HOUSEHOLD WELFARE AND POVERTY IN RURAL CHINA

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ABSTRACT

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The thesis examines three issues related to Chinese rural households' well-being and poverty status over the period of 1989-2006. Each of them corresponds to a substantive chapter (Chapter 3-5).

Chapter 1 introduces the stages of poverty reduction in rural China following the reforms that started in 1978 and discusses some problems related to further poverty reduction and increases in welfare.

Chapter 2 provides a general description of the data set used in the substantive chapters. It includes a discussion of the construction of the panel and the justification of the construction and use of the key economic variables. It also uses this panel to provide some preliminary explorations on households' poverty status and inequality.

Chapter 3 examines the welfare loss brought about by the increasing uncertainty attached to households' consumption flows. Along with significant economic growth over more than three decades, rural households' livelihood has become more uncertain in terms of greater volatility and inequality in their consumption. Our estimate is that households' welfare would have risen up by approximately one third if there were no such uncertainties. Farmers and the chronically poor appear to suffer most among all sub-groups from the welfare loss associated with this uncertainty.

Chapter 4 extends the existing literature on poverty in rural China from a perspective of households' agricultural asset holdings. The analysis finds multiple equilibria in asset dynamics. In the presence of limited insurance, households' exposure to various shocks and risk forces them to engage in conservative livelihood strategies: they may prefer low-risk low-return production to more profitable but riskier investment in asset accumulation. As a result, some households may be trapped into lower incomes in the long-term.

Based on the findings in Chapter 4, Chapter 5 empirically identifies the dynamic asset threshold. It categorises households into either the downward or upward mobility group in the long-term. Then, this chapter measures to what extent falling below this asset threshold may affect households' probabilities of being poor. Both static and dynamic estimates suggest that insufficient asset holdings substantially increase the chances of falling into poverty.

Chapter 6 summarises policy implications indicated by the empirical analyses in three substantive chapters. Overall, education, health insurance and off-farm employment appear to be the key factors if there is to be a further improvement in Chinese rural households' welfare and reduction in poverty.

DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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CHAPTER 1

INTRODUCTION

The ends and means of development require examination and scrutiny for a fuller understanding of the development process; ... economic growth cannot sensibly be treated as an end in itself. Development has to be more concerned with enhancing the lives we lead and the freedom we enjoy.

Professor Sir Amartya Kumar Sen, *Development As Freedom*

The biggest challenge facing most developing countries is sustained economic growth and poverty reduction. China is no exception to this. The economic reforms, which began in 1978, terminated China's closed-door policy and marked more than three decades of remarkable increases in economic expansion. However, new issues have emerged, which have brought new challenges for those concerned with a further and comprehensive development of rural households' well-being.

The objective of this thesis is to help improve the understanding of household welfare and poverty in rural China. This first chapter presents the challenges for Chinese rural development, which motivate the work in this thesis, and provides an overview.

1.1 Challenges for welfare improvement and poverty reduction

Since 1978, China has experienced an economic miracle in terms of fast economic growth, which has averaged 9.8 percent per annum. Rural households' per capita net income in real terms grew 7.6 percent per annum in the period 1978-2009.[1] This significant economic growth has allowed China to achieve tremendous successes in reducing poverty in the countryside. Measured against the official Chinese government poverty line, the poverty rate declined from 30.7 percent in 1978 to 2.3 percent in 2006, with 228.52 million escaping from poverty over this period (State Council, 2007). Human welfare was also dramatically improved. The Human Development Report (2010) estimates that the Chinese Human Development Index (HDI) rose from 0.368 in 1980 to 0.663 in 2010. Rural poverty reduction is of paramount importance for China's successful fight against poverty, as over 90 percent of the poor were rural residents during 1981-2003 based on Ravallion and Chen's (2007) basic needs poverty line (World Bank, 2009).

Despite substantial economic growth and poverty reduction, challenges have emerged. Both rural-urban and within rural areas income inequality have risen, which is largely attributable to de-equalising non-agricultural income and lowered growth of agricultural income, especially since the mid 1990s (Benjamin *et al.*, 2008). At the same time, alongside deeper and wider openness, marketisation and industrialisation, rural households have to confront more aggregate as well as idiosyncratic risks with which they find difficulties in coping, such as adverse price shocks, natural disasters, joblessness and illness (World Bank, 2009).

