulation, at each period the household must decide how much to produce, to consume and to put aside for future production (saving). We consider first the deterministic setting of the problem [20]. In this case, the asset k_t is the only state variable and c_t is the control. Solving this problem means to find the sequence of the control variable $\{c_t\}_{t=0}^{\infty}$ which solves the maximization problem in the system (2.6-2.9). We can rewrite the risk-free case using the recursive formulation suggested by dynamic programming techniques. Following Heer and Maussner (2005), we assume that we already know the solution $\{k_t^*\}_{t=0}^{\infty}$ so that we can compute the lifetime utility from:

$$V(k_0) = u(f(k_0) - (1-\delta)k_0 - k_1^*) + \sum_{t=1}^{\infty} \beta^t u(f(k_t^*) - (1-\delta)k_t^* - k_{t+1}^*) \tag{2.10}$$

The solution depends on k_0 and in our simulation we will choose a k_0 far below from the level of steady state because we are interested in analyzing the impact of risk on the consumption path of a poor household. Since k_0 is an arbitrary choice, we

the mean of the income process by only 2.4 points, from 7% to 9.4%.

[19] Actually, some of these researches (Fields et al., 2003 and Newhouse, 2005) find that the persistence of income shocks is even higher than one period. However, we prefer to use a first order autoregressive process to keep the model as simple as possible.

[20] It means that the two error processes are always equal to their unconditional mean, i.e. zero.

drop the time subscript and use k to indicate this variable and k' for all next-period variables. Then, we are allowed to write the Bellman Equation as:

$$V(k) = \max_{0 \leq k' \leq f(k)+(1-\delta)} u(f(k) + (1-\delta)k - k') + \beta V(k') \tag{2.11}$$

The Bellman Equation is composed by the utility of consumption as a function of the next-period asset stock and the discounted optimal value of lifetime utility if the sequence of optimal asset stock starts in the next period with k'. If we know the function V we can solve the optimization problem of the right hand side (RHS) of the Equation (2.11), which depends on the given value of k. It means that we can indicate the policy function of the agent as $k' = h(k)$, which is the same for all periods. Calculating recursively the function h allows as to determine the entire sequence of k^{*}[21]. Using the Bellman Equation we can show that the function h satisfies the Euler Equation. Deriving Equation (2.11) by k' gives us:

$$u'(f(k) + (1-\delta)k - k') = \beta V'(k') \tag{2.12}$$

Substituting the policy function h into the Bellman Equation we have:

$$V(k) = u(f(k) + (1-\delta)k - h(k)) + \beta V(h(k)) \tag{2.13}$$

Differentiating both sides of Equation (2.13) with respect to k:

$$V'(k) = u'(c)(f'(k) + (1-\delta) - h'(k)) + \beta V'(k')h'(k) \tag{2.14}$$

[21] We will not discuss here conditions under which this particular problem has a finite solution. Instead we will simply assume that a unique solution exists for every non-negative value of initial capital $k0$.

Using the first order condition (2.12) we get:

$$V'(k) = u'(c)(f'(k) + (1 - \delta)) \tag{2.15}$$

Postponing Equation (2.15) one period ahead and indicating with $u'(c')$ the next period's marginal utility of consumption, we can finally write the Euler Equation as:

$$\begin{aligned} 1 &= \beta \frac{u'(c')}{u'(c)} [f'(k') + (1 - \delta)] \\ &= \beta \frac{u'(f(k') + (1 - \delta) - k'')}{u'(f(k) + (1 - \delta) - k')} \left[f'(k') + (1 - \delta) \right] \end{aligned} \tag{2.16}$$

Equation (2.16) must hold for any three consecutive levels of asset (k, k', k'') in the optimal sequence $\{k_t^*\}_{t=1}^{\infty}$ which solves the deterministic version of the agent's problem (2.6-2.9).

In this deterministic setting the household is able to control everything, because we eliminated all the sources of risk. However, we are interested in understanding the impact of risk on the optimal choice of the household and measuring the welfare cost of the risk-induced changing behavior. It means that we need to compare the deterministic solution with the stochastic version of this growth model. In the Equation (2.7), we introduced two different sources of risk: one related to the income process and the other one to the asset accumulation process. As already explained, literature mainly focused its attention on understanding the impact of risk on capital accumulation (saving) introducing only an income shock. In the previous Paragraph, we saw that the introduction of income risk leads the household to change its consumption decisions by increasing saving. However, we also noticed that precautionary saving theory may lead to different conclusion when we consider lower-income countries. In particular, several authors pointed out that the impact on saving is less clear once we introduce risk also on the asset accumulation process

(Gunning, 2010; Dercon, 2005; Elbers, 2009) and we cannot establish ex-ante if the household is going to save more or less as response to the presence of risk. Then, in order to detect the impact of multiple sources of risk on household choice we need to use the stochastic version of the discrete-time Ramsey model.

The stochastic version of the model (2.6-2.9) implies to reformulate the decision problem in the framework of expected utility maximization. We can illustrate several differences with the deterministic case. First, both income and next period asset don't depend only on the current level of asset (k) but also on the realizations of two stochastic variables (A^y_t and A^k_t). We assume rational expectations: the household knows that both AR(1) error processes have an unconditional mean of zero, a standard deviation of σ_{A^y} and σ_{A^k} and a persistence parameter equal to ρ but they discover the real value of A^y_t and A^k_t only after their choice over k'. As consequence, the best strategy for the household is to maximize the expected value of his life-time utility using the probability distribution of the sequence of random variables $\{c_t\}_{t=0}^{\infty}$, given the information available at time 0 (Heer and Maussner, 2005).

As in the deterministic case, dynamic programming can be used to find the solution to the stochastic model. The value function $V(k, A^y_t, A^k_t)$ is now determined by three state variables, the level of asset (k) and the realizations of the two AR(1) error processes, A^y_t and A^k_t, and it can be written as:

$$\begin{aligned} V(k, A^y, A^k) = \max_{0 \le k' \le e^{A^y} f(k) + e^{A^k}(1-\delta)} \quad & u(e^{A^y} f(k) + e^{A^k}(1-\delta)k - k') + \\ & + \beta E[V(k', A'^y, A'^k) | A^y, A^k] \end{aligned} \tag{2.17}$$

where $E(.)$ indicates the expectation operator. The policy function associated with this problem is given by $k' = h(k, A^y, A^k)$. As for the deterministic case, dynamic programming delivers the stochastic Euler Equation. Differentiating $V(k, A^y, A^k)$ with respect to k' and following the same steps as in Equations (2.12)-(2.15), we get[22]:

$$1 = \beta E\left\{\frac{u'(c')}{u'(c)}[e^{A'^y}f'(k') + e^{A'^k}(1-\delta)] = \right.$$
$$= \beta E\left\{\frac{u'(e^{A'^y}f(k') + e^{A'^k}(1-\delta)k' - k'')}{u'(e^{A^y}f(k) + e^{A^k}(1-\delta)k - k')}[e^{A'^y}f'(k') + e^{A'^k}(1-\delta)]\right\} \tag{2.18}$$

We still have to specify the functional forms for the instantaneous utility function $u(c)$ and the production function $f(k)$. In the first case, we adopt the constant relative risk aversion (CRRA) function:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}$$

Where γ represents the coefficient of relative risk aversion. For what concerns the production function, we adopt a Constant Elasticity of Substitution (CES) function:

$$f(k) = (\alpha k^\theta + (1-\alpha))^{\frac{1}{\theta}}$$

Where k is the asset corrected by labor endowment, α indicates the asset share in the production process for a Cobb-Douglas case and θ the parameter which determines the elasticity of substitution between asset and labor ($\epsilon = 1/(1-\theta)$). It is worth to remember that one particular case of the CES production function is the Cobb-Douglas function, which is obtained when approaches to zero and, then, the elasticity of substitution to one.

2.3.2 Numerical Solution using Value Function Iteration

With these functional forms, the maximization problem has not an explicit solution as well as tractable closed forms (Blundell and Stoker, 1999). It means that we

[22] See Appendix 2.I

need to use numerical techniques that provide approximate solutions for solving the Bellman Equations (2.11) and (2.17) and finding the optimal sequence of the control variable. Among all the possible techniques developed by theory, we use the *Value Function Iteration*. This method works from the Bellman Equation to compute the value function by backward iterations on a initial guess (Adda and Cooper, 2003). Despite this method is slower compared to other techniques, it is trustworthy in that the solution can be reached by iterating the value function starting from an arbitrary initial value.

In order to avoid any useless repetition in the presentation, we describe only the stochastic case, which is a more general and complicated case with respect to the deterministic one. The first step is to discretize the state variable as well as the space of shocks. In other words we need to replace the original model with a model whose state space consists of a finite number of discrete points (Heer and Maussner, 2005). We first define a finite grid for asset k. Choosing a grid involves three choices: bound the state space between k_{min} and k_{max}, establishing the number of points in each dimension of the state space, and choosing the distance between each point. Assuming that the optimal sequence of asset stocks in the deterministic case monotonically converges to the stationary solution k*, it seems reasonable to assume that the minimum and the maximum levels of the asset include the steady state value, i.e. $K = \{k_{min}, k_2, ..., k^*, ..., k_{max}\}$. Leaving the choice of the number of points to the presentation of the simulation results, we impose also that the points are equally distributed in the interval $k_{min} - k_{max}$, with $k_{min} \geq 0$ in order to make the borrowing constraint works. The vector can be represented as:

$$\mathcal{K} = \begin{pmatrix} k_{min} \\ \vdots \\ k^* \\ \vdots \\ k_{max} \end{pmatrix}$$

Now we need to figure out how to calculate the expected value operator and discretize the two stochastic processes. Both the income and asset shocks follow an AR(1) process, which means that they are a first order Markov process. Information from period t is all we need to forecast the value of the shocks in period $t+1$. For computational purpose, the asset and income processes can be easily approximated with a finite-state Markov chain using Tauchen (1986) routine[23]. The routine produces a $S \times 1$ vector of grid points for A^y and a $M \times 1$ vector for A^k, as well as a $S{\times}S$ probability transition matrix for the income shock process (Π^y) and a $M \times M$ transition matrix for the asset shock process (Π^k), i.e.:

$$A^y = \begin{pmatrix} a_1^y \\ \vdots \\ \vdots \\ a_s^y \end{pmatrix} \qquad A^k = \begin{pmatrix} a_1^k \\ \vdots \\ \vdots \\ a_m^k \end{pmatrix}$$

$$\Pi^y = \begin{pmatrix} \pi_{11}^y & \cdots & \pi_{1s}^y \\ \vdots & \ddots & \vdots \\ \pi_{s1}^y & \cdots & \pi_{ss}^y \end{pmatrix} \qquad \Pi^k = \begin{pmatrix} \pi_{11}^k & \cdots & \pi_{1m}^k \\ \vdots & \ddots & \vdots \\ \pi_{m1}^k & \cdots & \pi_{mm}^k \end{pmatrix}$$

After the discretization we have one state variable (k) and two exogenous variables (A^y, A^k) which implies that the value function V and the policy function H

[23] See appendix 2.II

are two $(N \times S \times M) \times 1$ vectors where each row indicates a different combination of asset k and pair of shocks (a_s^y, a_m^k).

$$V(K, A^y, A^k) = \begin{pmatrix} V(K_{min}, a_1^y, a_1^k) \\ \vdots \\ V(K_{max}, a_1^y, a_1^k) \\ V(K_{min}, a_1^y, a_2^k) \\ \vdots \\ V(K_{max}, a_1^y, a_2^k) \\ \vdots \\ V(K_{max}, a_1^y, a_m^k) \\ V(K_{min}, a_2^y, a_1^k) \\ \vdots \\ V(K_{max}, a_s^y, a_m^k) \end{pmatrix} \qquad H(K, A^y, A^k) = \begin{pmatrix} H(K_{min}, a_1^y, a_1^k) \\ \vdots \\ H(K_{max}, a_1^y, a_1^k) \\ H(K_{min}, a_1^y, a_2^k) \\ \vdots \\ H(K_{max}, a_1^y, a_2^k) \\ \vdots \\ H(K_{max}, a_1^y, a_m^k) \\ H(K_{min}, a_2^y, a_1^k) \\ \vdots \\ H(K_{max}, a_s^y, a_m^k) \end{pmatrix}$$

The problem we have now is to determine V iteratively. The way to proceed is constructing a sequence of value functions and associated policy functions applying the following basic algorithm:

1. We choose an initial guess of $V^i(k', A'^y, A'^k)$ which is, in our case, a $(N \times S \times M) \times 1$ vector of zeros;

2. We update the value function using the following discrete-valued version of the Bellman Equation:

$$\begin{aligned} V_{i,s,m}^{i+1} = \max_{\{k' \in K\}} & u(e^{Ay} f(k) + e^{A^k}(1-\delta)k - k') + \\ & + \beta \sum_{a'^y \in A^y} \sum_{a'^k \in A^k} \pi(a'^y, a'^k | a^y, a^k) V^i(k', A'^y, A'^k) \end{aligned} \tag{2.19}$$

where $\pi(a'^y, a'^k | a^y, a^k)$ is the joint $(S \times M) \times (S \times M)$ transition matrix for asset and income shocks[24].

Specifically:

i) we fix the current asset and the two shocks at one of the possible grid points combination, beginning with (k_{min}, a_1^y, a_1^k);

ii) for each possible choice of next-period asset we calculate the value of the $(N{\times}S{\times}M){\times}K$ matrix $V^{i+1}_{(i,s,m),j}$ as follow:

$$V^{i+1}_{(i,s,m),j} = u(e^{A^y_s} f(k_i) + e^{A^k_m}(1-\delta)k_i - k'_j) + \beta E V^i$$

Each element of the matrix represents the value of the RHS of Equation (2.19), given the initial combination of the three state variables (k, A^y, A^k) and the respective choice of next-period asset, $V^{i+1}_{i,s,m} = \left\{ V^{i+1}_{(i,s,m),j} \right\}_{j=min}^{max}$

3. We find the location of the maximum of $V^{i+1}_{i,s,m}$ and store it as the i–th element of the updated value function. We also store the index of the next–period asset maximizer as the i–th element in the policy vector H. We repeat the operation for each possible initial combination of asset and shocks;

4. If $|V^{i+1}(k, A^y, A^k) - V^i(k, A^y, A^k)| < \epsilon$, with $\epsilon > 0$, we have solved the problem and we obtained the numerical estimates of the value and policy functions. If not, we use the computed $V^{i+1}(k, A^y, A^k)$ as new guess for $V^i(k, A^y, A^k)$and come back to step 2.

Under several conditions [25], the value function V^* which solves the above fixed point problem exists and it is unique (Stokey and Lucas, 1989). We also know that if we iterate the procedure many times the value function will converge monotonically to the V^*. It means that after many iterations, each subsequent iteration no longer

[24] We can do this because we assumed that the two AR(1) shocks are not cross-correlated.

[25] Among which beta has to be less than 1

changes our guess, i.e. $\lim_{n\to\infty} ||V^{n+1} - V^n|| = 0$. The fact that value function iteration will eventually converge for virtually any initial guess, make value function iteration a very stable algorithm.

2.3.3 Calibration

Since we are interested in understanding the impact of risks on the household behavior in a poverty context, it seems reasonable to calibrate the parameters using previous studies on developing countries. All the parameters are calibrated on a yearly basis. The definition of the discount factor β poses no problems. Usually, it is set between 0.95 and 0.97, for both developing and developed countries (Pallage and Robe, 2003) even if Ostry and Reinhart (1992) finds that for the least developed countries in Africa the discount factor may be smaller, i.e. 0.94. Considering that varying the discount factor between the range 0.94-0.97 doesn't provide any meaningful change in the simulation results, we choose the most common value of 0.95 which implies an approximate discount rate of 0.05,

More difficult is to define the coefficient of relative risk aversion γ, because of the lack of consensus in the empirical literature. The large body of studies provides widely dispersed results. For example, Morduch (1990) and Rosenzweig and Wolpin (1993) estimate a low rates of 1.39 and 0.964 for households in the ICRISAT villages. Fafchamps and Pender (1997) estimate relative risk aversion of 2.8 to 2.9 for households in Kanzara village in India (ICRISAT). Alderman and Paxson (1994) provides an interesting survey on a series of studies which estimated the risk aversion using different techniques. In particular, some of these studies estimated the CRRA coefficient observing allocation decisions and their difference with profit maximization (Antle, 1987 and Hezell, 1982) while other authors conducted experiments in which poor farmers choose among a set of gambles with non-trivial payoffs (Binswanger, 1980; Binswanger and Siller, 1983 and Grisley and Kellog, 1987). Both methodologies seems to support the idea of moderate amounts of risk aversion in developing countries, with γ between 1 and 2. Other studies using data on insurance produce estimates of γ ranging from 2 to 10 (Walley, 2009) while Schechter (2007) shows some cases where the implied coefficients of relative risk aversion are absurdly high[26] . Despite these few exceptions, Carroll (2009) suggests that a plausible range for the value of γ should be between 1 and 5. In the baseline simulation, we decide to be cautious and follow the most common strand of studies setting the baseline value of γ equal to 2[27] .

Calibrating the CES production function means to set the values of the elasticity of substitution parameter θ and the distribution parameter α. In the last 50 years, much empirical evidence suggests that the Cobb-Douglas version of the CES production function is a reasonable representation of the reality. This would imply the choice of θ equal to zero and an elasticity of substitution between asset and labor equal to one (see, for example, Lucas, 1988; Barro, 1990; Jones, 1995). However, recent authors suggested a modification to the econometric approach to the estimate of the CES parameters, leading to the conclusion that the range of ϵ is 0.5-0.7 (see Turnovsky, 2008, Antras 2004; Klump and Saam, 2008). Particularly interesting in our case is the work of Duffy and Papageorgiou (2000) who estimate the elasticity of substitution using cross-sectional data by groups of countries. Their results show that ϵ exceeds the unity for rich countries, but it is less than unity for low income countries. In other words, their estimate suggests that in developing countries with a low level of per-capita physical capital, asset and labor can be considered as more complementary to production than would be in the case of a Cobb-Douglas production function. Following Duffy and Papageorgiou (2000), we set the baseline value of θ to -0.21, which implies an elasticity of substitution equal to 0.83.

[26]For example, Binswanger (1980) reports much higher rates of 6.98 to 18.8 using experimental data from Indian farmers.

[27]We also use other values of - between 1 and 3 - and show how the results are influenced by the value of the relative risk aversion coefficient.

The parameter α indicates the capital share of output in the Cobb Douglas case. Even if the interpretation of this parameter is no longer so straightforward in a more CES general case, we follow the common practice to set α as if it is indicating the asset share in the production process (Klump,2008). Estimates by Gollin (2002) suggest that the asset share is roughly constant within countries and time, without any relationship to the level of economic development. The plausible range seems to be from 0.2 to 0.4. However, there is still some evidence that confirms a higher value of asset share for poor countries with respect to rich countries (Gollin, 2002). It allows us to set the value of the parameter α equal to 0.4, which is the upper bound of the reasonable range [28]. Finally, we choose a depreciation rate δ equal to 0.08, which is in line with the empirical studies on developing countries (Schundeln, 2007).

The last part of the calibration implies to define shocks approximation together with their persistence (ρ) and their variances $\sigma^2_{A^y}$ and $\sigma^2_{A^k}$. Considering we have to simulate a model with one state variable and two exogenous variables, we prefer to choose a limited number of possible realizations for A^y and A^k, in order to avoid the well-known curse of dimensionality problem. We approximate both AR(1) shock processes by a four-state Markov chain (VERY LOW, LOW, HIGH, VERY HIGH)[29]:

$$A^y = \begin{pmatrix} a^y_{VL} \\ a^y_L \\ a^y_H \\ a^y_{VH} \end{pmatrix} \qquad A^k = \begin{pmatrix} a^k_{VL} \\ a^k_L \\ a^k_H \\ a^k_{VH} \end{pmatrix}$$

We also assume high persistence in income and asset process, with a common

[28]We test also the lower bound imposing equal to 0.2 and the results show to be not sensitive to this choice.