[1] These two figures are the author's calculations based on data from various issues of the China Statistical Yearbook.

Taking the above phenomena into account, the following three issues should be addressed if we wish to investigate whether and by how much rural households are better-off. That is, increased uncertainty attached to income and consumption, uninsured risk and shocks and insufficient agricultural assets. They motivate the work in three substantive chapters 3 to 5 respectively.

1.1.1 Uncertainty and welfare loss

In the reform period, Chinese rural households confront increased uncertainties associated with inequality and risk. Firstly, there is escalating concern over the growing inequality in income and consumption. Income inequality has been described in a considerable literature. Knight (2008) provides a recent comprehensive review of wealth and income inequality, and their causes and relationship with poverty alleviation. The view held by the majority of former studies is that, since the opening-up began, inequality has widened not only between (Ravallion and Chen, 2007; Kanbur and Zhang, 2005; Sicular *et al.*, 2007) but also within rural and urban areas (Khan *et al.*, 1999; Wan, 2007).

Many have argued that increasing income disparity is not only detrimental to the country's long-term growth (Yao, 2000; Wan *et al.*, 2006), but could also dampen the effects of economic growth on poverty reduction (Yao *et al.*, 2004; Ravallion, 2005; Ravallion and Chen, 2007; Zhang and Wan, 2006c; Huang *et al.*, 2008). Success in fighting poverty would have been greater if the growth of inequality had been controlled (Ravallion and Chen, 2007). Moreover, recent literature on relative inequality and subjective well-being suggests that the low relative income position makes rural households less content with their life (Knight *et al.*, 2009b). This implies that inequality has a direct welfare or utility cost, which detracts from the otherwise welfare enhancing effect of rising average incomes.

Secondly, radical economic and institutional reforms have created more opportunities for rural households and in the meantime, brought more risks, as reflected in the greater intertemporal variability of rural households' income and consumption. Consequently, Chinese rural households are found to fall into and move out of poverty quite frequently (Jalan and Ravallion, 1998a,b, 1999; McCulloch and Calandrino, 2003). More volatile income and consumption also give rise to a greater chance of falling behind again for those have initially escaped from poverty once (Zhang and Wan, 2006b).

Considering increasingly uncertain livelihoods faced with rural households, Chapter 3 will quantify welfare losses due to greater variability and volatility in household consumption, which is termed 'vulnerability as uncertain welfare' (Thorbecke, 2004). It should be noted that vulnerability as uncertain welfare is pertinent to households' real utility costs, and different from 'vulnerability to poverty', which is the probability that a household's consumption or income would fall below the poverty line. Given this concept of 'vulnerability as uncertain welfare', Chapter 3 will employ a utilitarian approach to provide estimates of rural households' welfare losses caused by increased uncertainties during Chinese economic reforms. By looking beyond consistent economic growth and successful poverty reduction, it is hoped that this assessment of household vulnerability would push the frontiers of our understanding and thinking about welfare gains and losses of Chinese rural development.

1.1.2 Risk and persistent poverty

The second issue that may call for a policy response lies in the tenacious persistence of poverty. Since the late 1990s, the reduction of poverty incidence has slowed down and appears to be more difficult when it falls below both the official Chinese government poverty line and the international poverty line (Chen and Ravallion, 2008; Huang *et al.*, 2008). Over the period 1981-2005, 681 million escaped income poverty when measured against the poverty line US$1.25/day. However, 77 percent of this reduction had occurred before 1996 and the average annual reduction of the population in poverty in the period 1996-2005 was only half of that in the period 1981-1996.[2]

In order to explain why this is the case, the existing literature focuses most on the impact of living in remote rural areas (Jalan and Ravallion, 2002), limited health and insurance schemes (Cao *et al.*, 2009) and inadequate and unequal educational opportunities received by rural residents (Knight *et al.*, 2009a; 2010). However, little effort has been made to study the possible association between risk and household persistent poverty. Yet Chinese rural households, especially the poor, are highly susceptible to various risks: the rural poor's income is heavily affected by weather conditions (Yang, 2007); imperfect credit and insurance arrangements leave farm households unprotected from income risk (Jalan and Ravallion, 1998a,b, 1999); structural economic changes have also contributed to the uncertainty of farm

[2] Arthur's calculation based on data in the last column of Table 2 in Chen and Ravallion (2008).

households' income. When faced with uninsured risk and shocks, rural households may change their livelihood strategies which in turn may affect long-term incomes and poverty status.