[29]The higher is the number of shock realization and the more precise is the approximation of the AR(1) process. Literature provide a large variety of examples, and the grid of shocks is usually in a range from 2 to 10. We prefer to keep the number of shocks quite low because we have two stochastic processes and a higher number of realizations is quite time-consuming.

parameter ρ equal to 0.95. Literature doesn't provide enough information to differentiate the parameter ρ between the two processes, as well as it seems quite difficult to determine if there is any difference between developed and developing countries. Even if we don't have an empirical counterpart which can help us to determine the level of persistence in a poverty context, using an high level of autocorrelation allow us to better explore the difference between model with log-normal shocks (Elbers, 2009) and model with AR(1) shock processes. Furthermore, we assume that the standard deviation of the *i.i.d.* component in the income (σ_{ϵ^y}) and asset (σ_{ϵ^k}) error processes are equal to, respectively, 0.1 and 0.2. Empirical evidence seems to support the idea that in developing countries asset are more volatile than income, mainly because asset have multiple functions in traditional economies, i.e. they are at the same time the input for production, the good used for postponing consumption and mean for saving. As consequence, assets are more exposed to risk and vary more frequently [30].

2.3.4 The Results

In this section we present the simulation results for the deterministic and stochastic models, calibrated with the above-mentioned baseline parameters and an asset grid K of 500 points. First, we begin with the deterministic case. Figures 2.1 and 2.2 show the value function and the policy function of the model when risks are absent. The value function is a concave increasing function of individual asset as well as the policy function for next-period asset has a positive and less than unity slope. The policy function crosses the 45° line from above and therefore there is a unique non-zero steady state and the state variable converges towards its steady state, i.e. $k^* = 4.2068$, regardless the initial asset endowments.

[30] The unconditional standard deviation of the processes are calculated as $\sigma^2_{A^y} = \sqrt{\sigma^2_{\epsilon^y}/(1-\rho^2)}$ and $\sigma^2_{A^k} = \sqrt{\sigma^2_{\epsilon^k}/(1-\rho^2)}$

Figure 2.1

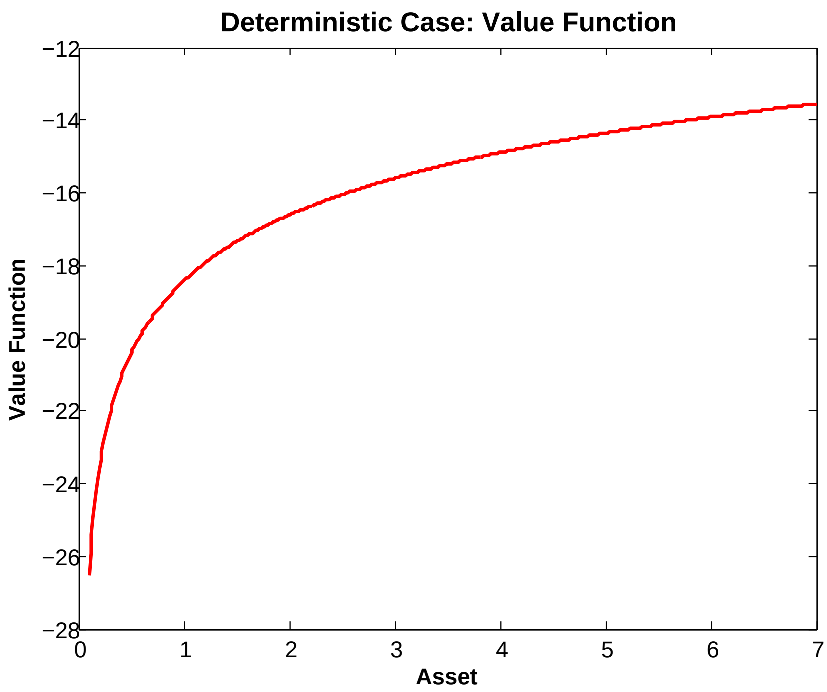


Figure 2.2

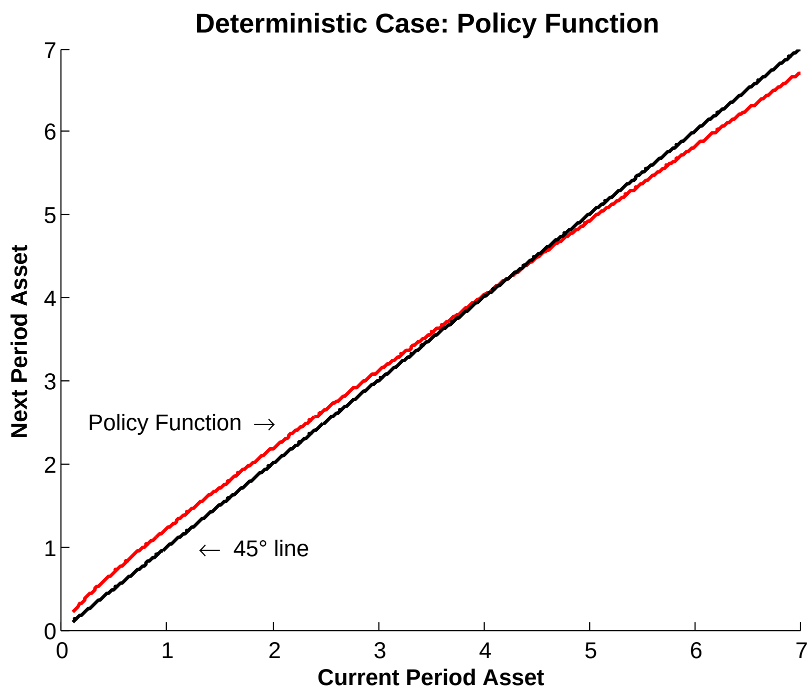


Figure 2.3

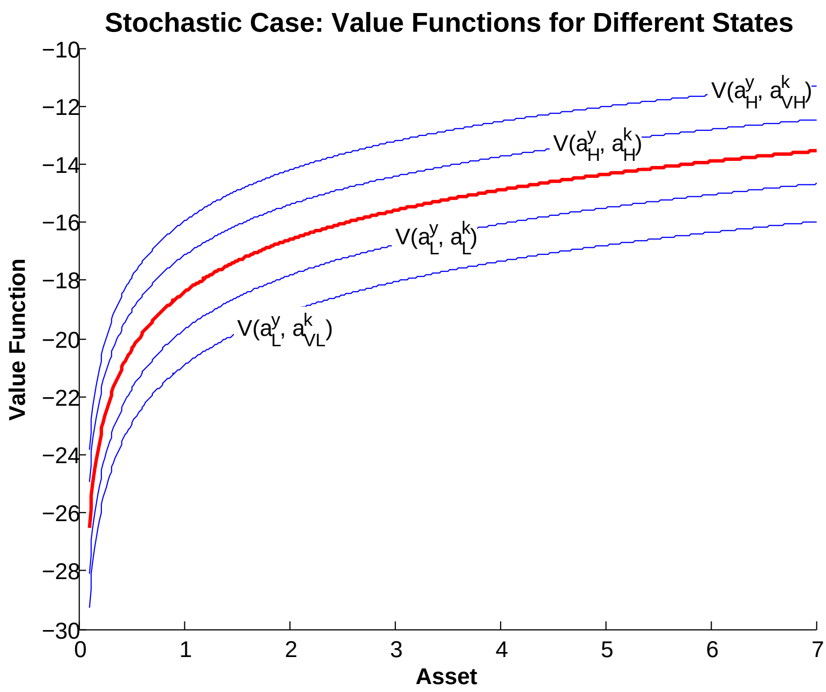
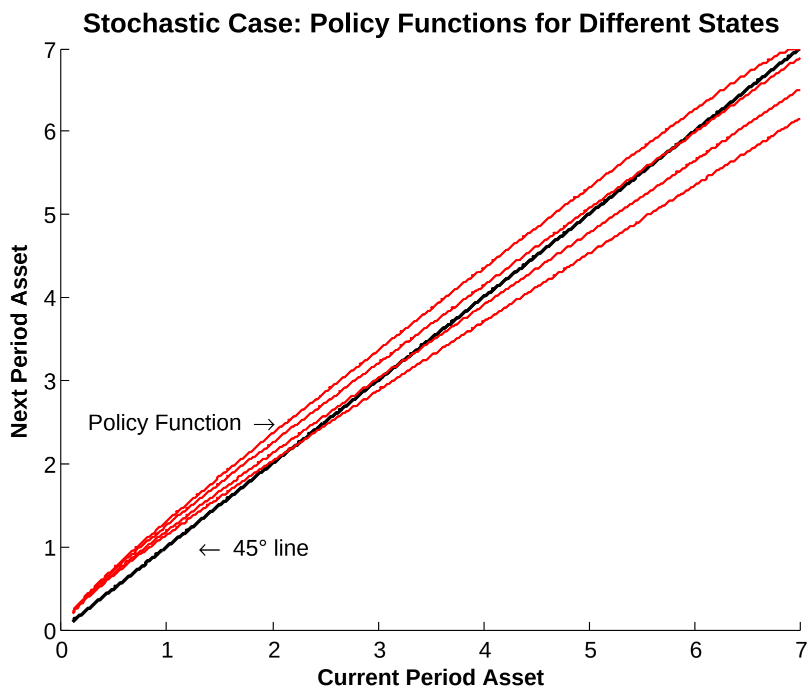


Figure 2.4



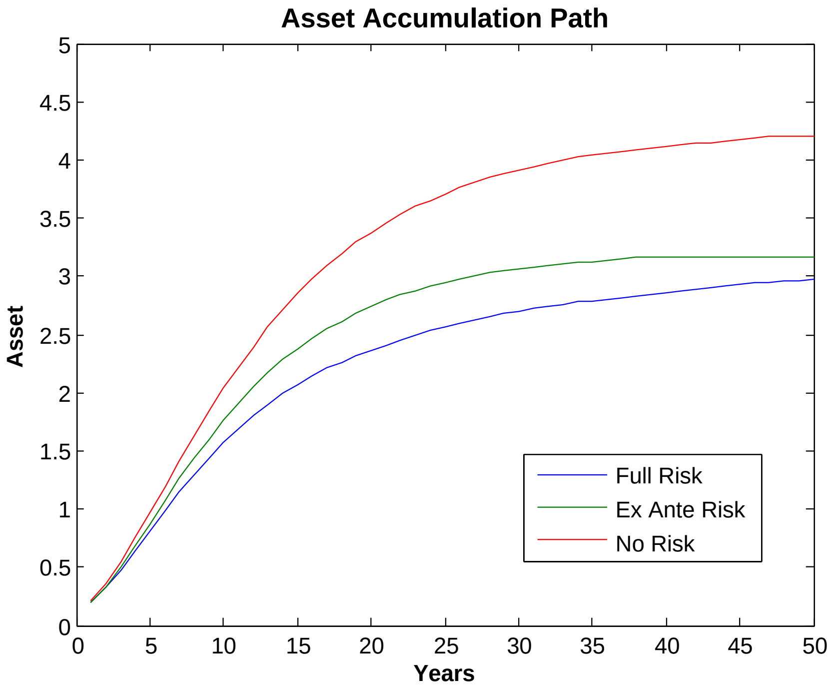
For what concerns the stochastic simulation, Figure 2.3 depicts the value function for different states corresponding to different pairs of shocks. As for the deterministic case, all the value functions are concave and increasing in the initial value of asset. The higher the level of the two shocks, the higher the value of the function. In particular, we can see how the value function is below the deterministic case when we consider a pair of bad shocks while the function is above the deterministic case when we consider positive pairs of shocks. Figure 2.4 shows the different policy functions for different level of shocks. Again, the higher the level of the two shocks and the higher the optimal asset choice for the household, regardless of its initial condition. The fact that all the policy functions crosses the 45° line seems to indicate that we have an unique and invariant solution also in the stochastic model.

In Paragraph 1.4 we point out that measuring vulnerability means assessing the future level of the household's welfare in order to evaluate its chances of being below some pre-determined poverty threshold. If the threats of future poverty is significant, the following step is decomposing the welfare cost between the poverty line and the future consumption caused by the structural characteristics of the household, from the negative impact of risk realizations or the risk-induced changing behavior triggered by the precautionary motive. For separating the last two elements from the other, the first step is to calculate the total contribution of risk to vulnerability and then isolate the welfare cost induced specifically by the changing behavior. This operation can be done using the method already applied by several authors (Elbers et al. 2007, Elbers et al. 2009, Carter and Ikegami, 2009) which consists of a comparison between simulated asset and consumption processes. In particular, we first simulate asset, consumption and welfare paths for a 50-year period under the assumption that the household lives in a deterministic context. Considering that we are interested in the impact of risk on the transitional dynamics of poor households, the simulation will be carried out on a representative household with the lowest level of initial asset endowment ($k_0 = k_{min}$). In the deterministic case the simulation implies just to follow the simple policy rule for next-period asset as function of the current period asset. For each period, once we know the optimal level of current and next period asset we can also calculate the optimal level of current consumption, following the budget constraint in Equation (2.7). In turn, from the evolution of consumption we can simulate the welfare path plugging the consumption level into the CRRA utility function used in the numerical simulation of the model. Secondly, we repeat the same steps under the full stochastic hypothesis. It means that - starting again from the lowest level of initial asset and from a randomly selected pair of shocks - we follow the stochastic policy rule $k' = h(k, A^y, A^k)$ for determining the optimal choice of k' and, as consequence, the optimal level of current consumption and welfare. Unlike the deterministic case, each period the household experiences the two shocks on the income and asset according to the probabilities of the Joint Transition Matrix π. We perform the same simulation 1000 times and, for each period, we take the average. The total effect of risk (TER) for the 50-year period is calculated as the sum of the discounted differences – in terms of utils – between each period deterministic $U(c_t^{DET})$ and stochastic $U(c_t^{FS})$ expected utility, i.e.

$$TER = E_0 \sum_{t=0}^{50} \beta^t [U(c_t^{DET}) - U(c_t^{FS})]$$

This procedure still doesn't shed enough light on the causes of these losses. For example, when we observe a household with a low level of c_t^{FS}, we don't know if it experienced a series of very bad shocks or if it made some wrong investment decisions. In other words, we don't know if the poor performances are determined by the negative impact of shocks or by the risk-induced changing behavior. The better way to separate the impact of risk-induced changing behavior from the exposure to shocks is to calculate the ex-ante and ex-post effect of risks[31]. As explained by Carter and Ikegami (2009), the ex-post effect of risk come about because negative events may destroy assets, forcing the household to additional savings and asset re-accumulation to come back on the expected consumption path.

Figure 2.5



Indeed, the ex-ante effect of risk influences the household's behavior through its subjective anticipation of what future shocks might be and generates a potentially harmful sense of insecurity. In order to introduce in our model the distinction between ex-ante and ex-post effect of risk on household's welfare, we re-simulate the asset, consumption and welfare paths as we did in the full-stochastic case, with the difference that now no shocks are actually realized. In other words, the household

[31]It is worth to remember that in this case the terms ex-ante and ex-post have nothing to do with the ex-ante and ex-post strategies to mitigate risk we mentioned before in the first and second chapters. In that case we referred to ex-ante and ex-post household behavior (risk management and risk coping strategies) while in this case we are referring to the ex-ante and ex-post effects of risk on welfare.

Figure 2.6

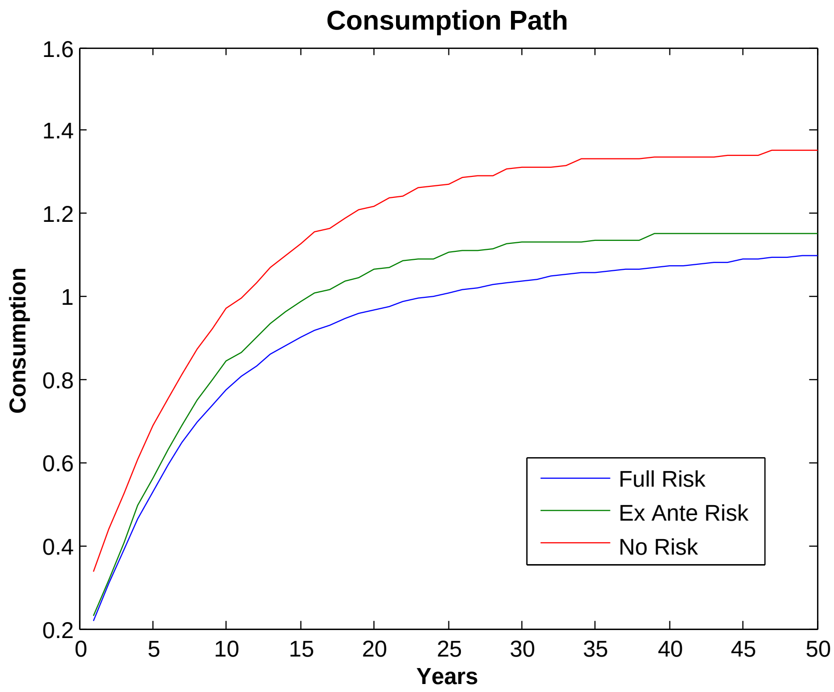
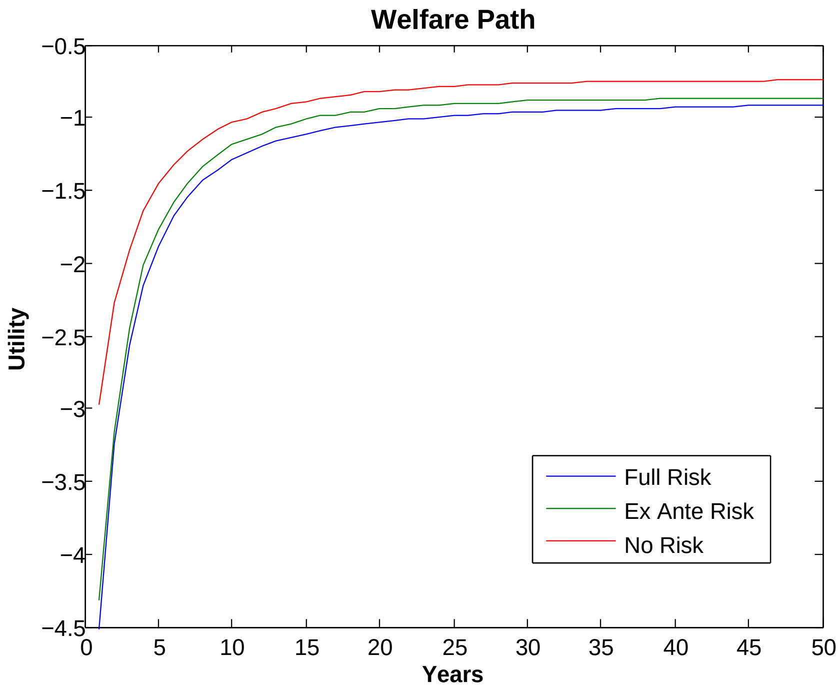


Figure 2.7



behaves as if shocks are expected to occur but they never hit the income or the asset processes. Now we can break down the TER considering the ex-ante impact of risk on welfare as the discounted differences, in each period, between the $U(c_t^{DET})$ and their ex-ante counterfactuals $U(c_t^{EA})$. The residuals $U(c_t^{EA}) - U(c_t^{FS})$ measure the ex-post effect, i.e.:

$$TER = E_0 \sum_{t=0}^{50} \beta^t \left\{ \underbrace{[U(c_t^{DET}) - U(c_t^{EA})]}_{\text{Ex-ante Effect}} + \underbrace{[U(c_t^{EA}) - U(c_t^{FS})]}_{\text{Ex-post Effect}} \right\}$$

Figures 2.5, 2.6 and 2.7 show the results using the baseline calibration previously illustrated. For this particular model, the deterministic path of asset is constantly above the full-stochastic counterfactual, implying that the impact of risk on saving is largely negative. This is a major difference with the standard model of precautionary saving where, introducing just a normally distributed income risk, the impact on savings can only be positive (Elbers et al. 2009)[32]. In Figure 2.5, which depicts the asset accumulation process for the three different counterfactuals, we can see that after a 50-year simulation period the level of asset in the full-stochastic case is about 30% lower than its deterministic counterpart (2.9791). Moreover, in the last period of the simulation, the ex-ante level of asset is equal to 3.1697, 25% lower than the deterministic case. The total distance between no-risk and full stochastic-risk cases (1.23) can be further decomposed: 16% depends on the ex-post effect while the 84% depends on the ex-ante effect. It is worth to note that this result is specific to our baseline simulation, which is calibrated using the parameters provided by literature on developing countries. However, there might be other cases where the impact of risk on asset accumulation is not so straightforward. We can have a positive ex-ante impact of risk on saving and a contemporary negative ex-post effect, as well as the

[32]See appendix 2.III

opposite. This result is in line with Gunning (2010) who demonstrates that the introduction of a second source of risk in a standard precautionary saving model leads to ambiguous results which cannot be predicted in advance.