This possible behavioural response to risk has been studied in many African and some Asian counties. However, it is still unclear if this mechanism could help with explaining persistent poverty in rural China. Therefore, Chapter 4 will investigate whether households' exposure to risk and shocks would predispose them to choose conservative agricultural production instead of profitable asset accumulation, and if so, to what extent the uninsured risk and shocks can discourage households' asset accumulation.

1.1.3 Agricultural assets and persistent and structural poverty

The above discussion calls into question the income and consumption-based studies on poverty. In fact, the literature on asset poverty suggests that the conventional monetary approach can be complemented by the analysis of asset accumulation and its impact on household poverty status in at least two aspects. The asset-based method is not only able to reveal how households' long-run livelihoods and poverty status would change with less biased estimates (Carter and May, 2001; Carter and Barrett, 2007), but also extends our understanding of the multi-dimensional concept of poverty and the complexity of the processes underlying poverty reduction (Adato *et al.*, 2006; Addison *et al.*, 2009).

Inspired by the asset perspective, after finding the relationship between households' behavioural responses to risk and low-equilibrium assets in Chapter 4, it should be useful to examine how important insufficient asset holdings are in affecting household long-term poverty status and the role of assets in transferring past poverty into the future. This will be done in Chapter 5.

In particular, based on the conceptual framework established by Carter and Barrett (2006, 2007), Chapter 5 will empirically pinpoint a dynamic asset threshold and separate households into downward or upward mobility regimes in terms of their agricultural asset holdings to identify underperforming households, and estimate how much their probability of falling below the consumption poverty line could be affected by owning insufficient assets relative to the dynamic threshold. Moreover, by utilising recent econometric advances, our empirical framework may help overcome the possible difficulties, such as endogeneity in accumulation decisions and household heterogeneity, which have confronted many previous studies.

Thus, by analyses in Chapters 4 and 5, we will find what can be the ways out for those having remained in poverty for a long time and found difficulties in extricating from poverty.

1.2 An outline of the thesis

The thesis is organised as follows. Chapter 2 provides a general description of the data set used in this thesis. It introduces the panel extracted from original surveys and justifies the construction of key variables. It proceeds to describe basic features of the panel and provides some preliminary evidence on poverty, inequality and rural households' livelihood. Three substantive chapters 3 to 5 address three different issues emerging during Chinese rural development, as described in Sections 1.1.1 to

1.1.3. Finally, Chapter 6 summarises the findings of the thesis and discusses the pertinent policy implications.

In this thesis, we will use rigorous econometric modelling and in-depth analyses. We seek to offer better ways of measuring and shed new light on Chinese rural households' well-being and poverty status. The results of this research are expected to inform future policy-making helping the remaining poor in rural areas and enhancing rural households' capabilities for further human development.

Chapter 2

An Exploratory Data Analysis of the CHNS

2.1 Introduction

Any empirical investigation of household welfare and poverty in rural China relies on micro level data. The approach adopted here is to use a micro-level panel to track the same collection of households through time. However, before undertaking any modelling, it is often useful to undertake an exploratory data analysis. The purpose of this chapter is to allow the data to give us a feel for what has happened in rural China. In particular, this chapter seeks to provide *prima facie* explanations for poverty, inequality and household well-being in rural China which appear plausible. Such an examination should increase the reliability of the subsequent econometric modelling and the statistical inference undertaken in the following three substantive chapters.

This chapter is structured as follows. The China Health and Nutrition Survey (CHNS) is briefly introduced in the next section. Section 2.3 gives summary statistics for these constructed variables and other common variables used in the following chapters. It also compares and explains the trends of poverty and inequality in rural China based on this data and on two other nation-wide household surveys.

2.2 General description of data set

This sub-section includes a description of how samples were selected and adjusted to be consistent across different rounds of surveys in Section 2.2.1 and the general quality of surveys in Section 2.2.2. Sections 2.2.3 and 2.2.4 outline the procedures for constructing the panel and key variables such as prices, income and consumption, which are commonly used in all substantive chapters.