Figure 2.6 shows the consumption path under the three different circumstances. The analysis of the consumption path is usually overlooked by literature and numerical simulations just provide evidence on the asset accumulation path and saving decisions. However, considering the complexity of the model given by the two sources of risk and that we are interested in measuring the impact of risk on the household's welfare, it is worth to pay attention to the consumption paths under the three hypotheses. Once more, the deterministic path is well-above the full stochastic case and the ex-ante impact of risk seems to play the most important role. This result is again in contrast with the saving and consumption results provided by literature on precautionary saving. With one source of risk the consumption path is usually lower in the first years – as consequence of higher savings – but its growth rate is higher with respect to the deterministic case, leading to higher consumption levels in the last lifetime periods[33]. However, once we eliminate the unrealistic hypotheses that the asset accumulation process in the developing world is risk-free and we modify the consideration on the persistence of the shocks, using AR(1) processes, we have that the presence of risk has a long-run impact on the well-being of the poorer households. In our simulation, the consumption path at the end of the 50-year period in the full-risk case is about 20% less than the no-risk case and the 80% of this difference depends on the ex-ante effect of risk. Finally, Figure 2.7 reports the welfare path and confirms the ranking of the other two Figures: the perception of risk can be by itself a source of future welfare loss and can potentially contribute to increase the household's vulnerability. In particular, the changing behavior triggered by an increase in the sources and the magnitude of risk in the economic system could lead

[33]See Appendix 2.III

to a consumption path permanently lower than the deterministic case, implying a cost in terms of welfare which doesn't depend on the effective realizations of shocks.

2.4 Towards a new Measure of Vulnerability to Poverty

The results presented in the previous Paragraph demonstrate that the effect of risk on the household's welfare is not straightforward and it is composed by different elements. In this section we use these results to propose a new vulnerability measure which is able to take into consideration the main shortcoming of existing analyses, i.e. the lack of a solid micro-foundation. Moreover, we use the results of the numerical simulation to provide a sensitivity analysis to explain how the new measure is influenced by factors like risk aversion, persistence of the error process and the distribution of shocks.

2.4.1 The Micro-Founded Measure

We start from the model proposed by the work of Elbers and Gunning (2003). The authors are the first to acknowledge the role of ex-ante and ex-post risk in the framework of vulnerability analysis, but they didn't explicit model a new measure based on this distinction. Using a stochastic simulation similar to the analysis carried out in Paragraph 2.3[34], they assume that vulnerability at time t is the shortfall of perceived welfare (U) from the welfare level the household would attain if its consumption would be equal to the poverty line in every period:

$$V_{ht} = U(z) - U(c_{ht}^{FS}) \text{ for } \forall \text{ t} \tag{2.20}$$

[34]Despite the similarities, the simulation they perform is different for several reasons. First of all, they don't consider AR(1) shocks, assuming that the income and asset shocks are normally distributed and cross-correlated. They allow for differences in the productivity levels among households and calibrate their model using data from Tanzania. Their calibration makes their model a particular and less general case with respect to our simulation, which is calibrated on more reasonably and largely accepted parameters.

Where c^{FS} is the consumption level in the full stochastic case at time t. Following the ex-ante/ex-post decomposition technique we can further decompose the *instantaneous* vulnerability measure adding and subtracting the welfare level obtained from two consumption counterfactuals:

i) C^{DT}, which is the amount of consumption we would obtain in a deterministic context;

ii) C^{EA}, which is the consumption level we would have if the household correctly perceives the distribution of asset and income shocks but never actually experience them, i.e. the ex-ante consumption counterfactual.

Rearranging the six terms we can write the vulnerability measure for household h at time t as:

$$V_{ht} = [U(z) - U(c_{ht}^{DT})] + [U(c_{ht}^{DT}) - U(c_{ht}^{EA})] + [U(c_{ht}^{EA}) - U(c_{ht}^{FS})] \tag{2.21}$$

The first squared bracket term measures the contribution of poverty to vulnerability which is due to the characteristics of the household, i.e. the structural component of vulnerability. This term is similar to the poverty component of vulnerability proposed by the VEU approach. The second term measures the contribution of the presence of risk on the vulnerability index and this is the term which captures the cost caused by the changing behavior. Finally, the last term measures the impact of realized shocks due to the household's exposure to risk.

To further refine our index, we pay attention to another issue overlooked by current literature on vulnerability. As shown in the previous Paragraph, the welfare cost of changing behavior cannot be considered in a static and timeless framework, because it evolves over time. Calvo and Dercon (2007b) point out that measuring poverty over time means defining a series of criteria which allow us to assess the different trajectories of the standard of living. Granting to the household the gift of perfect foresight, the same concept can be applied when we construct a forward-looking and dynamic measure of vulnerability, with the only difference that in each period we need to take care of the different states of the world instead of a single realization as in a risk-free poverty context. Despite the literature provides different measures and methodologies for assessing poverty over time, the work of Calvo and Dercon (2007b) seems to be the more suitable to our purpose[35].

The authors illustrate the possible normative choice to be made on specific alternative axioms in order to evaluate different time-trajectories. In particular, there are three key decisions to be made which will influence the result of the analysis. The first decision regards the *Focus Axiom.* We need to decide if there is any *compensation* of vulnerability spells by non-vulnerability spells. In static poverty, across individuals, the issue is usually solved by considering the non-poor's outcome as if they just have reached the poverty line (see for example FGT measure) while in static vulnerability analysis the same logic is applied across states of the world. In fact, using Calvo and Dercon (2007b) words, *"..If vulnerability is understood as a burden caused by the threat of future poverty, it should not be compensated by simultaneous (ex ante) possibilities of being well off.."*. Despite using the same concept over time is more difficult to motivate because expected bad spells may be thought to be less harmful if they are followed by expected good spells, we prefer to apply the focus axiom also over time. Rephrasing Calvo and Dercon (2007b), we assume that spells of expected poverty may cause shock and distress to such an extent that they would leave an indelible mark on the household's welfare path. This intuition is also justified by the assumption made over the AR(1) shock processes, because the household knows that an expected bad outcome for its consumption is probably followed by several other periods of hardship.

[35]For more information on the recent debate, see Foster (2007), Hoy and Zheng (2009), Bossert (2010), Mendola (2010).

The second decision is over *transformation.* It means that we need to find a functional form for the index which ensures that a transfer of consumption from a very poor spell to a not-so-poor spell results in greater vulnerability[36]. Formally, we need to respect the following relation:

$$V_h(c_{h1}^{FS}, ..., c_{hk}^{FS}, ..., c_{hn}^{FS}) - V_h(c_{h1}^{FS}, ..., c_{hk}^{FS} + d, ..., c_{hn}^{FS}) >$$
$$V_h(c_{h1}^{FS}, ..., c_{hk}^{FS} + d, ..., c_{hn}^{FS}) - V_h(c_{h1}^{FS}, ..., c_{hk}^{FS} + 2d, ..., c_{hn}^{FS}) \text{ for } d > 0$$

In other words, consumption must be transformed at some point by a strictly convex function and the easiest way is to use a CRRA utility function[37]. The third decision relates to the *aggregation* choice because we need to combine each realization of V_{ht} into one single measure. We decide to sum up the different spells using the discount factor β as weight, in order to give more importance to the imminent threats of poverty.

Besides the three different decisions over the axioms, we need also to determine the sequence of these decisions, because it influences the final measure. For example, if we aggregate before transformation and focus we implicitly accept compensation across time and there is not increasing cost of hardship. The best sequence to follow in order to keep all the characteristics we want in our measure, is: 1) transforming the full-stochastic consumption into an instantaneous vulnerability index; 2) applying the focus axiom to avoid compensation across time; 3) aggregating over the different periods[38]. With this order we have the following vulnerability measure:

[36]Of course, this is valid only if we assume equally valued spells.

[37]From an analytical point of view, it means that $V'(c^{SC}) < 0$ and $V''(c^{SC}) > 0$. If we apply a CRRA function to U in Equation 2.20, we have that $V'(c^{FS}) = -(c^{FS})^{-\gamma}$ while $V''(c^{FS}) = \gamma(c^{FS})^{-(1+\gamma)}$. For more information on the argument, see Ligon and Schecter (2004).

[38] This corresponds to the T-F.A hypothesis presented by Calvo and Dercon (2007b)

$$V_h = \sum_{t=0}^{T} \beta^t T_t \left\{ [U(z) - U(c_{ht}^{DT})] + [U(c_{ht}^{DT}) - U(c_{ht}^{EA})] + [U(c_{ht}^{EA}) - U(c_{ht}^{FS})] \right\} \tag{2.22}$$

$$\text{where } T_t \begin{cases} 1 \text{ if } [U(z) - U(c_{ht}^{FS})] \geq 0 \\ 0 \text{ if } [U(z) - U(c_{ht}^{FS})] \leq 0 \end{cases}$$

T_t is an indicator function which allows us to consider only the spells where the vulnerability index is not negative, which means also that the consumption is not above the poverty line. Instead, if the vulnerability measure is positive or equal to zero, we decompose it in the above-mentioned three components: poverty component, ex-ante component (due to changing behavior) and ex-post component (due to shocks).

It is worth to note how the proposed index is comprehensive of and consistent with the most up-to-date analyses on the impact of risk on consumption and it also provides a solid micro-foundation to the vulnerability analysis, which is the main shortcoming of the current approaches. The main added value is to provide a decomposition able to disentangle the structural component of the vulnerability from the impact of household's exposure to risk and the effect of the risk-induced changing behavior, enabling the policymakers to design more suitable poverty alleviation schemes. As pointed out by Chaudhuri (2003), the primary aim of vulnerability is helping to better understand the distinction between ex-ante prevention interventions and the ex-post alleviation interventions. In particular, vulnerability analysis should be an instrument for both preventing shocks to cause irreversible damages such as distress of productive assets, reduction of calories intake, decrease in education investment and - at the same time - avoiding that erroneous risk coping and mitigating strategies exacerbate the potentially harmful consequences of uncertainty. The measure proposed in Equation (2.22) is able to catch the relative importance of both aspects on the household's well-being and - as consequence - could favor a better distribution of resources to more effective poverty reduction programs.

2.4.2 Simulation Results and Sensitivity Analysis

In this Paragraph we apply the new definition of vulnerability provided by Equation (2.22) to the results of the stochastic simulation in Paragraph 2.3. We will also alter the risk-related parameters - i.e. the coefficient of relative risk aversion, the persistence and the standard deviation of shocks - in order to analyze how the household changes its behavioural responses with respect to a modification of the stochastic environment. We start assuming that the deterministic path of consumption is equal to the poverty line in each period t. It allows us to rule out the first term of the Equation (2.22) and to focus the analysis on the ex-ante and ex-post components of the measure. Using the baseline parameters reported in Paragraph 2.2, the total vulnerability is equal to 7,1091 utils and the relative weight of the ex-ante component is much higher that the ex-post component. In particular, the ex-ante component seems to account for 70% of the total vulnerability, denoting how the effect of changing behaviour is the most important part of the vulnerability analysis. This result is constant over the entire sensitivity analysis, conforming its robustness. For what concerns the role played by the shocks persistence, Table 2.1 shows that reducing the parameter for the asset process by almost 50% (from 0,95 to 0,50) has the consequence to reduce total vulnerability by almost 20%, i.e. to 5,7060 [39]. This result confirms the important role played in the vulnerability analysis by the structure of the shocks we consider. Since now literature overlooked the shock process simply assuming a normal distribution for modelling the error component of the consumption.

[39]The simulation relates only to a reduction in the persistence of the asset shock. A further reduction in the persistence of the income shock would reinforce this results.

Table 2.1: Vulnerability Measure for a 50-year Simulation

Parameters	($\rho_y = \rho_k = .95$)			($\rho_y = .95$ and $\rho_k = .50$)		
$\sigma_y = .01$ and $\sigma_k = .02$	**Total**	**Ex-Ante**	**Ex-Post**	**Total**	**Ex-Ante**	**Ex-Post**
$\gamma = 1$	5,1071	3,7296	1,3775	3,9563	2,9849	0,9715
$\gamma = 2$	7,1091	5,2966	1,8125	5,7060	4,5599	1,1462
$\gamma = 3$	12,0296	9,0225	3,0041	10,2374	8,1015	2,1360
$\sigma_y = .015$ and $\sigma_k = .03$	**Total**	**Ex-Ante**	**Ex-Post**	**Total**	**Ex-Ante**	**Ex-Post**
$\gamma = 1$	6,4260	4,6478	1,7782	5,1040	3,5687	1,4453
$\gamma = 2$	9,0327	6,4099	2,6228	7,0640	5,2775	1,7865
$\gamma = 3$	15,7844	10,7601	5,0244	12,7933	9,2971	3,4962

The stochastic simulation demonstrates that without considering the serial correlation in the analysis we may actually underestimate the overall amount of vulnerability [40]. Table 2.1 also confirms us that the higher household's aversion to risk, the higher the vulnerability index, coherently with the results of Ligon and Schecter (2003). In our baseline simulation the coefficient of relative risk aversion, γ, is equal to 2. We run the same simulation using other two different values of the coefficient: $\gamma = 1$ - which implies a logarithmic utility function - and $\gamma = 3$. Keeping constant all the other parameters, we can see how an increase in the CRRA coefficient leads to an increase in the vulnerability index from 7,1091 to 12,0296, which is a raise of almost 70%. At the same time, a reduction of the CRRA coefficient from 2 to 1 leads to a decrease of 28%, showing that the relation between γ and the index is increasing but non-linear. The household's degree of risk aversion is, then, a major determinant of the vulnerability index and has an important effect in terms of expected welfare. This finding is in line with the literature which analyzes the link

[40] In Chapter 3, we see that the assumption of normal distribution for the asset and income errors is ruled out also by the empirical evidence in favour of an AR(1) process

between risk and poverty. For Dercon (2005), risk aversion may explain differences in portfolio's across households and poor households may stay poor in the long run just because they are extremely risk averse.

The last element to analyze is the impact of an increase in risk on the vulnerability measure. The increase in risk is meant as a mean-preserving spread in the distribution of ϵ_y and ϵ_k and the results are showed in the lower part of the Table 2.1[41]. Both the standard deviation of the income and asset errors are increased by 50% and, as consequence, the vulnerability raises from the baseline value of 7,1091 to 9,0327, which is an increase of 27%. It is evident from this result that the impact of risk on the household's expected welfare is negative. As already pointed out by Elbers et al. (2009), the literature is still far from accepting this result and it depends on the model we adopt and our assumption on the household risk aversion. As we saw in Paragraph 2.1, the effect of risk on savings is usually positive and the precautionary savings motive (Deaton, 1992; Kimball, 1990) is exacerbated by the degree of risk aversion: the more risk averse the household, the larger is its incentive to save in order to increase its optimal consumption path (Dercon, 1998). In fact, saving provides for the accumulation of asset which, in turn, produces additional income that can be used for consumption in the future (Gersovitz, 1988). If labor income is the only stochastic component of the household's wealth, the effect of risk on welfare seems to be at least non-negative in the long-run thanks to the consumptions smoothing strategy.

However, the effectiveness of this strategy is reduced for poor in developing countries because of the circumstances they face. The lack of integration of asset market and the difficulties the poor face in obtaining access to internationally traded assets limit their portfolio choices (Dercon, 2005). As previously pointed out, in most of the least developed countries assets are kept in form of livestock and food crops

[41] For more information on the definition of a mean-preserving increase in risk, see Rothschild and Stiglitz (1970)

and they can be easily affected by sudden episodes of illness or draught, as well as exposed to theft. Our simulation provides just an example of what the effect on saving and - consequently - on welfare could be but it is sensible to the structure of risk and the other parameters of the model. However, our goal is not to directly contribute to the debate of the impact of risk on household's welfare, rather to provide a new measure of vulnerability which is able to take into consideration the theoretical debate on this issue. The micro-foundation and the sensitivity analysis in Table 2.1 indicate that the proposed measure could be defined as a dynamic "*risk-sensitive*" vulnerability measure - in the sense of Ligon and Schechter (2004). Nevertheless, its sensitiveness to the preferences over risk and to the total amount of uncertainty doesn't depend only on the choice of the functional form of the index but - for the first time in the literature - it considers directly the impact of the household's behavior on its own expected level of welfare.

2.5 Conclusion

We proposed a micro-founded measure of vulnerability to poverty based on a model of precautionary saving adapted to the special features of the poor households in developing countries. In particular, households are assumed to be credit constrained while asset and income are risky.

The main contributions of this Chapter are three. Firstly, the results of the dynamic and stochastic simulation show that the risk-induced rational behavior of the household may have a cost in terms of future welfare, confirming the results of Dercon (2005), Elbers and Gunning (2007), Carter and Ikegami (2009) and Elbers et al. (2009). However, while the other authors don't consider the serial correlation of the income and asset risks and calibrate their model using country-specific parameters, we propose a more generalized version thanks to the introduction of shock persistence and to the calibration based on parameters provided by the economic literature on developing countries. With this specification, risk reduces the asset accumulation process with respect to its deterministic counterfactual by almost 20% and the 80% of this difference depends on the risk-induced changing behavior. As consequence, the lifetime consumption path is tilted down and the household experiences a significant welfare loss.

Secondly, we exploit the simulation results to build up a monetary vulnerability measure based on a counterfactual decomposition method which captures the different impact of the risk components in the determination of future poverty. In particular, the measure separates the contribution to future poverty due to the characteristics of the household (poverty component) from the contribution of the changing behavior (ex-ante component) and the risk realizations (ex-post component). We quantify the relative weights of these components on the total vulnerability in terms of utils and it comes out that the 70% of future welfare losses caused by the exposure to risk depends on the ex-ante component, i.e. the effect of the rational risk-induced behavioral choice of the households. We also show that the higher is household's risk aversion, the persistence of the shocks or the total amount of income and asset risks, the higher is the total level of vulnerability.

Thirdly, the proposed micro-founded measure is a potential instrument to improve the debate on poverty prevention interventions and social protection. This is a major difference with the previous monetary measurements of vulnerability which are not able to distinguish among the different causes of future poverty. In particular, if the households are likely to remain or to become poor in the near future because of their characteristics or the realizations of bad shocks, the public action should be oriented to provide transfer through reliable safety net appropriately targeted to ensure some minimally accepted level of well-being to everyone. On the contrary, if the most important cause of future poverty is the welfare costs caused by the household behavior as in our simulation, the intervention must support the households to better protect themselves against risk. For example, Dercon (2006) sustains that it can be done supporting self-insurance via savings (through micro-financial instruments), assisting income risk management by providing access to credit, sustaining community-based risk-sharing and pushing the public and private institutions to develop new products such as life and health insurance. In our opinion, particular attention should be given to the first intervention because developing more sustainable saving instruments could be the better way to reduce the existing self-insurance practices based on risky and unproductive assets.

Appendix 2.I: The Derivation of the Euler Equation in the Stochastic Case

The Bellman Equation in the stochastic case is:

$$V(k, A^y, A^k) = \max_{0 \leq k' \leq e^{A^y} f(k) + e^{A^k}(1-\delta)} u(e^{A^y} f(k) + e^{A^k}(1-\delta)k - k') + \\ + \beta E[V(k', A'^y, A'^k)|A^y, A^k]$$

Deriving previous Equation by k' gives us the following first order condition:

$$u'(e^{A^y} f(k) + e^{A^k}(1-\delta)k - k') = \beta E \left\{ V'[(k', A'^y, A'^k)|A^y, A^k] \right\}$$

Substituting the policy function h into the Bellman Equation we have:

$$V(k, A^y, A^k) = u[e^{A^y} f(k) + e^{A^k}(1-\delta)k - h(k, A^y_t, A^k_t)] + \\ + \beta E \left\{ V'[(h(k, A^y_t, A^k_t), A'^y, A'^k)|A^y, A^k] \right\}$$

Using the first order condition we get:

$$V(k, A^y, A^k) = u'(c)[e^{A^y} f'(k) + e^{A^k}(1-\delta)]$$

Postponing the previous Equation one period ahead and indicating with $u'(c')$ the next period marginal utility of consumption, we can finally write the Euler Equation as:

$$1 = \beta E \left\{ \frac{u'(c')}{u'(c)} [e^{A'^y} f'(k') + e^{A'^k}(1-\delta)] = \right. \\ \left. = \beta E \left\{ \frac{u'(e^{A'^y} f(k') + e^{A'^k}(1-\delta)k' - k'')}{u'(e^{A^y} f(k) + e^{A^k}(1-\delta)k - k')} [e^{A'^y} f'(k') + e^{A'^k}(1-\delta)] \right\} \right.$$

It must hold for any three consecutive levels of asset (k, k', k'') in the optimal sequence $\{k^*_t\}_{t=1}^{\infty}$ which solves the agent problem (2.6-2.9).

Appendix 2.II: Markov Chain Approximations of an AR(1) Process

Tauchen (1986) develops a method for choosing the values for the realizations and the transition matrix so that the resulting Markov Chain closely mimics the underlying continuous valued auto-regressive process[42]. Consider our income process in Equation (2.8)[43] :

$$A^y_t = \rho A^y_{t-1} + \epsilon^y_t$$

where $\epsilon^y_t \sim N(0, \sigma^2_{\epsilon^y})$. The unconditional mean and variance of this process are 0 and $\sigma^2_{A^y} = \sigma^2_{\epsilon^y}/(1-\rho^2)$. Tauchen proposes to choose a grid $A^y = [a^y_1, a^y_2, ..., a^y_s]$ of equidistant points $a^y_1 < a^y_2, ..., < a^y_s$, whose upper end point is a multiple, say λ, of the unconditional standard deviation of the autoregressive process $a^y_s = \lambda \sigma_{A^y}$ and whose lower end point is $a^y_1 = -a^y_s$. For a given realization $a^y_i \in A^y$ the variable $a^y = \rho a^y_i + \epsilon$ is normally distributed with mean ρa^y_i and variance $\sigma^2_{\epsilon^y}$. Let da^y denote half of the distance between two consecutive grid points. The probability that a^y is in the interval $[a^y_j - da^y, a^y_j + da^y]$ is given by:

$$prob(a^y_j - da^y \leq z \leq a^y_j + da^y) = \pi(a^y_j + da^y) - \pi(a^y_j - da^y)$$

where $\pi(\cdot)$ denotes the cumulative distribution function of the normal distribution with mean ρa^y_i and variance $\sigma^2_{\epsilon^y}$. Equivalently, the variable $v := (a^y - \rho a^y_i)/\sigma_{\epsilon^y}$ has a standard normal distribution. Thus the probability to switch from state a^y_i to state a^y_j for $j = 2, 3, ..., s-1$, say π^y_{ij}, is given by the area under the probability density

[42] This appendix strictly follows the Haus and Maussner (2005) demonstration in Chapter 9.

[43] We don't discuss the approximation of the asset process because it is identical the approximation of the income process

function of the standard normal distribution in the interval:

$$\left\{ \frac{a_j^y - \rho a_i^y - da^y}{\sigma_{\epsilon^y}}, \frac{a_j^y - \rho a_i^y + da^y}{\sigma_{\epsilon^y}} \right\}$$

The probability to arrive at state a_1^y is the area under the probability density in the interval $[-\infty, a_1^y + da^y]$. Since $\sum_j \pi_{ij}^y = 1$, the probability to go from any state i to the upper bound a_s^y is simply $\pi_{is}^y = 1 - \sum_{j=1}^{s-1} \pi_{ij}^y$. The algorithm implemented for obtaining the vector of grid points and the probability transition matrix is:

- **STEP 1**: we compute the discrete approximation of the realizations: let ρ and σ_{ϵ^y} indicate the autoregressive parameter and the standard deviation of the income innovation. We select the size of the grid by choosing the parameter λ so that $a_s^y = \lambda \sigma_{\epsilon^y} / \sqrt{1-\rho^2}$. We choose the number of grid points S. The step is calculated as $a_s^y - a_1^y / S - 1$ and for $i = 2, ..., S-1$ we compute $a_i^y = a_1^y + (i-1) * step$;

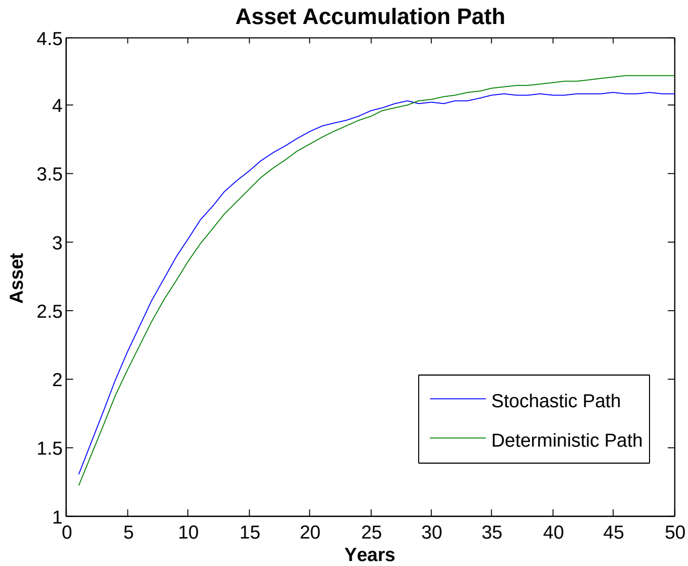
- **STEP 2**: we compute the transition matrix $\Pi^y = (\pi_{ij}^y)$. Let $P(\cdot)$ indicate the cumulative distribution function of the standard normal distribution. For $i = 1, 2, ..., S$, we calculate:

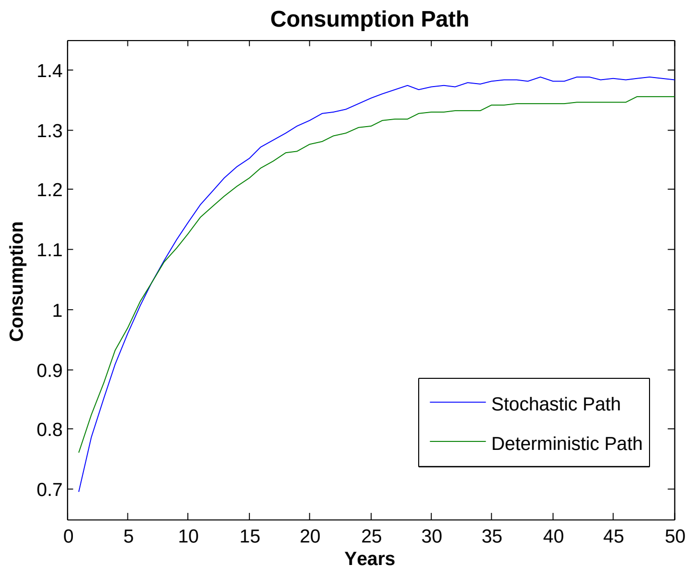
$$\pi_{i1} = P\left\{ \frac{a_1^y - \rho a_i^y}{\sigma_{\epsilon^y}} + \frac{step}{2\sigma_{\epsilon^y}} \right\}$$

$$\pi_{ij} = P\left\{ \frac{a_j^y - \rho a_i^y}{\sigma_{\epsilon^y}} + \frac{step}{2\sigma_{\epsilon^y}} \right\} - P\left\{ \frac{a_j^y - \rho a_i^y}{\sigma_{\epsilon^y}} + \frac{step}{2\sigma_{\epsilon^y}} \right\} \text{ for } j = 2, ..., S-1$$

$$\pi_{is} = 1 - \sum_{j=1}^{s-1} \pi_{ij}^y$$

Appendix 2.III: Asset/Consumption Paths with a Normal Shock on Income





The model is simulated using the same parameters presented in Paragraph 2.3.3 with the difference that asset accumulation is not risky and the income shocks are drawn from a normal distribution with mean 0 and variance $\sigma^2_{\epsilon^y} = 0.1$

Chapter 3

The Empirical Evidence: The Vietnamese Case

3.1 Introduction

The lack of a solid micro-foundation to the monetary measures of vulnerability to poverty results in a series of empirical approaches which are not able to properly catch the impact of risk on the future level of welfare. In particular, Chapter 1 revealed that existing vulnerability analyses regress consumption on a set of household's and village's characteristics and - where the design of the survey allows the researcher to collect enough information - on aggregate and idiosyncratic shocks. They usually rule out assets and the characteristics of the distribution of shocks, raising several theoretical and econometric problems which may bias the vulnerability estimates and - as consequence - suggest wrong policy decisions. In addressing these issues, the present Chapter proposes a new empirical strategy for the measurement of vulnerability to poverty based on the monetary index presented in Chapter 2 which separates the contribution to future poverty due to the characteristics of the household (poverty component) from the contribution of the changing behavior (ex-ante component) and the risk realizations (ex-post component). We test this strategy through a practical application on Vietnam, using a three-wave panel (2002-2004-2006) with household-level data collected by the Vietnamese Households Living Standards Survey (VHLSS).

Measuring vulnerability to poverty means making inference about future consumption which is influenced by several factors such as the household's tastes and composition, current and future income, physical assets, risks realizations and the ability to smooth consumption (Elbers and Gunning, 2003; Chaudhuri, 2003). In modeling the consumption function, our econometric method exploits the considerations on household's behavior in developing countries emerged in Chapter 2 and combines it with the empirical strategy used to test the presence of the precautionary motive based on linear regression techniques. This body of literature is more suitable to our purpose because it allows us to face directly the impact of different sources of risk on the future level of consumption. In particular, the method is based on a three-stage strategy which allows to evaluate the influence of asset and income risks on the household's behavior and - at the same time - provides a valid instrument to construct the series of empirical consumption counterfactuals needed for measuring the different vulnerability components. Following a large number of works provided by the literature (Guiso et al. 1992, Carroll, 1994; Carroll and Samwick, 1997 and 1998; Jalan and Ravallion, 2001; Giles and Yoo, 2007) the first stage individuates two workable proxies for income and asset risks, calculated as the variance of the innovations of the income and asset processes. The second stage of the method estimates the full consumption function while in the third stage we exploit the results of the first two steps to build up the series of empirical counterfactuals for calculating the vulnerability measure.

We apply this three-stage procedure to the household-level data provided by VHLSS between 2002 and 2006. The results of the empirical application sustains several considerations presented during this research. First of all, the estimation of the consumption function indicates that once we consider income and asset risks, their net effect on household's saving is less clear than the standard model of precautionary saving. In fact, while income risk reduces the current level of consumption as predicted by theory, in our estimation the asset risk has the opposite effect. In this particular case the effect of asset risk completely offsets the negative impact of income risk, implying a reduction of saving for the Vietnamese households. Secondly, the calculation of the future consumption counterfactuals and the subsequent vulnerability measure show that almost one third of the future welfare losses are caused by the risk-induced changing behavior of the households (ex-ante component) while almost 60% is due to the exposure to uninsured shocks (ex-post component). Even if the relative weight of the ex-ante component is consistently less than what we found in the numerical simulation in Chapter 2, the results still imply that policy-makers should be interested in developing poverty prevention programs able to improve the self-insurance mechanisms of the Vietnamese households and to promote the creation of new insurance products.

3.2 A new Empirical Strategy for Estimating Vulnerability

In Chapter 2, we proposed the following measure of vulnerability:

$$V_h = \sum_{t=0}^{T} \beta^t T_t \left\{ [U(z) - U(c_{ht}^{DT})] + [U(c_{ht}^{DT}) - U(c_{ht}^{EA})] + [U(c_{ht}^{EA}) - U(c_{ht}^{FS})] \right\}$$

$$\text{where } T_t \begin{cases} 1 \text{ if } [U(z) - U(c_{ht}^{FS})] \geq 0 \\ 0 \text{ if } [U(z) - U(c_{ht}^{FS})] \leq 0 \end{cases}$$

Where z is the time-specific poverty line, c^{DT} is the consumption counterfactual when income and asset are risk-free (Deterministic Consumption), c^{EA} is the consumption counterfactual with only income and asset ex-ante perception of risk (Ex-Ante Consumption) while c^{FS} is the consumption counterfactual with both income and asset risk plus the shocks realizations (Full Stochastic Consumption). In order to implement a robust empirical test of this measure, we set up a functional form of the consumption process which allows us to estimate the three different counterfactuals, considering both the theoretical issues emerged in Chapter 2 and the empirical problems analyzed in Chapter 1. The better way to do that is exploiting the empirical literature on precautionary saving based on linear regression techniques and adapting them to our consideration on consumption behavior in developing countries[1]. This part of literature attempts to estimate the direct relationship between in-

[1] Carroll and Kimball (2007) present four different methodological approaches to estimate the presence and the relative magnitude of precautionary saving. In particular, i) the Euler Equation estimation; ii) the structural estimation using Micro Data; iii) the regression evidence between uncertainty and wealth and, finally, iv)the survey evidence, based on direct questions to the survey

come risk and household's welfare including some measure of risk either in a saving/wealth equation or in a Euler Equation and then testing for its significance[2] . In the framework of the vulnerability to poverty analysis, these tests are more appropriate than the other precautionary saving empirical strategies because they allow to face directly an important limit of the current approaches to vulnerability, i.e. the impact of different sources of risk on the expected level of consumption.

The fundamental issue that faces who applies this method is to identify an observable and exogenous proxy of income risk. However, income risk is only a part of the total amount of uncertainty experienced by the households in developing countries because they also have to deal with asset risk which endangers their saving accumulation process. To address all these issues at the same time, we propose an empirical strategy to measure our vulnerability index based on a three-stage procedure. In the first stage, we focus our attention on measuring both income and asset risks, calculated as the variance of the innovations in the income and asset equations. In the second stage, we estimate the impact of these proxies on the consumption level in order to assess if and how income and asset risks contribute to determine the risk-induced behavioral changes predicted by the numerical simulation of Chapter 2. Finally, in the third stage we exploit the results provided by the previous steps to build up the series of consumption counterfactuals and calculate the proposed vulnerability measure.

3.2.1 Estimating Income and Asset Risk

Extracting robust information from households' survey on income risk has been one of the main effort produced by the empirical literature on precautionary saving. As already told, the regression techniques used to test the presence of precautionary motive attempt to assess directly the relationship between income uncertainty and consumption and the empirical works on this subject provides numerous examples on how to calculate this link. The only measure of income risk actually based on the theory of precautionary saving, the Equivalent Precautionary Premium (EPP), is based on Kimball (1990) work. Let assume that the consumption is randomly distributed with a multiplicative shock ϵ around a level

participants.

[2]Browning and Lusardi (1996) provide an excellent survey of the empirical test on precautionary saving based on linear regression.

$\bar{c}$, $c = \bar{c} * \epsilon$. In a two period model, the EPP is defined as:

$$u'(\bar{c} - \psi) = E[u'(c)] \tag{3.1}$$

In other words, the EPP is a direct measure on the intensity of the precautionary motive at the point of zero precautionary saving. If we adopt a CRRA utility function, the EPP turns out to be:

$$\psi = \bar{c}(1 - [E(\epsilon)^{-\rho}]^{-(1/\rho)} \tag{3.2}$$

Carroll and Samwick (1998) estimate this measure in its relative form, dividing both side of the Equation (3.2) by c^* and testing it on a seven-year U.S Panel Study of Income Dynamic (PSID). They find out that the Relative EPP is strongly and positively correlated with the target "wealth/permanent income ratio", confirming Carroll (1992, 1997) and Deaton (1991) buffer-stock saving model. Some other authors tried to estimate the impact of uncertainty on household's behavior exploiting the Euler Equation and trying to understand if the coefficient of relative prudence were significantly different from zero[3] . Using this approach, Dynan (1993) finds no evidence that consumption growth is connected with its variance, questioning the existence of precautionary saving. However, this approach has been criticized because of the choice to use quarterly data on consumption, which probably reflect seasonal fluctuations rather than consumption uncertainty (Carroll, 1994), as well as for applying the Euler Equation estimation which seems to be unable to uncover structural parameters from a dataset (Carroll 1997, Carroll, 2001).

Another way to measure the impact of uncertainty on household's behavior is calculating the variance of income and considering it as a proxy of the income uncertainty. The variance could be calculated using observations over time of the same household - which requires long panel data - or using the variation of income across groups of households sharing the same demographic and economic characteristics in single cross-sections. Considering the chronic lack of long panel data in developing countries, the second method is more applied. There is no theoretical justification for this approach but it is easy to calculate and interpret: if the coefficient of the income variance on a linear regression on total wealth is positive, it means

[3]It is worth to remember that without prudence the motive for precautionary saving disappears.

that uncertainty is increasing saving and there is evidence of precautionary motive. Even if this method is completely atheoretical and less elegant than the EPP or the Euler Equation methods, Carroll and Samwick (1998) empirical work shows that regressing household's total wealth on the EPP measure or on the variance of the log of income gives back the same results. The main problem in using this method is to find enough exogenous variation in uncertainty across households, especially when the panel data length is limited. The standard method uses patterns of variation based on households' characteristics such as age, occupation, education and industry and other characteristics. It is worth to remember that some of these characteristics may raise selection bias problems because they are correlated with the risk aversion of the household. For example, people who are more willing to risk may choose to work in riskier industry and to keep their saving at a lower level, with the consequence that the estimated impact of an exogenous change in risk can be biased downward (Carroll, 2007)[4].