2.2.1 Survey design

The CHNS project has been managed by the Carolina Population Centre at the University of North Carolina, the National Institute of Nutrition and Food Safety, and the Chinese Centre for Disease Control and Prevention. It started in 1989 covering 9 provinces drawn from three income layers (low, medium, high). Since then, the surveys have been conducted in six rounds in 1991, 1993, 1997, 2000, 2004 and 2006.[3]

The survey used a multistage, random cluster process to select individuals in both urban and rural areas. Four counties in each province were randomly selected by a weighted sampling scheme. Specifically, counties in every province are stratified based on the gross value of agricultural and industrial output, and one county is selected from each quintile. In addition, the provincial capital and a lower income city were selected where feasible, except that other large cities rather than provincial capitals had to be selected in two provinces. Villages and townships within the counties and urban and suburban neighbourhoods within the cities were selected

[3] As a statistical tradition in China, the data collected in effect are records of the year previous to the surveyed year. To reduce potential confusion, we simply use the survey years as labels throughout the thesis.

randomly. In 1989-1993 there were 190 primary sampling units: 32 urban neighbourhoods, 30 suburban neighbourhoods, 32 towns (county capital city), and 96 rural villages. Since 2000, the primary sampling units have increased to 216: 36 urban neighbourhoods, 36 suburban neighbourhoods, 36 towns and 108 villages.

Households were also randomly chosen in each geographic location. CHNS regards individuals as 'rural' who are not only registered as rural households in 1989, but also resided in the countryside,[4] while the official Rural Household Surveys (RHS) conducted by the National Bureau of Statistics (NBS) only refer to the households' registration records.[5] The 1989 survey included 3,795 households. In 1993, all new households formed from sample households who resided in sample areas were added to this sample. The total numbers of individual participants were 15,917 in the 1989 survey and 14,778, 13,893, 14,426 and 15,648 in the following rounds.

2.2.2 Representativeness

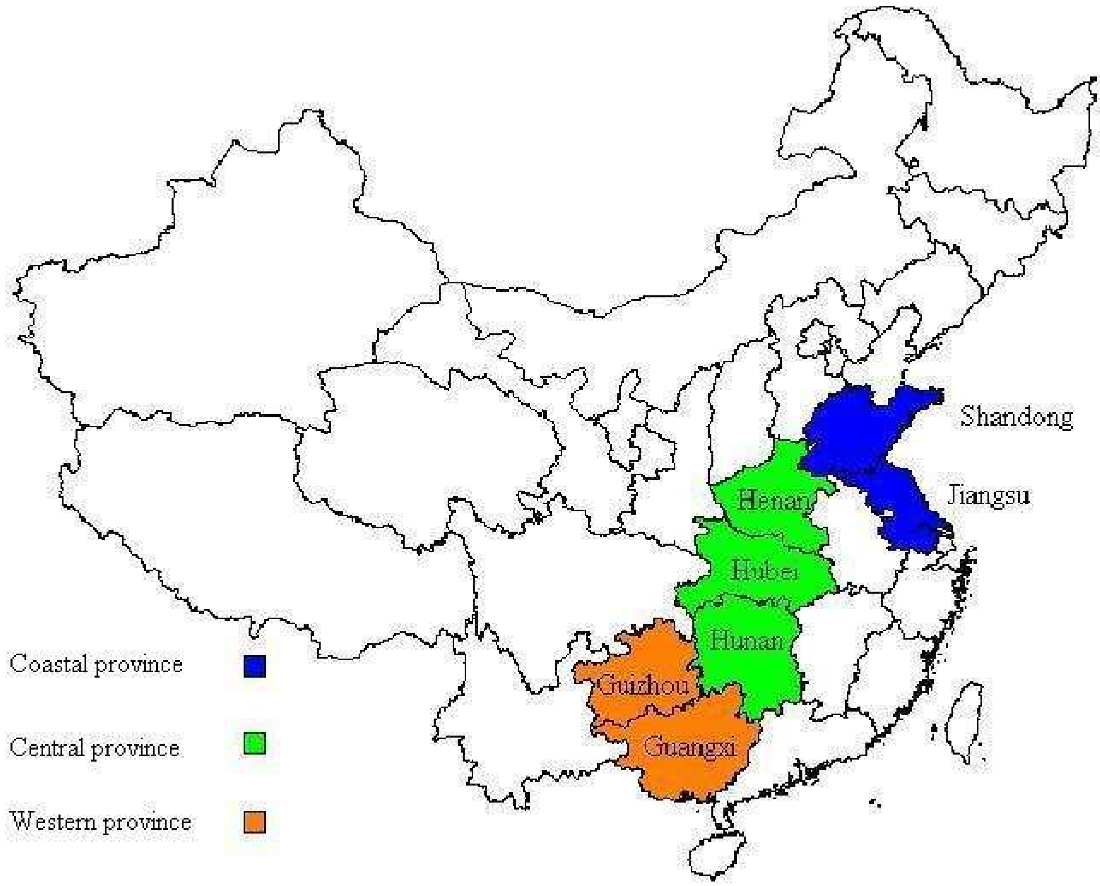
The data set used in this thesis covers seven provinces (Fig. 2.1) and is representative in many aspects, such as geography, ethnicity, economic and human development.