Finally, the more promising way to extract parsimonious information on income uncertainty from data is to calculate the variance of innovations to income, defined by Carroll and Samwick (1997) as "*the theoretically correct measure of uncertainty*" for these models. This definition comes from the fact that looking at the fluctuation of the income innovations allows to consider only that part of income variation which is not explained by the household characteristics and then cannot be foreseen in advance by the households. The first step of this extensively applied methodology (see also Hubbard et al, 1994; Gourinchas and Parker, 2002; Meghir and Pistaferri, 2004; Storesletten et al., 2004) is to estimate the innovation errors as the residuals of the income process. Carroll and Samwick (1997) and Carroll (1997) apply this technique estimating two separately income processes, one for the permanent income and the other for the transitory income, because their aim is to differentiate between transitory and permanent uncertainty. However, calculating this measure implies to exploit the time dimension of the panel data, which brings us back to the already mentioned missing data problem, especially for poverty contexts. One way to overcome this

[4]One way to solve this exogeneity problem is to see whether consumption is related to a self-reported expected variance of income, as performed by Guiso, Jappelli and Terlizzese (1992). Of course, this method are quite costly because it needs a specific and really clear survey design, otherwise the respondents could be easily misled by the questions.

issue is to follow Jalan and Ravallion (2001) work, estimating the following income process:

$$y_{ht} = \alpha + Z'_{ht}\beta + \epsilon_{ht} \tag{3.3}$$

where y_{ht} is the log of per capita income of household h at time t, and Z_{ht} is a vector of independent variables which describes the income process such as demographic, educational and occupational characteristics . The error structure ϵ is assumed to be:

$$\epsilon_{ht} = \eta^y_h + v^y_{ht} \tag{3.4}$$

where η^y_h is a random individual component with mean 0 and constant variance σ^2 while v^y_{ht} is the income shock of the present period which contains the idiosyncratic income innovation. To separate the income innovation from the income shocks, we need to take into consideration the serial correlation across shocks. Current vulnerability analyses assume that v^y_{ht} is independent and identically distributed even if - as already explained in Chapter 2 - it seems quite unlikely that past unobserved shocks are not affecting at least present error. In other words, serial correlation is ruled out from the analysis, risking to provide inefficient estimates of the income process and - more important - biased estimates of the income uncertainty. To take into consideration the serial correlation between errors, we impose the following AR(1) process to the income shock v^y_{ht}:

$$v^y_{ht} = \rho v^y_{h,t-1} + \omega_{ht} \tag{3.5}$$

where ρ (with $|\rho| < 1$) is the autocorrelation coefficient and ω_{ht} is a random i.i.d. error, i.e. our income innovation. Once we have a robust estimate of the innovations to income, we must calculate their variance in order to obtain a measure of income uncertainty. We have two possibilities: we use the time dimension of our panel or we group innovations according to pre-selected household's characteristics. In the first case, for each household h we obtain that:

$$\sigma^2_{y,h} = \sum_{t=1}^{T} (\omega_{ht} - \bar{\omega})^2 / T \tag{3.6}$$

where T in the time length of the panel data. This measure can be used only if the number of periods available are enough to capture the variation of the income [5]. Considering that our empirical test will be conducted exploiting three waves of the Vietnamese Household Living Standards Survey (VHLSS) (2002, 2004, 2006), it seems better to relax Jalan and Ravallion (2001) method by dividing the whole sample in several sub-samples and calculate the intra-group variances. In this framework, groups are usually based on the households' head characteristics as well as on information of the geographical origin (e.g. province, commune, village). In the latter case, grouping for geographic location may be a good way to gather households with the same level of aggregate risk but it's not taking care of the idiosyncratic part of the income fluctuation. Therefore, we adopt a solution based on the first strategy and we group the households according to the occupation and level of education of their head. It is broadly recognized that these two factors have an important role in determining the level of income of the household as well as the level of its riskiness (Dardanoni, 1991). In fact, it is reasonable to assume that households engaged in the same occupation and with the same level of education share a similar level of risk. In simple markets such that in developing countries, income from farm activities are affected by the same shocks such as bad weather, crops failure or livestock diseases. These sources of risk are totally different from white collars or people engaged in sales and services activities. The level of education further differentiates among groups with the same occupation because people with higher level of education are usually more prepared to deal with risk and to reduce its presence. Following this approach, we estimate the income risk calculating the variance of the income innovations in each survey by groups g composed according to the occupation and the education of the household head:

$$\sigma^2_{y,g,t} = \sum_{h=1}^{n} (\omega_{h,g,t} - \bar{\omega})^2 / n \tag{3.7}$$

where $\omega_{h,g,t}$ indicates the income innovation of household h at time t and with the head in group g. Following Skinner (1988), Guiso et al. (1992), Blundell and Stoker (1998), Banks et al. (2001) and Giles and Yoo (2007) it is possible to further refine this uncertainty measure, scaling it by a specific factor (π_{ht}) based on the expected wealth of the household.

[5] For example, Jalan and Ravallion (2001) use this index even if their panel data has only six waves.

In particular, these authors show that with CRRA preferences it is not sufficient to enter the income risk term alone in the consumption function because the linear relationship between c_t and $\sigma^2_{y,g,t}$ would be independent of wealth, i.e. the same for rich and poor. Coherently with this part of literature, we assume that poorer individuals are more responsive to changes in risk so we scale up the variance of income innovations by the square of the ratio between current household's income and expected lifetime wealth[6]. Our final proxy for income risk will be:

$$\sigma^2_{y,h,t} = \pi_{ht}\sigma^2_{y,g,t} \text{ with } \pi_{ht} = \left(\frac{y_{ht}}{\hat{w_h}}\right)^2 \tag{3.8}$$

Despite its theoretical foundation, the scaling term has two other advantages. First of all, it allows us to have a specific measure of uncertainty for each household in each period, guaranteeing to exploit all the available sample. Secondly, it picks up the remaining part of risk which is not explained by the occupation/education breakdown, differentiating across the households belonging to the same group.

In our analysis income uncertainty is only a part of the risk the household faces. The other autonomous source of risk which influences saving decisions is asset risk which operates independently of income risk. Asset risk is a plausible hypothesis especially in developing countries where assets such as livestock and stored crops are the only way for households to smooth consumption and generate income. Following Jalan and Ravallion (2001) we can estimate the asset uncertainty using the same procedure adopted for income risk. The first step is to estimate the asset process:

$$k_{ht} = \delta + Z'_{ht}\Upsilon + \mu_{ht} \tag{3.9}$$

where k_{ht} indicates the log of per capita assets. In order to simplify the analysis, the set of covariates Z is the same used for the income process. Again, the variable μ_{ht} is composed by a random individual component η^k_h and a serially correlated asset shock v^k_{ht}. To control for the presence of autocorrelation, the random variable v^k_{ht} is represented as an

[6] According to Skinner (1988) and Guiso et al (1992), the exponent of the scaling factor measures the sensitivity to the level of expected wealth exhibited by the reaction to uncertainty. If the exponent is more than zero, the effect of risk on consumption declines with the household's resources and the decline is faster the higher is the value. Usually, the adopted value is two and this is why we use the square of that ratio.

AR(1) process, i.e. $v^k_{ht} = \rho v^k_{ht-1} + \zeta_{ht}$ where ζ_{ht} is the asset innovation we use to estimate the asset risk. As before, we estimate the asset uncertainty calculating the variance of the asset innovations in each survey by groups composed according to the occupation and the education of the household head:

$$\sigma^2_{k,g,t} = \sum_{h=1}^{n} (\zeta_{h,g,t} - \bar{\zeta})^2 / n \tag{3.10}$$

Finally, we further assume that that poorer individuals are more responsive also to changes in asset uncertainty and then we scale up $\sigma^2_{k,g,t}$ using the term λ_{ht}, i.e. the square of the ratio between current household's assets and wealth:

$$\sigma^2_{k,h,t} = \lambda_{ht} \sigma^2_{k,g,t} \text{ with } \lambda_{ht} = \left(\frac{k_{ht}}{\hat{w_h}} \right)^2 \tag{3.11}$$

Therefore, Equations (3.8) and (3.11) will be our proxies to measure the impact of uncertainty on household's consumption and saving decisions. In the second stage of the procedure we will insert these measures in the consumption function in order to verify if the income and asset risks affect the agents' behavior and if there is a negative impact on the household's welfare.

3.2.2 Estimating the Consumption Function

Assessing vulnerability means making inference about future consumption prospects, paying attention explicitly to its cross-sectional and inter-temporal determinants. Literature has largely investigated these issues, reaching the conclusion that individual consumption in any period depends on several factors, among which household's tastes and composition, expectations on future income, current physical assets, the risks it faces and its ability to smooth consumption. In turn, each of these factors is determined by a variety of observable household characteristics such as demographics, education, place of residence and occupation as well as from unobservable factors like abilities and motivations (Guiso et al., 1992; Deaton, 1992; Carroll, 1994; Chaudhuri, 2003). Following this body of literature, we propose a consumption function based on two main components: a first part which captures the certainty equivalence level of lifetime resources, i.e. the permanent income plus the available physical resources, and a second part which captures the precautionary motive trigged by income and asset risks. In particular, we estimate the following reduced form of the consumption function:

$$c_{ht} = \varphi X_{ht} + \theta_1 \hat{y}_h^p + \theta_2 \hat{k}_{ht} + \theta_3 \sigma^2_{y,h,t} + \theta_4 \sigma^2_{k,h,t} + \epsilon_{ht} \tag{3.12}$$

where c_{ht} indicates the log of capita consumption. The X vector takes into account the effects of tastes and family composition on the propensity to consume and it contains the same variables of vector Z we used in Equations (3.3) and (3.9). However, in order to identify Equation (3.12), we follow Kazarosian (1997) and Jalan and Ravallion (2001) in excluding occupation characteristics from X, which are assumed to influence consumption behavior only through the permanent income and the income uncertainty. $\hat{y}_h^p$ and $\hat{k}_{ht}$ are respectively the permanent income and the value of productive assets and capture the impact of the lifetime resources on the level of consumption. The permanent income is calculated using the average over time of the predicted income from Equation (3.3)[7], while $\hat{k}_{ht}$ is the predicted value of the productive asset for household h at date t from Equation (3.9)[8]. Finally, the terms $\sigma^2_{y,h,t}$ and $\sigma^2_{k,h,t}$ measure the income and asset risks and take into account the precautionary motive component of consumption while ϵ_{ht} is an i.i.d. error term [9].

Following the standard precautionary saving empirical literature, the coefficients θ_3 and θ_4 are the focus of our analysis because they reveal the impact of risk on the households behavior. A negative coefficient indicates that risk is lowering current consumption and then increasing saving, confirming the presence of a positive precautionary motive. However, our analysis differs from the standard tests of this literature because it introduces two different sources of risk. While we expect that income risk is still decreasing current consumption, we are not able to impose a specific sign on the asset risk. From the stochastic simulation in the Chapter 2 we saw that the final effect of uncertainty on the lifetime consumption path is quite unclear and can be solved only by looking at the available data. If θ_4 turns out to be negative as well, it means that asset uncertainty is actually reinforcing the precautionary motive, partially invalidating our prevision that once we control for multiple sources of risk

[7] i.e. $\hat{y}_h^p = \frac{1}{T}\sum_1^T \hat{y}_{ht}$

[8] It is worth to remember that using this procedure also allows to reduce potential measurement error problems which rises from data on income and assets.

[9] During the robustness tests we will remove this last hypothesis allowing the error term to be serially correlated.

uncertainty can slow down consumption growth and then household's future welfare. On the contrary, if θ_4 is positive it means that the two sources of uncertainty are working in opposite directions, leaving unclear the net effect on the consumption path. The magnitude of the two coefficients would help to understand which effect is prevailing, even if we have to interpret it very carefully because it could be influenced by the unit of measurement of the two variables.

Before paying attention to the construction of the consumption counterfactuals and the vulnerability measure in Equation (2.22), we would like to briefly clarify the choice of the per-capita consumption as dependent variable. In fact, one may argue that looking at the direct impact of risk on consumption is not the best way to assess the presence of precautionary motive. Carroll and Samwick (1997) sustain that the appropriate response to greater uncertainty is to hold more wealth while it is not necessary to depress consumption forever. This implies no direct relationship between risk and consumption and it suggests that precautionary motive should be tested either on a wealth-to-income ratio or on the saving/income ratio. Actually, most of the empirical works which try to test the impact of income risk on household's behavior follows this recommendation. However, there are several reasons why precautionary savings in developing countries should be testable even on the level of consumption. First of all, the proposition of Carroll and Samwick (1997) is valid only if the household has reached its steady-state value foreseen by their buffer-stock model but until the optimal stock is achieved consumption has to be depressed in order to build up a bigger amount of wealth. Even accepting that poor households in developing countries have some kind of optimum wealth-to-income ratio they want to reach, it is very difficult to justify that this ratio has already been reached in situation of extreme poverty characterized by the lack of saving, productive assets and functioning credit markets.

The other reasons why we prefer to use consumption instead of saving or wealth as dependent variable are less theoretical and more practical. First of all, even if household's saving behavior is important to understand risk management strategies, savings is really difficult to measure especially in developing countries (Ersardo et al., 2003). Most studies on household surveys in LDC's take savings as the residual of observed income and consumption but usually income appears to be heavily underreported relative to consumption, with the consequence that saving turns out to be too low (Paxson, 1992, Deaton, 1989). On the other hand, consumption is reported more precisely because it's easier for the respondents to quantify and it doesn't suffer the seasonal variation exhibited by income. Finally, using consumption as dependent variable in Equation (3.12) allows us to build up the counterfactuals we need to calculate the vulnerability measure proposed in Equation (2.22).

3.2.3 The Consumption Counterfactuals and Vulnerability Measure

The last step is to build up a series of consumption counterfactuals which can enter in Equation (2.22) and allow us to test if risk has any impact on household's welfare. In order to decompose the total vulnerability measure we need to estimate three different counterfactuals: 1) the Deterministic Consumption (c^{DT}) which is the consumption counterfactual when the household is free of income and asset risks ; 2) the Ex-Ante Consumption (c^{EA}) which includes the impact of the risk-induced changing behavior of the household but not the effect of risk realizations; and 3) the Full Stochastic Consumption (c^{FS}) which contains both the impact of changing behavior and the effect of risk realizations. Taking advantage of different estimated versions of Equation (3.12), these consumption counterfactuals will be estimated as follow:

- c^{CD} for household h at time t will be equal to the predicted value of the consumption function estimated without considering the effect income and asset uncertainty:

$$\hat{c}^{CD}_{ht} = \breve{\varphi} X_{ht} + \breve{\theta}_1 \hat{y}^p_h + \breve{\theta}_2 \hat{k}_{ht} \tag{3.13}$$

- c^{EA} for household h at time t will be equal to the predicted value of the consumption function estimated including asset and income uncertainty:

$$\hat{c}^{EA}_{ht} = \hat{\varphi} X_{ht} + \hat{\theta}_1 \hat{y}^p_h + \hat{\theta}_2 \hat{k}_{ht} + \hat{\theta}_3 \sigma^2_{y,h,t} + \hat{\theta}_4 \sigma^2_{k,h,t} \tag{3.14}$$

- c^{FS} for household h at time t will be equal to the predicted value of the estimated consumption - including asset and income uncertainty - plus the intra-group average value of the shock ϵ which can be considered as the most probable risk realization:

$$\hat{c}_{ht}^{FS} = \hat{\varphi} X_{ht} + \hat{\theta}_1 \hat{y}_h^p + \hat{\theta}_2 \hat{k}_{ht} + \hat{\theta}_3 \sigma_{y,h,t}^2 + \hat{\theta}_4 \sigma_{k,h,t}^2 + \bar{\epsilon}_{ht} \tag{3.15}$$

Once we obtain the consumption counterfactuals, we can plug them into the vulnerability index, which gives us the empirical version of Equation (2.22):

$$\hat{V}_h = \sum_{t=0}^{T} \beta^t T_t \left\{ [U(z) - U(\hat{c}_{ht}^{DT})] + [U(\hat{c}_{ht}^{DT}) - U(\hat{c}_{ht}^{EA})] + [U(\hat{c}_{ht}^{EA}) - U(\hat{c}_{ht}^{FS})] \right\} \tag{3.16}$$

$$\text{where } T_t \begin{cases} 1 \text{ if } [U(z) - U(\hat{c}_{ht}^{FS})] \geq 0 \\ 0 \text{ if } [U(z) - U(\hat{c}_{ht}^{FS})] \leq 0 \end{cases}$$

This three-stage procedure to calculate vulnerability has several advantages. First of all, the consumption estimations take into account the most up-to-date theoretical and empirical debate on both household's behavior and vulnerability. Thanks to a modified version of the empirical strategy to estimate precautionary saving we are able to test if the risk-induced changing behavior plays any role in the determination of the future household's welfare and we are able to synthesize this information in a dynamic vulnerability measure. Secondly, the construction of the different consumption counterfactuals are based on solid regressions which consider a broader and more solid version of the consumption function. The main difference with the previous approaches to vulnerability is that we control for the level of productive asset and - more important - we measure the impact of different sources of risks on the expected value of future welfare. However, this formulation still suffers a major problem related to the cross-stationarity of the consumption distribution. In fact, considering the lack of long panel data we have to rely on the usual assumption that observed inter-household distribution of consumption at a point in time represents the future distribution of consumption across states of nature for each household, missing the impact of household-invariant but t-variant shocks.

3.3 The Vietnamese Case

The empirical exercise is implemented using data on Vietnam from 2002 to 2006. Researchers are extensively studying Vietnam since the 1980s, when it was one of the poorest countries in the world and adopted a series of economic reforms, called “doi moi”, to move from a centrally planned to a market-oriented economy. During this period, land has been allocated to individual households, private economic activities were legalized and control on prices removed. Trade barriers have been reduced or eliminated while foreign direct investment has been legalized. The results of these policies have been surprising and poverty reduced dramatically in the last 20 years. According to the General Statistics Office (GSO), between 1990 and 2005 real GDP grew at around 7/8 per cent per annum and the remarkable growth has been coupled with a strong overall reduction of poverty from 58.1% of the population in 1992 to less than 15% in 2008. However, the reduction in poverty was more pronounced for some sub-groups of the population, especially for urban households in the south of the country (Justino et al. 2008) while a significant number of the population remained poor and the gap between rich and poor as well as urban and rural areas is widening (Liu, 2001; Thoburn, 2004; Heo and Doanh 2009). More interesting to our analysis, the “doi moi” economic reforms have introduced in the economic system a series of new sources of risks which could negatively influence the households’ behavior and their choices (Niimi et al, 2007). For example, the trade liberalization, the market deregulation and the abolition of price controls on commodities could have increased the perceived uncertainty and pushed the poorest households to put in place wrong coping mechanisms which decreased their expected lifetime welfare.

3.3.1 The VHLSS Data

The present research uses Vietnam Household Living Standard Surveys developed by the GSO, together with the United Nations Development Program (UNDP) and the Swedish International Development Agency (SIDA) and technical assistance from the World Bank. In particular, we exploit the data from three consecutive waves undertaken in 2002, 2004 and 2006. VHLSS are nationally representative surveys and provide a good picture of the

Vietnamese households. In each wave we have two different questionnaires, one household questionnaire and one community questionnaire. The first one contains detailed information on household demographic characteristics, education, health and healthcare, income, expenditures, assets and durable goods and accommodation as well as participation in poverty reduction programs. The community questionnaire gathers information on the demographic, health, education and infrastructure of all rural communities. The sample consists of 29.530 households for 2002, 9.188 for 2004 and 9.189 for 2006 while the number of surveyed communes are, respectively, 2091, 3063 and 3065.

Even if the original VHLSS panel between 2002 and 2006 counts 1941 households[10] , several restriction are introduced on the sample in order to ensure that the income and asset fluctuations are not influenced by unobservable behavior. First of all, we drop the households where the head has changed during the panel period 02-06 and where we don't have any information on income, consumption and assets. Following the empirical literature on precautionary saving (see for example Carroll and Samwick, 1998; Dardanoni, 1991), we keep only the households with the head still in the labor force, which means eliminating those outside the range 25-70 and those who are currently unemployed or retired. Even if unemployment is one of the main sources of uncertainty, we prefer to limit the analysis to the households fully operating on the market. In order to prevent our results to be affected by outliers, we further refine our sample removing households with per capita income, consumption or assets in either the first or the last percentile. Finally, we keep only the households with observations for all the three years of the survey, making our panel strongly balanced. The result of these restrictions is that the sample decreases from 1941 households per year to 1185[11].

For what concerns the variables used in the analysis, the VHLSS provides directly information on the annual per capita consumption and assets, but we don't have a unique measure for the overall income and we have to build up this measure. Per capita consumption is calculated as the sum of food and non-food household expenditures in the past 12 months. Food expenditure includes information on both market purchases and consumption

[10] The households' code to link the three waves of the panel has been provided by Brian McCaig who developed a new method because of the inconsistencies showed by the one released by the GSO.

[11] For more info on the sample restrictions see Appendix 3.I

from home production of 58 items while the non-food expenditure collects information on 32 items such as fabric, clothing, blankets, pillows, tailoring or laundry services, shoes, nylon sheeting, electric stuff, ect. For what concerns assets, the VHLSS collects information about the current value of 59 kinds of fixed assets and durable goods, including perennial crops garden, aquaculture production area, other production land area, buffalo, cows, horses for production and breeding, feed grinding machines, rice, milling machines, cars, trailers, motorbikes, wagons, boats with engine and a set of goods to be used for domestic purpose such as telephone, television, air conditioner, etc. From the current total value of these assets, we calculate the household per capita asset value, to be used in the empirical test.

It is worth to note that we don't consider any form of liquid assets (e.g. cash in hand) or financial assets (bank accounts, loans, ect) in our variable. We have two possible explanations. On the one hand, in the theoretical model of the Chapter 2 we restricted our interest to that part of assets which can be used both for smoothing consumption and generating income because we assumed the presence of liquidity constraints and the lack of an accessible credit market for poor households. At this purpose, even if Vietnam improved the quality of its financial institutions in the last ten years, the shortage of access to credit is still a serious problem for both enterprises and households (Rand et al., 2009), which implies that our assumption is not far from reality. On the other hand, the second reason to consider only the list of physical productive assets is a practical one: the VHLSS doesn't provide any information on the financial assets held by the households, as well as we don't know if they carry on any liquid asset from one period to another.

For what concerns the household per capita income, the VHLSS doesn't make available a single measure which synthesizes the overall amount but it is possible to reconstruct it from various sections of the survey. We proceed following the approach proposed by Briandt et al. (2009). We aggregate income into six major categories: income from crops, income from agricultural sidelines, household business income, wage income, gifts and remittances, and *other* residuals sources of income. Income from crops is net income (gross revenue minus current expenditures) from rice; other cereal, vegetable, and annual crops; industrial crops; fruit crops; and crop by-products such as straw, leaves, etc. Agricultural sidelines include livestock and other animal products, agricultural services, forestry services, hunting, trapping, and domesticating wild animals, and aquaculture. Household business income is net income from non-agriculture, non-forestry, and non-aquaculture businesses run by the household and includes the processing of agricultural, forestry, and aquaculture products. Wage income includes salary or wage payments plus additional payments such as holiday contributions, social insurance payments, etc. for all jobs worked by the individual during the past 12 months. Gifts and remittances include payments from both domestic and overseas sources. Finally, *other* residual sources of income include items such as government transfers and earned interest as well as rental income from land and housing.

Lastly, we convert all nominal variables into nationally representative January 2006 prices using three different set of deflators, as suggested by Briandt et al. (2009). Considering that households within each survey are interviewed during different months, the first set are monthly deflators, which are needed to convert the income, consumption and assets values to January prices of the respective year. Secondly, to take into consideration the differences in the cost of living across regions we use regional deflators[12]. Thirdly, to link January prices of 2002 and 2004 to January 2006, we use the Consumer Price Index (CPI) inflators provided by the GSO, which are 1.279 for 2002 and 1.193 for 2004.

3.3.2 The First Stage Results: Income and Asset Regressions

Table 3.1 gives descriptive statistics for the main variables used in the regressions. The mean per capita income increased steadily over the four years with an impressive rate of more than 8%, coherently with the data reported by other studies over the entire sample (Briandt et al. 2009). Unsurprisingly the most important component is the crop income, followed by wage, business and sidelines while it is interesting to note that the crop income share increased by 3% over the period, despite the share of workers engaged in the agricultural sector decreased by almost 5%, indicating an increase in productivity. Income from remittances is quite low (on average less than 7%) and its weight on total income doesn't change over time. Consumption growth has been slower compared to income, even if between 2002 and 2006 we had an average increase of 6.5% per annum.

[12]Considering that regional deflators provided by the GSO in the dataset shows some problems, we use the regional deflators provided by Briandt et al. (2009). For more info see Appendix 3.I

Table 3.1: Descriptive Statistics

	2002	2004	2006
Log per capita Income (Mean)	8.35	8.54	8.88
Crop %	33.10	32.30	36.40
Business %	16.50	17.30	16.20
Sideline %	14.50	14.10	11.00
Wage %	26.20	28.50	26.60
Other %	3.64	0.52	2.95
Remittances %	6.06	7.28	6.85
Log per capita Consumption (Mean)	8.11	8.29	8.42
Log per capita Asset (Mean)	9.35	9.76	9.95
Age of the HH Head (Mean)	42.26	44.21	46.21
HH size (Mean)	4.66	4.56	4.41
No. Children (Mean)	1.40	1.16	0.97
Married Head (%)	90.00	90.30	89.50
Male HH Head (%)	84.80	84.60	83.90
No education (%)	22.72	21.49	20.42
Primary (%)	28.40	27.10	27.50
Lower Secondary (%)	32.60	32.60	33.60
Upper Secondary (%)	8.35	6.41	5.57
Technical (%)	5.65	9.62	9.96
University (%)	2.28	2.78	2.95
White Collar (%)	7.72	8.20	8.10
Sales/Services (%)	1.18	10.60	12.00
Production (%)	28.20	21.80	22.20
Agriculture (%)	62.90	59.40	57.70
Observations	1,185	1,185	1,185

More pronounced the growth of the asset value between the 2002 and 2006, equal to an average rate of 12%, which seems to suggest an increasing accumulation of wealth by the surveyed households.

The same concept is confirmed by Figures 3.1, 3.2 and 3.3, which represent the kernel density function for, respectively, income, consumption and asset for each year in the survey. It seems clear that the distribution are moving right over time as well as their tails are growing. This last particular could indicate that the impressive economic growth in Vietnam is also generating more dispersion in these key variables and, probably, more uncertainty.

Figure 3.1

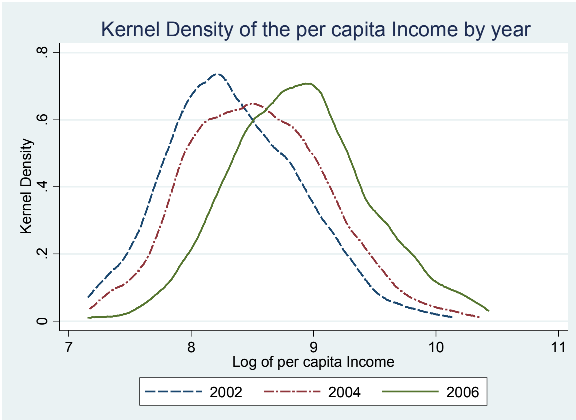


Figure 3.2

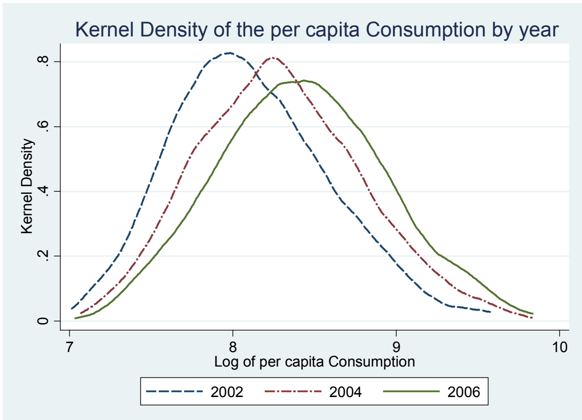
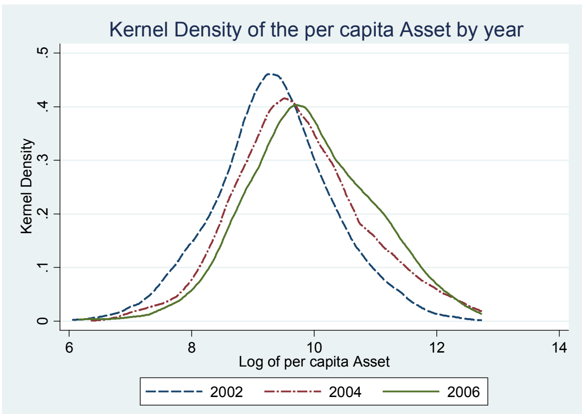


Figure 3.3



The demographic variables indicate a slightly decrease in the average size of the household, from 4.6 members to 4.4. More interesting, the average number of children decreased from 1.3 to 0.9, suggesting a reduction in the birth rate. For what concerns the education of the household head, the relative majority of the sample has completed a lower secondary school (32%), while the 28% has a primary education and more than 20% didn't attend any school. In the meanwhile, technical education has more than doubled its figures, from 5% to almost 10%, indicating a possible trend for the human capital in Vietnam, oriented towards more qualified jobs. Lastly, more than 60% of the households are involved in the agricultural sector, especially in rice production. However, the relative importance of the agricultural sector in the labor force is decreasing over time, together with the share of the people working in the production sector. At the same time, the labor force engaged in sales and services grew up from 1% to 12% in less than 5 years.

In the previous Paragraph we presented a three stages procedure to measure the new index of vulnerability. The first step is to separately estimate Equation (3.3) and Equation (3.9) in order to obtain, respectively, the innovations to income and asset which will be exploited to calculate the two proxies of risk. The set of explanatory variables Z used to estimate the two functions are composed by a series of demographic variables (age and its square of the household head, household size and its square, number of children, a dummy equal to one if the household head is married and zero otherwise, a dummy equal to one if he is male and zero if she is female), educational dummies which indicate the highest level achieved by the household head (primary, lower secondary, upper secondary, technical or vocational, university) and occupational dummies (white collar, sales or services, agriculture and production)[13]. We also control for spatial and time specific factors introducing dummies for regional provenience and quarter of interview for each wave. The households have been interviewed in different months of the year, meaning that our dependent variable could be influenced by seasonal factors. Therefore, controlling for the quarter of interview eliminates this potential problem and captures possible time trends.

Considering the error structure we imposed to the income and asset innovations in Equation (3.8) and Equation (3.11), we need a robust method to correct for serial correlation. However, temporal dependencies is not the only problem we need to solve when we deal

[13]We also tested the occupational dummies and their interactions with the head age but we had to refuse this specification otherwise the model would be over-identified.

with microeconometric panels because we have to control also for heteroskedasticity and cross-correlation within waves. We test serial correlation using both the Baltagi and Li (1995) and the Wooldridge (2002) tests for panel data which confirm the presence of time dependencies across innovations for both income and assets regressions, even if it seems less pronounced for the first one. Moreover, the Pesaran (2004) test suggests also the presence of cross-correlation in both cases[14]. One way to account for heteroskedasticity as well as for temporal and spatial dependence in the residuals is to use the generalized least squares (GLS) method based on the Beck and Kats (1995) suggestion to rely on OLS coefficient estimates with panel corrected standard errors using a Prais-Winsten transformation[15]. This feasible GLS estimation is obtained simply regressing the OLS residuals of Equations (3.3) and (3.9) on its lagged counterpart and using this estimate, $\hat{\rho}$, to get the quasi-differenced variables for $t > 1$:

$$\begin{aligned} y^*_{ht} &= y_{ht} - \hat{\rho} y_{h,t-1} \\ k^*_{ht} &= k_{ht} - \hat{\rho} k_{h,t-1} \\ Z^*_{ht} &= Z_{ht} - \hat{\rho} Z_{h,t-1} \end{aligned} \tag{3.17}$$

While for $t = 1$ we simply multiply each variable for $\sqrt{(1-\rho^2)}$. The following step is to estimate an OLS regression with panel corrected standard errors of y^* and k^* on Z^*. Once the FGLS estimator is found, we iterate the procedure: computing a new set of residuals; obtaining a new estimator of $\hat{\rho}$; transforming the data with the new $\hat{\rho}$, and estimating by OLS. We repeat the operation until the difference of $\hat{\rho}$ between two iterations is small enough (Wooldridge, 2005). The Prais-Winsten regression is preferable to other methodologies because it preserves the first observation for each household and it can be performed even with a short panel data, which is definitely our case.

[14]For serial correlation, the Baltagi and Li (1995) test gives us back a chi-square statistic with one degree of freedom equal to 1785.55 (p-value=0.000) for the asset regression and equal to 1054.04 (p-value=0.000) for the income regression. The Wooldridge (2002) test provides an F-statistic (1,1184) of 19.949 (p-value=0.000) for asset and 3.237(p-value=0.0723) for income. For cross-correlation, the Pesarans statistic which follows a standard normal distribution is equal to 2.496 (p-value=0.01) for asset and equal to 23.469 (p-value=0.000) for income.

[15]Another way is to use the feasible generalized least squares (FGLS) based on the Kmenta (1986) algorithm. Unfortunately, this method is inappropriate for use with medium and large scale panels, where the panel time dimension T is smaller than its cross-sectional dimension N. The reason is due to the impossibility to obtain a nonsingular estimate of the $N \times N$ matrix of cross-sectional covariances when $T < N$. See Beck and Katz (1995) for details.

Table 3.2 shows the results from the income regression. The demographic variables are all statistically significant, except for the sex of the household head. The coefficients of age and its square confirm the well-known concave age-income profile: income grows together with the age but at a decreasing rate. The highest level of the lifetime income trajectory is - on average - when the head is almost 54 years old. Not surprisingly, having children reduces per capita income while being married increases it. The education variables behave according to our prediction - the higher is the level, the higher is the income[16] - while the occupation dummies confirm that who works in the agricultural sector earns less than the others (e.g. the difference with people who is engaged in services or sales is more than 10%).

The R-square is equal to 0.926 denoting a really good overall fit of the model, while the estimated coefficient of autocorrelation is equal to 0.66 indicating persistence in the income innovation errors. The DurbinWatson test raised its value from 0.72 to 1.65. Even if the modified statistic is closer than the original to the value of 2, we are still in the indecision zone, suggesting that we could have a higher serial correlation.

Table 3.3 presents the results for the asset regression. As before, the estimated coefficients are almost all significant even if there are some differences. The lifetime profile of the asset value is concave in the head age as in the case of income and it gets its highest point almost in the same year, when the head is 54. The other demographic variables and the educational variables have the same sign and significance of the income regression, except for the number of children which doesn't seem to account for the asset accumulation process. One difference raises from the occupational dummies, where the coefficients are significantly bigger than for the income regression One reason could be that the productive assets held by the farmers have a lower value with respect to the asset held by industrial goods producers or their sellers. Finally, it is interesting to compare the seasonality dummies inserted to capture the time trends. Especially for the asset regression, there is a strong difference between who has been interviewed during the first quarter of the year with the others. For example, the difference between first and second quarter in 2002 is more than 40% , indicating probably the presence of seasonal factors which influence the asset behavior of the

[16]For example, who achieves a lower secondary education earns on average and ceteris paribus, $(e^{0.151-1}) * 100 = 16.4\%$ more than who is without education. For people with the degree the difference is almost 50%

Table 3.2: Income Regression

	Coefficients	**t-statistics**
Demographic characteristics		
Age of the household head	0.055***	5.013
Age2 of the household head	-0.001***	-4.283
Household Size	-0.188***	-6.878
Household Size2	0.010***	4.385
No. of Children	-0.082***	-6.456
Married Head	0.211***	4.129
Male Head of Household	-0.056	-1.356
Education		
(No education)		
Primary School	0.060**	2.242
Lower secondary school	0.151***	4.898
Upper secondary school	0.188***	4.091
Tech/voc school	0.286***	6.474
University	0.398***	5.679
Occupation (Head)		
White Collar	0.096**	2.384
Sales/Services	0.100***	2.671
Production	0.093***	4.3
(Agriculture)		
Region		
(Red River Delta)		
North East	-0.009	-0.201
North West	-0.193***	-2.992
North Central Coast	-0.083*	-1.763
South Central Coast	0.084*	1.807
Central Highlands	0.163***	2.829
South East	0.284***	5.886
Mekong River Delta	0.283***	6.403
Seasonality (quarter)		
Interviewed 2st 2002	-0.275***	-6.069
Interviewed 3st 2002	-0.183***	-8.848
Interviewed 4st 2002	-0.224***	-10.081
Interviewed 3st 2004	-0.125***	-6.229
Interviewed 4st 2004	-0.119***	-2.924
Interviewed 3st 2006	0.205***	8.337
Interviewed 4st 2006	0.279***	8.526
Constant	7.596***	29.889
R^2	0.926	
No. of observations	3555	
Durbin-Watson (original)	0.721	
Durbin-Watson (original)	1.648	
Rho	0.657	

Table 3.3: Asset Regression

	Coefficients	**t-statistics**
Demographic characteristics		
Age of the household head	0.116***	5.722
Age2 of the household head	-0.001***	-5.05
Household Size	-0.367***	-7.57
Household Size2	0.019***	4.31
No. of Children	-0.022	-0.934
Married Head	0.263***	2.774
Male Head of Household	-0.072	-0.836
Education		
(No education)		
Primary School	0.214***	4.274
Lower secondary school	0.359***	6.455
Upper secondary school	0.474***	6.107
Tech/voc school	0.470***	6.217
University	0.686***	5.358
Occupation (Head)		
White Collar	0.237***	2.711
Sales/Services	0.261***	4.517
Production	0.112***	2.958
(Agriculture)		
Region		
(Red River Delta)		
North East	-0.281***	-3.564
North West	-0.368***	-2.784
North Central Coast	-0.309***	-3.85
South Central Coast	-0.085	-0.894
Central Highlands	0.082	0.778
South East	0.285***	2.882
Mekong River Delta	-0.113	-1.392
Seasonality (quarter)		
Interviewed 2st 2002	-0.523***	-5.713
Interviewed 3st 2002	-0.259***	-7.449
Interviewed 4st 2002	-0.339***	-8.906
Interviewed 3st 2004	0.012	0.357
Interviewed 4st 2004	-0.091	-1.505
Interviewed 3st 2006	0.086**	2.092
Interviewed 4st 2006	0.202***	4.301
Constant	7.689***	15.913
R^2	0.857	
No. of observations	3555	
Durbin-Watson (original)	0.547	
Durbin-Watson (original)	1.677	
Rho	0.75	

Table 3.4: Mean Income and Asset Residuals

		Asset Residuals	Income Residuals
Occupation	**Education**		
White Collar	None	-0.2580	0.1566
White Collar	Primary	-0.1559	0.0097
White Collar	Secondary or higher	0.1177	0.0787
Sales/Services	None	-0.1518	-0.0727
Sales/Services	Primary	-0.0530	0.0783
Sales/Services	Secondary or higher	0.3968	0.0814
Production	None	-0.0425	-0.0750
Production	Primary	0.0269	-0.0407
Production	Secondary or higher	0.1673	0.0431
Agriculture	None	-0.0927	-0.0412
Agriculture	Primary	-0.0697	-0.0290
Agriculture	Secondary or higher	-0.0873	-0.0333
Anova Test (F-statistics)		7.07	2.90
p-value		0.0000	0.0008

households. Finally, we can note that the overall fit of the model is good also in the asset regression, certified by a R^2 of 0.86, while the coefficient of autocorrelation in this case is higher with respect to income (0.75 vs 0.65), indicating higher persistence in the residuals. As before, the modified version of the Durbin-Watson test raised its value (from 0.55 to 1.68), but it is still in the indecision zone.

Now we focus our attention on the estimated measures of risk, calculated using Equation (3.8) and Equation (3.11). First of all, we perform a oneway ANOVA test on the income and asset residuals to verify if there is a statistically significant difference across the 12 occupation/education groups (Table 3.4). The F-statistics reject in both cases the null hypothesis that the mean residuals are identical across groups, allowing us to create sub-samples of the population according to the occupation and the education of the household head. Table 3.5 reports some statistics related to the mean of the estimated income and asset risks based on education, occupation and age characteristics. For simplicity, we group the head age in nine 5-year cohorts. For both asset and income risks we can barely see a lifetime pattern. It seems that young and middle-age people suffer more asset uncertainty than older people because the estimated risk remains above its average until the age of 55.

Table 3.5: Estimated Income and Asset Risks

	Asset Risk	**Income Risk**
	Mean	Mean
Total Sample	0.8968	0.4958
Head Age 25/30	0.8995	0.4948
Head Age 31/35	0.9025	0.4928
Head Age 36/40	0.9071	0.4922
Head Age 41/45	0.9028	0.4901
Head Age 46/50	0.9001	0.4897
Head Age 51/55	0.8996	0.4916
Head Age 56/60	0.8880	0.4970
Head Age 61/65	0.8906	0.5017
Head Age 66/70	0.8813	0.5123
Occupation		
White Collar	0.9522	0.4002
Sales/Services	0.9535	0.5266
Production	0.9688	0.4759
Agriculture	0.8594	0.5071
Education		
No education	0.8885	0.5061
Primary	0.8896	0.5025
Secondary or higher	0.9118	0.4814

However, the difference is not substantial and both the minimum (0.8813) and the maximum (0.9071) are quite close to the mean level (0.8968). Different path for the evolution of income risk which is higher during the first years of life (25/30), decreases below the average during the working age (30/55) and increases again close to the retirement.

These results partially confirm the considerations on the lifetime path of income risk made by Feifennbaum and Li (2010): younger people who are entering now in the labor market are more uncertainty than middle age persons with a family and a stable career path[17]. However, the difference across age profiles in Table 3.5 doesn't seem to be so significant to sustain the presence of an U-shaped lifetime pattern for income risk. For what

[17]Using PSID data from 1968 to 2005, Feifennbaum and Li (2011) show that uncertainty profile has a U-shaped pattern over the entire life cycle. The income variance is high when the head is young and declines over time, before rising again in the mid-fifties, just before the head approaches to retirement. The same pattern emerges also from the analyses of Gordon (1984) and more recently of Baker and Solon (2003), with the difference that the U-shaped pattern is limited to the transitory variance and not even to the permanent fluctuation of income.

concerns the occupational breakdown, asset risk is lower for people involved in farm activities with respect to the other categories. On the contrary, income risk is higher if the household head is working in the sales/services sector and agriculture. White collars show the lower level of income fluctuation, clearly due to the stability provided by the nature of their jobs. Looking at the education breakdown, more educated people have the highest level of asset risk and the lowest level of income risk. It is interesting to note that frequently the level of asset and income risks are not correlated across categories and - in some cases - they operate in opposite directions. The reason is probably due to the fact that shocks on asset and income are not cross-correlated as predicted by Elbers et. al (2009) and Dercon (2005) but they are statistically independent as we assumed in the dynamic simulation provided in Chapter 2.

3.3.3 The Second Stage Results: the Consumption Regression

The second step in our method is to estimate Equation (3.12) in order to verify if income and asset risks determine the household behavior and how it influences its welfare. This causal relationship can be estimated using different assumptions over the effect of unobservable variables which influence the relationship between consumption, risk and household's behavior. A natural starting point for that specification is a pooled OLS regression of consumption over the income and asset proxies of uncertainty, the estimated permanent level of income and the estimated value of assets, as well as the set of observable characteristics X. Using a pooled OLS for repeated cross-sections imposes to deal with the problem that the errors are not independently and identically distributed because they are at least correlated over time for a given households. At this purpose, both heteroskedasticity and serial correlation are solved using cluster-robust standards errors that cluster on individuals, applying the generalized estimator proposed by Rogers (1993)[18]. The pooled OLS yields unbiased results only if we unrealistically assume that omitted and unobservable factors are not influencing consumption and saving choices. Nevertheless, it seems quite obvious that consumption and saving decisions are likely to be affected by a myriad of unobservable characteristics which depend on the household's behavior and its attitude towards risk. These individual

[18] We are implicitly excluding cross-correlation between groups of individuals.

characteristics can be either constant across time or be distributed as random variables. In the first case we would estimate our model using a fixed effect (FE) specification while in the second case we would use random effects (RE) model. Considering the complexity of the relationship between household's choices and risk, it seems better allowing the unobserved heterogeneity between individuals not to be fixed and estimating Equation (3.12) using a random effects model.

For sake of simplicity Table 3.6 reports only the parameters concerning the precautionary motive while Appendix 3.II reports the full results of the consumption regressions. The first two columns of Table 3.6 report respectively the results for the Pooled OLS and the Random Effects models, without considering the estimated level of asset and asset risk. These two specifications are similar to those performed by standard precautionary saving theory and suffer the same problem of the current vulnerability analyses which don't take into account the role played by assets. In the same Table, Column 3 and 4 show the results for the full model proposed in Equation (3.12). Our main interest is to understand if asset and income risks have any effect on the level of consumption and if these impacts confirm the results of the stochastic simulation presented in the Chapter 2. We insert these two variables in their logarithmic form in order to simplify the interpretation of the results. Without considering assets and asset risk, our estimations provide evidence of the presence of the standard precautionary motive. The sign of the income risk proxy is negative - as predicted by the precautionary saving theory - and highly significant. In particular, a 50% increase in the income risk has the effect to reduce the current consumption by almost 10%. This results seem to be coherent with that part of empirical literature which finds a substantial impact of income risk on the household's behavior. However, once we control for both the estimated level of asset and the asset risk, an interesting and different pattern of precautionary motive seems to emerge from columns 3-6.

First of all, income risk maintains its negative sign but the coefficient is significantly smaller with respect to the previous specifications, i.e. -0.116 for OLS and -0.124 for RE. Therefore, a 50% increase in the income risk would decrease consumption by 6%. Even if the impact of income risk on consumption is still highly significant, it is quantitatively smaller than the specification in the first two columns of Table 3.6. On the other hand, asset risk has

Table 3.6: Consumption Regression

	POLS (1)	RE (2)	POLS (3)	RE (4)	LAD (5)	RE PW (6)
Precautionary Motive						
Income Risk	-0.1954***	-0.2053***	-0.1160**	-0.1244**	-0.1720***	-0.1477**
Asset Risk			0.2427***	0.1853***	0.2360***	0.1417**
Estimated Permanent Income	0.4117***	0.3857***	0.2672***	0.3200***	0.2633***	0.3104***
Estimated Asset Value			0.1531***	0.1201***	0.1639***	0.0986***
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Seasonality (quarter)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.8321***	3.7336***	4.1754***	3.8218***	4.0599***	3.8870***
R^2	0.4295	0.4189	0.5653	0.5574	0.3875	0.9605
No. of observations	3555	3555	3555	3555	3555	3555
Durbin-Watson (original)						0.8491
Durbin-Watson (transformed)						1.649
Rho						0.6415
BPLM test (OLS vs RE)	966.28 (p=0.0000)		425.05 (p=0.0000)			
Hausman test (RE vs FE)	202.27 (p=0.0000)		390.40 (p=0.0000)			

a positive and strongly significant impact, confirming our prediction that income risk is not the only factor which drives the household's changing behavior. These results are confirmed by both the estimation techniques (i.e. 0.2427 for OLS and 0.1853 for RE), suggesting that this coefficient doesn't depend on the econometric specification. A 50% increase in the asset risk would increase the household's consumption by 12.1% with the OLS specification (column 3) and 9.2% with the RE model (column 4). The net effect of a 50% reduction of the overall risk would have a positive impact on consumption equal to 6%, meaning a parallel reduction in savings to be invested in the future. Even if we are not able to test this prediction because of the short time horizon of our panel, we can imagine that a lower level of savings caused by an excessive asset uncertainty has the consequence to lower the household's welfare in the long run, as predicted by other authors (see for example Deaton, 1989). If the households are forced to sell assets for consuming more because their buffer-stock is low and there are liquidity constraints, the presence of asset risk can exacerbate the negative consequences. The higher is the fear of losing assets because of the their exposure to risk, the higher is the incentive to sell the productive components of the portfolio to earn more. However, the new portfolio of assets will be less productive than the previous one with the consequence to increase the probability to fall into poverty in the future.

Permanent income is strongly positive and significant and the coefficients indicate that households consume more than 40% of it if we don't control for assets (column 1 and 2) while it reduces to 30% once we insert the other variables (column 3 and 4). In both cases the coefficients are quite low with respect to other previous empirical analyses in developing countries (Paxson, 1992; Ersado et al. 2003) where it is usually close to 70%. The first explanation to this result could be that the impressive Vietnamese economic growth of the last decades is increasing the households' rate of saving - as already seen in China - and therefore lowering the marginal propensity to consume out of permanent income. The second explanation is related to our method: we are not considering separately the permanent and transitory incomes because of the length of our panel data. Considering that the MPC out of transitory income is usually lower than the MPC out of permanent income, our coefficient could be influenced by a downward bias caused by the omission of the transient income component. As foreseen, even the coefficient of the estimated level of assets is positive and statistically significant (column 3 and 4), confirming Elbers and Gunning (2003) intuition that households with the same characteristics except for the level of assets behave differently: the households with higher K can better afford to smooth consumption. In this case, a 10% increase in the estimated value of assets will increase the level of consumption by 1.5% in the case of the Pooled OLS and by 1.2% for the RE model. The importance of assets is also confirmed by the difference in the goodness of fit of the different models: the R-squared increase from 0.43 to 0.56 in the Pooled OLS and from 0.42 to 0.56 in the RE model.

In Appendix 3.III we can see other factors which influence the level of consumption as demographic variables and education as well as regional and time controls. The signs and the significance is almost as expected in all cases for both models, so we don't describe them in details because the interpretation is similar to what we have already said for the income and asset regressions. More interesting, we have to verify if the choice to identify our model by excluding the occupational variables is sustainable. We assumed that the occupational dummies influence the level of consumption only through their impact on the level of income and asset. We perform an F-test on the joint significance of the occupational dummies in the income and asset regressions and it gives us two p-values of 0.000 [19], excluding any weak instruments problem. For what concerns the over-identification problem, we test it following Carroll and Samwick (1998) re-estimating our model in a generalized method of moments (GMM) framework and using the heteroskedasticity-robust Hansen test of the overidentifying restrictions. For the first specification in column 1 and 2 (without asset as endogenous covariate), the J-statistics is equal to 1.403 with a p-value of 0.4959 while for the second specification in column 3 and 4 (with asset as second endogenous regressor together with income) the J-statistics is equal to 0.09 with a p-value of 0.76. The acceptance of the null hypothesis means that we are using valid instruments, uncorrelated with the error term and correctly excluded from the consumption regression. Then, we don't have any problem of overidentifying restrictions.

Lastly, we run other two versions of Equation (3.12) to verify the robustness of our estimates. Especially in the pooled OLS specification, our results could be influenced by outliers and heavy tails in the distribution of the dependent variable, which could departs

[19] The F-statistic for the income regression is 8.83 while for the asset regression is 7.25.

from normality. We test this hypothesis and unsurprisingly certify that the distribution of the log of the per-capita consumption is not normal[20]. Following Jalan and Ravallion (2001), we evaluate how serious this problem is for our regressions estimating again Equation (3.12) using a Least Absolute Deviation procedure (LAD) at the 50^{th} percentile[21]. This *quantile* regression is reported in column 5 of the Table 3.6. The signs and the significance of the parameters are similar to column 3 and 4. However, an interesting difference emerges from the fact that the impact of income risk is definitely higher than the Pooled OLS model in column 3 (-0.172), while the effect of asset risk slightly decreases (0.23). It implies that the net impact of risk is still negative on consumption, even if smaller compared to the other regressions.

Finally, as in the case of income and asset, consumption regression can be affected by serial correlation[22]. We apply the same panel corrected standard errors PW transformation as in the previous cases and we obtain the output in column 6. The results are quite different from the previous specifications. In particular, the impact of income and asset uncertainty continues to be highly significant and with opposite sign but the magnitude of the two coefficients is really similar (-0.1477 vs 0.1417), suggesting that impacts of asset and income uncertainties cancels out. The estimated value of the coefficient of autocorrelation is equal to 0.63 while the Durbin-Watson statistic raises from 0.85 to 1.65. The R-square is equal to 0.96, showing an impressive overall goodness of fit with respect to the other regressions.

3.3.4 The Third Stage Results: Vulnerability Analysis

The last step requires to estimate the vulnerability index for the period 2002-2006 using the decomposition proposed in Chapter 2. At this purpose, we follow the method suggested in Paragraph 3.2.3 and estimate the three different consumption counterfactuals using the RE model presented in column 4 of the Table 3.6. In particular, for estimating c^{DT} we regress

[20] The skewness and the kurtosis of the per capita log-consumption are respectively 0.2576 and 2.71 while the associated chi-square normality test has a p-value of 0.000.

[21] We tried also to estimate the same Equation at different percentiles (0.1 0.25 0.75 0.9). However, the inter-quantile difference across the estimates is never significant from the median value of the consumption distribution and therefore we report just one regression.

[22] We test this hypothesis using the Baltagi and Li (1995) and the Wooldridge (2002) tests. While the former confirm the presence of autocorrelation, giving back a chi-square statistic with one degree of freedom equal to 636.58 (p-value=0.000), the latter seems to refuse it, providing an F-statistic (1,1184) of 2.130 (p-value=0.1447).

Equation (3.12) without considering the asset and income uncertainty proxies and take the fitted values of this regression. We use the same approach for calculating the c^{EA} except that this time we introduce the two risk variables while for c^{FS} we add up the group-specific expected shock to the fitted values of the regression in column 4 of Table 3.6. Once we have all three consumption counterfactuals we calculate Equation (3.16), i.e.:

$$\hat{V}_h = \sum_{t=0}^{T} \beta^t T_t \left\{ [U(z) - U(\hat{c}_{ht}^{DT})] + [U(\hat{c}_{ht}^{DT}) - U(\hat{c}_{ht}^{EA})] + [U(\hat{c}_{ht}^{EA}) - U(\hat{c}_{ht}^{FS})] \right\} \tag{3.18}$$

$$\text{where } T_t \begin{cases} 1 \text{ if } [U(z) - U(\hat{c}_{ht}^{FS})] \geq 0 \\ 0 \text{ if } [U(z) - U(\hat{c}_{ht}^{FS})] \leq 0 \end{cases}$$

For the instantaneous utility function we choose the logarithmic version of the CRRA imposing γ, the coefficient of relative risk aversion, equal to 1[23]. Table 3.7 reports the results for different categories of households. The first column reports the percentage of households who are vulnerable, i.e. those with a positive sum of the discounted differences between the level of the welfare at the poverty line ($U(z)$) and the level of welfare obtained from the predicted full-stochastic consumptions ($U(c_{ht}^{FS})$)[24]. The second column indicates the mean value - expressed in utils - of V_h while the last three columns report the relative percentage of the three vulnerability components calculated exploiting the deterministic and ex-ante consumption counterfactuals and applying Equation (3.16). The results show that the 28% of the entire sample is vulnerable while the overall mean level of vulnerability is equal to 16.05 utils. More interesting, the breakdown of the vulnerability indicates that the most relevant component of the measure is the ex-post effect of risk (57.30%) and the ex-ante component accounts for almost one third of the total vulnerability (29.25%). Poverty seems to be the less relevant part of the index, with only the 13.45%. Even if the short panel data limits the lifetime analysis to only 4 years (2002-2006), these results seem to be coherent with the actual situation of Vietnam characterized by a continuous reduction of poverty in

[23]We also try the value of 2 and 3 and we obtain higher level of vulnerability, as predicted by the measure. However, the relative magnitudes of the different components are not sensitive to the concavity of the utility function as well as the relative difference between different categories. For this reason, we prefer to use 1 as the baseline value.

[24]i.e. $V_h = \sum_{t=2002}^{2006} \beta^t T_t [U(z) - U(c_{ht}^{FS})] > 0$

Table 3.7: Estimated Vulnerability: 2002-2006

	$V > 0$	**Mean**	**Poverty**	**Ex-ante**	**Ex-Post**
	%	Utils	%	%	%
Total Sample	28.44	16.05	13.45	29.25	57.30
Head Age					
Head Age < 40	36.93	21.86	19.32	27.42	53.26
Head Age 41/50	24.42	12.80	6.86	31.83	61.31
Head Age 51/60	17.23	10.09	10.35	33.80	55.85
Head Age > 60	33.80	17.69	7.37	23.33	69.29
Occupation					
White Collar	7.72	4.31	17.08	18.70	64.22
Sales/Services	10.99	6.08	16.70	27.28	56.03
Production	19.42	8.84	10.51	25.61	63.88
Agriculture	37.13	21.83	13.84	30.39	55.78
Education					
No education	44.46	30.87	19.39	29.41	51.20
Primary	33.47	16.68	14.16	27.77	58.07
Secondary or higher	18.89	9.41	6.81	30.52	62.66
Region					
Red River Delta	15.97	6.98	1.06	31.51	67.43
North East	39.80	22.73	18.56	34.06	47.38
North West	63.83	44.76	23.12	24.18	52.70
North Central Coast	49.37	27.76	20.13	24.66	55.22
South Central Coast	17.09	7.25	3.59	34.91	61.50
Central Highlands	46.84	30.57	17.36	26.21	56.42
South East	14.40	6.39	6.00	24.45	70.00
Mekong River Delta	16.36	10.18	0.80	32.75	66.45

the last two decades but also by an increasing uncertainty due to the introduction in the economic system of new sources of risk such as prices fluctuations, market deregulation and trade liberalization (Winters et al, 2004; Niimi et al, 2007).

For what concerns the lifetime profile of vulnerability in Vietnam, we group households according to the age of the head. Interestingly, vulnerability seems to be higher for younger and older people, while in the central part of life (for the decades 41/50 and 51/60) the risk of being poor seems to be relatively low. Vulnerability decreases from a value of 21.86 in the first decade to 10.09 in the third decade, before increasing again when the head age is more than 60. It is worth to note that even if both younger and older people suffer a high level of vulnerability, the internal breakdown is quite different. For the household heads below the 40 the poverty component is above the overall average (19.32%) while the ex-post component is below it (53.26%). On the contrary, for households with the head above 60, the poverty component is really low (7.37%) and the ex-post component really important (69.29%). It might indicate the fact that younger people are usually poorer but also more insecure about their future, while older persons live in a more stable environment and could fall into poverty only because of unexpected shocks.

Unsurprisingly, the analysis of occupation indicates that farmers are the most vulnerable (21.83) while white collars are the less vulnerable (4.31). This difference reflects the fact that farmers are certainly more poor and more insecure about their future with respect to people with a safe job as - for example - public employees. In this case, the internal breakdown is quite stable and it doesn't change across categories. For the level of education we have that the higher is the level the lower is the vulnerability measure. Therefore, vulnerability is similar to poverty analysis, meaning that a higher level of education ensures both a higher level of current welfare but also better expected living standards in the future. Lastly, Table 3.7 provides a glance at the geographical distribution of vulnerability in Vietnam, showing how its incidence has a strong regional dimension. The most vulnerable regions are the North West (44.76) and the Central Highlands (30.57), the same regions which are also characterized by the higher incidence of poverty, probably because of their high specialization in agriculture. This characteristic is also confirmed by the internal breakdown of the vulnerability which confirms that the poverty component is far above the national average for both North West (23.12) and Central Highlands (17.36).

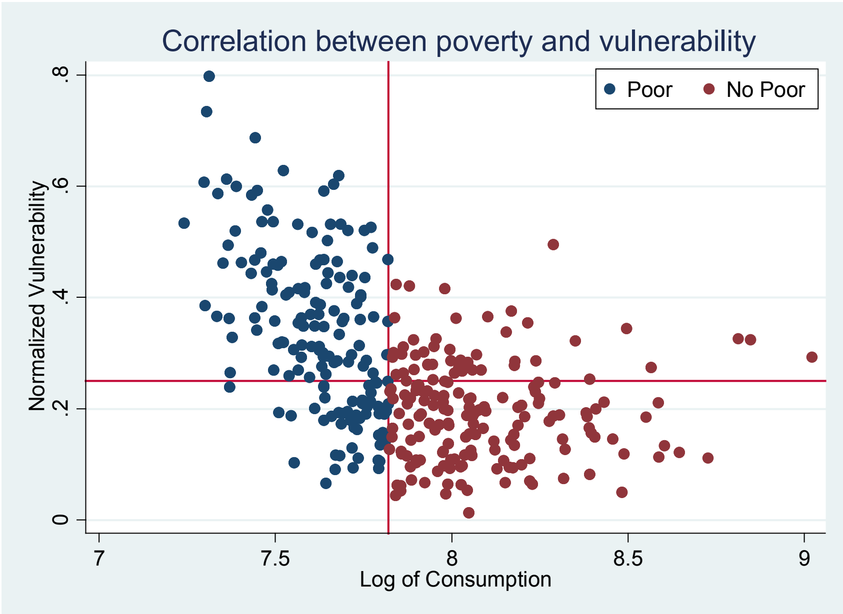
Table 3.7 can be compared with the numerical simulation results provided in Chapter 2. In that case, the ex-ante component of vulnerability was the most important and accounted for almost 70% of the total welfare losses due to risk. The difference between the theoretical model and the empirical estimate implies that the ex-ante component is less important than we originally assumed. However, it must be remembered that in the numerical simulation we assumed $U(z) = U(c_{ht}^{DT})$ for each t, which means ruling out the poverty component and overestimating the weight of the ex-ante and ex-post elements. Moreover, the difference in the results can be motivated by the fact that the two analyses are performed over different temporal horizons: in Chapter 2 we had the chance to simulate a 50-year period while now we have only three observations for each households. One may argue that the numerical simulation is more robust because it doesn't suffer the problems raised by short-panel data. Nevertheless, it must be noted that the numerical simulation is based on the representative agent hypothesis which destroys all the individual heterogeneity provided by the real world and that can be caught only exploiting at the best the available household-level data. Therefore, it is more appropriate to sustain that even if both models presents their own weaknesses, their results share some commonalities such as the fact that the risk-induced changing behavior has a welfare cost and contributes to the determination of the future level of poverty.

This conclusion supports our original intention to demonstrate that the household's behavioral responses play an autonomous role in determining the level of welfare and the future poverty status in developing countries. The threat of being poor depends not only on the observable characteristics of the households or on the idiosyncratic and covariate shocks, but also on rational behavioral changes triggered by risk. A workable empirical measure of this cost is given by the difference between two welfare counterfactuals: one determined by the deterministic consumption and the other by the ex-ante consumption. It must be specified that this difference doesn't depend exclusively on the net effect of the two sources of risk but also on their indirect impact on the other parameters of the model. In Table 3.6 the asset risk offsets the negative impact of income risk on the predicted consumption and then one may correctly argues that actually risk is increasing the household's welfare because it increases consumption. However, it is worth to remember that $c^{DT}$and c^{EA} are estimated separately[25] and - as consequence - the estimated coefficients of the vector X (i.e. Φ) and of the certainty equivalent level of lifetime resources (θ_1 and θ_2) differ as well. It means that the introduction of the two risk proxies influences the propensity to consume out of permanent income/physical resources and the household's tastes in such a manner that the resulting ex-ante consumption will be on average lower than the deterministic one, despite we are in a context where the precautionary motive has a negative impact on saving.

Unlike the previous monetary approaches to vulnerability (e.g. VEP, VEU and VFP), the proposed empirical strategy - inspired by the micro-foundation discussed in Chapter 2 -

[25] See Equations (3.13) and (3.14)

Figure 3.4



provides an unbiased and complete analysis of the contribution of risk to future poverty in developing countries. In fact, for the first time in this body of literature vulnerability analysis is able to fully measure the impact of risk on the future level of welfare without wasting any useful information for policy intervention. In particular, the risk-induced behavioral choices are not considered just because of their contribution to the consumption fluctuations around its mean, but they are rigorously introduced as an active and direct component in the determination of the expected level of welfare.

Lastly, we use Figure 3.4 to briefly compare poverty and vulnerability for the households which reported a positive level of lifetime vulnerability and the relative policy implications. We report on the horizontal axis the log of the average observed consumption over the three surveyed periods together with the average threshold of poverty indicated by the vertical line. On the vertical axis we report the normalized level of vulnerability together with the its average, indicated by the horizontal axis. For convenience, we consider the households with a vulnerability measure above the average as *highly vulnerable*. The blue dots indicate poor households while the red dots indicate households with an average consumption above the average poverty threshold.

Let assume that policy makers want to intervene to reduce poverty and the allocation of resources is granted on the basis of the observed consumption distribution. This is not an unrealistic scenario and it is confirmed by more than one provision contained in the Vietnamese National Program on Poverty Reduction as well as in the Poverty Reduction Strategy Paper developed with the IMF. The quadrant is divided in four parts, each one indicating a particular combination between vulnerability and poverty. We have four possible situations: a household could be classified as highly vulnerable but non-poor, highly vulnerable and poor, non- highly vulnerable and non-poor, non- highly vulnerable and poor. Considering that non-highly-vulnerable-non-poor households don't need any specific intervention, and assuming that policymakers consider only poor households on the basis of the observed consumption level, we are excluding from any social protection the households in the North-East quadrant. It implies that some non-poor but highly vulnerable households will likely experience a welfare loss in the near future due to several causes (poverty, ex-ante changing behavior or ex-post shocks), without any intervention of the authorities. In the Vietnamese case, this is equal to almost 5% of the population.

3.4 Conclusion

The main contribution of this Chapter is to provide an empirical method for estimating the micro-founded measure of vulnerability to poverty proposed in Chapter 2 using household-level data. Inspired to the current empirical literature on precautionary saving, we propose a three-stage procedure which allows us to extract proxies for income and asset risks, evaluate their impact on the level of consumption and calculate the vulnerability index differentiating among its poverty, ex-ante and ex-post components. We implement this procedure using a three-wave panel data on Vietnam provided by the VHLSS which covers the period 2002-2006. Our results provide two main conclusions which contribute to the debate on risk and future poverty. First of all, the analysis of the impact of risk on consumption behavior performed in the first two stages of the procedure confirms that if the presence of risky income is coupled with the risky assets hypothesis, the net impact on saving is negative and this is coherent with the numerical simulation presented in Chapter 2. For Vietnamese households, an increase of 50% in the total amount of asset and income risks results in a net increase of current consumption equal to 5%. Even if the magnitude of the net impact is not important, the result is totally different from the previous empirical tests of precautionary saving which focuses only on income risk and conclude that it increases savings.

Secondly, the last stage of the procedure calculates the vulnerability measure indicating the relative weights of its main determinants. The most vulnerable households are those with a young head, employed in the agricutural sector and with no education. The results also suggest that in Vietnam the vulnerability to poverty calculated on the basis of the available panel data mostly depends on the potential damages caused by uninsured shocks. For those households which report a positive level of vulnerability, the ex-post component accounts for the 57% of the total measure. At the same time, almost 30% of the future welfare losses are caused by the ex-ante component, confirming that forms of rational behavior such as precautionary motive may have a cost. Lastly, the poverty component which depends on the households' structural characteristics account for the 13% of total vulnerability. This results are in line with the current situation of Vietnam characterized by a continuous reduction of poverty in the last two decades but also by an increasing presence of risk caused by the introduction in the economic system of new sources of uncertainty such as prices fluctuations, market deregulation and trade liberalization.

Finally, comparing these results with those provided by the numerical simulation in Chapter 2 we note that the ex-ante component of vulnerability has reduced its importance in the determination of future poverty. This discrepancy can be motivated by the methodological approaches (representative agent vs. linear regression) and the choice of the temporal horizons (50-year period vs. 3 panel waves). Despite these differences, however, both models supports the original intention to demonstrate that risk-induced changing behavior produces a welfare cost and contributes to the determination of the future level of poverty. The threat of being poor depends not only on the observable characteristics of the households or on the idiosyncratic and covariate shocks, but also on rational behavioral changes triggered by risk. In particular, despite the asset risk offsets the negative impact of income risk on the predicted consumption, the introduction of the two risk proxies in the estimation influences the other parameters of the model in such a manner that for the vulnerable households the resulting ex-ante consumption will be on average lower than the deterministic one, even though we are in a context where precautionary motive has a negative impact on saving. Once again, it confirms that the development of new instruments to improve the risk-mitigating mechanisms of the poor households should be one of the top priorities in the agenda of the policy makers engaged in the design of poverty prevention programs.

Appendix 3.I: Sample Restrictions and Regional Deflators

Table 3.8: Sample Restrictions

	No. of HH Eliminated	No. of HH Remaining
Full Sample		1941
Same HH Head from 2002 to 2006	69	1872
HH in working age	335	1537
Outliers	73	1464
Non-missing value in all years	279	1185

Table 3.9: Regional Deflators

Region	2002	2004	2006
		URBAN	
Red River Delta	1.07	1.077	1.084
North East	0.978	0.97	0.963
North West	1.007	1.013	1.02
North Central Coast	1.011	1.003	0.996
South Central Coast	1.063	1.068	1.073
Central Highlands	1.036	1.036	1.036
South East	1.183	1.208	1.234
Mekong River Delta	1.054	1.075	1.096
		RURAL	
Red River Delta	0.961	0.984	1.007
North East	0.981	0.944	0.908
North West	1.024	1.006	0.989
North Central Coast	0.899	0.88	0.862
South Central Coast	0.975	0.976	0.976
Central Highlands	0.994	0.962	0.931
South East	1.012	1.036	1.061
Mekong River Delta	0.992	0.975	0.958

Regional deflators are provided by Brian McCaig

Appendix 3.II: Consumption Regression (Full Version)

	POLS	RE	POLS	RE	LAD	RE PW
Precautionary Motive						
Income Uncertainty	-0.1954***	-0.2053***	-0.1160**	-0.1244**	-0.1720***	-0.1477**
Asset Uncertainty			0.2427***	0.1853***	0.2360***	0.1417**
Estimated Permanent Income	0.4117***	0.3857***	0.2672***	0.3200***	0.2633***	0.3104***
Estimated Asset Value			0.1531***	0.1201***	0.1639***	0.0986***
Demographic characteristics						
Age of the household head	0.0201**	0.0374***	0.0172**	0.0241***	0.0102	0.0317***
Age2 of the household head	-0.0002**	-0.0004***	-0.0002**	-0.0002***	-0.0001	-0.0003***
Household Size	-0.0689***	-0.1149***	-0.0411*	-0.0613***	-0.0502**	-0.0835***
Household Size2	0.0039*	0.0053***	0.0022	0.0026	0.0033*	0.0034*
No. of Children	-0.0738***	-0.0520***	-0.0679***	-0.0541***	-0.0686***	-0.0513***
Married Head	0.1648***	0.1571***	0.1026***	0.1138***	0.1260***	0.1308***
Male Head of Household	-0.1006***	-0.0617*	-0.0663**	-0.0564**	-0.0561**	-0.0593*
Education						
(No education)						
Primary School	0.0894***	0.0796***	0.0569***	0.0575***	0.0587***	0.0469**
Lower secondary school	0.1797***	0.1554***	0.1173***	0.1146***	0.1236***	0.0948***
Upper secondary school	0.2094***	0.1796***	0.1261***	0.1228***	0.1454***	0.1072***
Tech/voc school	0.4141***	0.2879***	0.2809***	0.2381***	0.2778***	0.1910***
University	0.5650***	0.4466***	0.4237***	0.3885***	0.3995***	0.3731***
Region						
(Red River Delta)						
North East	-0.0747**	-0.0615*	-0.0104	-0.0186	-0.0279	-0.0266
North West	-0.049	-0.0453	0.0014	-0.0013	-0.0324	-0.0112
North Central Coast	-0.0869**	-0.0890**	-0.0389	-0.0485*	-0.0733***	-0.0643*
South Central Coast	0.0972***	0.0942**	0.1180***	0.1083***	0.1183***	0.0984***
Central Highlands	-0.0211	-0.0114	-0.0039	-0.0098	-0.015	-0.0072
South East	0.2333***	0.2345***	0.2339***	0.2229***	0.1938***	0.2099***
Mekong River Delta	0.1152***	0.1069***	0.1816***	0.1515***	0.1821***	0.1345***
Seasonality (quarter)						
Interviewed 2st 2002	-0.2940***	-0.2606***	-0.1481***	-0.1631***	-0.1231***	-0.1899***
Interviewed 3st 2002	-0.1826***	-0.1938***	-0.1136***	-0.1353***	-0.1236***	-0.1253***
Interviewed 4st 2002	-0.2263***	-0.2098***	-0.1287***	-0.1398***	-0.1352***	-0.1434***
Interviewed 3st 2004	-0.0662***	-0.0551***	-0.0552***	-0.0534***	-0.0571***	-0.0454***
Interviewed 4st 2004	-0.0684*	-0.0588*	-0.0518	-0.0448	-0.0172	-0.0372
Interviewed 3st 2006	0.0897***	0.0992***	0.0549***	0.0727***	0.0558**	0.0854***
Interviewed 4st 2006	0.0382	0.0807***	0.0056	0.0345	0.0348	0.0526**
Constant	3.8321***	3.7336***	4.1754***	3.8218***	4.0599***	3.8870***
R^2	0.4295	0.4189	0.5653	0.5574	0.3875	0.9605
No. of observations	3555	3555	3555	3555	3555	3555
Durbin-Watson (original)						0.8491
Durbin-Watson (transformed)						1.649
Rho						0.6415

Conclusion

Challenging the common view that looks at the coping and managing strategies as an optimal ”ex-ante” behavior to reduce the potentially harmful consequences of risk, this work demonstrates (theoretically and empirically) that the risk-induced changing behavior actually has a cost in terms of welfare, especially for poor households in developing contexts. If it is the case, current monetary approaches to vulnerability to poverty lead to bias poverty prevention recommendations.

From the theoretical point of view the thesis proposes a micro-founded measure which distinguishes among the different causes of future poverty. The micro-foundation is based on a model of precautionary saving adapted to the special features of developing contexts, where households are assumed to be credit constrained with risky income and assets. The results of the dynamic and stochastic simulation show that the risk-induced rational behavior of the household has a cost in terms of future welfare and, in particular, risk reduces the asset and consumption paths with respect to its deterministic counterfactual by almost 20%. The 80% of this difference depends on the risk-induced changing behavior while the remaining part is caused by the ex-post realization of shocks. Subsequently, these results are exploited to propose a monetary measure of vulnerability which separates the contribution to future poverty due to the characteristics of the household (poverty component) from the contribution of the risk-induced changing behavior (ex-ante component) and the risk realizations (ex-post component). Applying the new measure to the simulation results we quantify that the 70% of the total vulnerability of a representative poor household is due to the ex-ante component. The simulation also shows that the higher is household’s risk aversion, the persistence of the shocks or the total amount of income and asset risks, the higher is the total level of vulnerability.

From an empirical point of view the thesis adopts a three-stage procedure to make the proposed vulnerability index operative and measureable using short panel household-level data. In particular, it allows to extract information on income and asset risks, evaluate their impact on consumption and saving decisions and calculate the empirical version of the vulnerability index. We implement this procedure using a three-wave panel data on Vietnam provided by the VHLSS which covers the period 2002-2006. The results provides two main conclusions. Firstly, if the presence of risky income is coupled with the risky assets hypothesis, the net impact on saving is negative. For Vietnamese households, an increase of 50% in the total amount of asset and income risks results in a net increase of current consumption equal to 5%. Secondly, the vulnerability to poverty in Vietnam in the surveyed period mostly depends on the potential damages caused by uninsured shocks. For those households which report a positive level of vulnerability, the ex-post component accounts for the 57% of the total measure. At the same time, almost 30% of the future welfare losses are caused by the ex-ante component. It confirms the theoretical suggestions that precautionary behavior does have a cost. Lastly, the poverty component which depends on the households' structural characteristics accounts for the 13% of total vulnerability.

Even if the ex-ante component reduced its relative weight with respect to the results of the simulation in Chapter 2, both models support the original idea that risk-induced changing behavior produces a welfare cost and contributes to the determination of the future level of poverty. In terms of policy recommendations, these results indicate that the development of new instruments to improve the risk-mitigating mechanisms of the poor households should be one of the top priorities in the agenda of the policy makers engaged in the design of poverty prevention programs. In the light of these results the most important findings of the research can be synthesized in the following points:

- Current monetary approaches to vulnerability are not able to consider that the threat of being poor depends not only on the observable characteristics of the households or on the idiosyncratic and covariate shocks, but also on behavioral changes triggered by risk.
- Both the theoretical model and the empirical application confirms that the risk-induced changing behavior has a welfare cost and substantially contributes to the

determination of the future level of poverty;

- The different components of vulnerability can be soundly measured using available household-level datasets in developing countries even if the time-length of the panel is limited

- A micro-founded vulnerability measure is a key instrument for policymaking because it contributes to sustain and facilitate an efficient allocation of resources between treatment and prevention of poverty (money transfer vs. development of self-protection instruments)

Despite the results of this work, vulnerability to poverty literature still needs further investigation to improve the theoretical framework and the relative empirical strategy. In particular, two main directions for future research should be followed:

- Firstly, the micro-foundation of the vulnerability measure can be further refined opening up the model to other risk-induced behavioral responses. As already explained, the household's decision over consumption and saving don't complete the set of possible behavioral responses in developing countries. For example, literature on static poverty has already analyzed how the households tend to smooth also income and asset as well as to reduce their exposition through the creation of risk-sharing networks or the choice to migrate. A useful new line of research of vulnerability analysis can be to consider also the impact of these other behavioral responses on the future welfare of the poor households living in developing contexts;

- Secondly, it could be worth to exploit the micro-foundation of the vulnerability measure to individuate which policies can be deployed to reduce the risk exposure of the weaker subsets of the population. In particular, vulnerability analysis can be addressed to individuate the households which are potentially more exposed to the harmful consequences of specific shocks and protect them with suitable public interventions. Moreover, vulnerability analysis could be also an important tool for facilitating the selection of the best instruments to mitigate the negative effects of the misperception of risk on the households' economic decisions

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