Geographically, the study provinces spread from coastal to in-land China. The population in these provinces covers 35.57 percent of the total population and 37.84 percent of the rural population at the end of 2006.

[4] In the following cross sections, the households are separated according to urban or rural residence as well. Besides, the surveys note the household's registration type.
[5] The income statistics in RHS may be upwardly biased because an increasing number of rural migrants spend much of the year working in cities and therefore may earn more than those who still reside in rural areas.

The two south-western provinces included, Guizhou and Guangxi, are regions where the proportion of ethnic minority (non-Han) groups is particularly high.

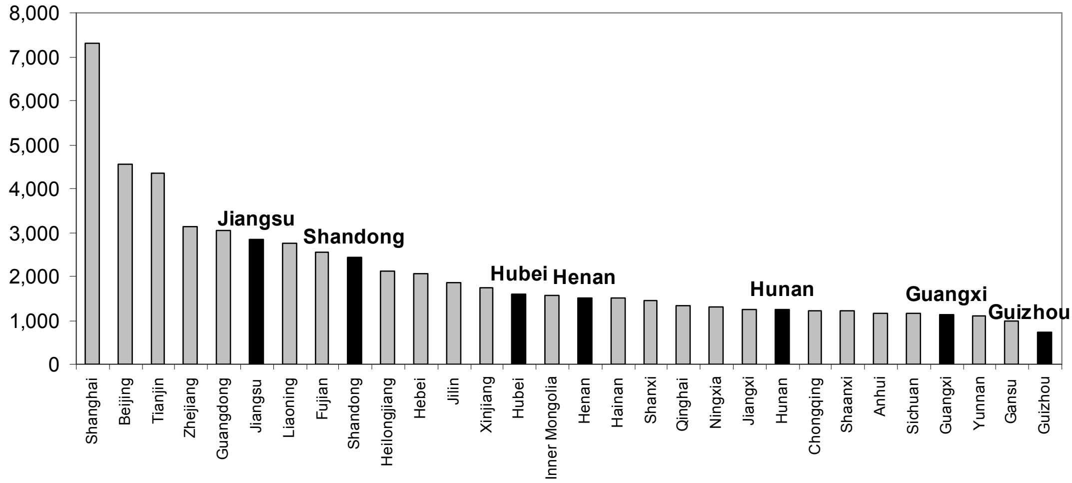
Figure 2.1 Map of the sample provinces



With respect to economic achievements, it can be seen from Fig. 2.2 that Jiangsu and Shandong have higher level of economic development. From 1985 to 2006, their real per capita GDP ranked in the top one third of 30 provinces in mainland China. Henan, Hubei and Hunan are centrally located and their per capita GDP in the same period were ranked in the middle. Guangxi and Guizhou are western provinces and less developed than others. Guizhou had the lowest real per capita GDP level during 1985-2006 among 30 provinces, which, in 2006, for example, only reached 8.7

percent of that of Beijing. Its investment in fixed assets was a mere 19.78 percent of that of Shandong at the end of 2006.[6]

Figure 2.2 Average real per capita GDP (*yuan* in 1985 price, 1985-2006)

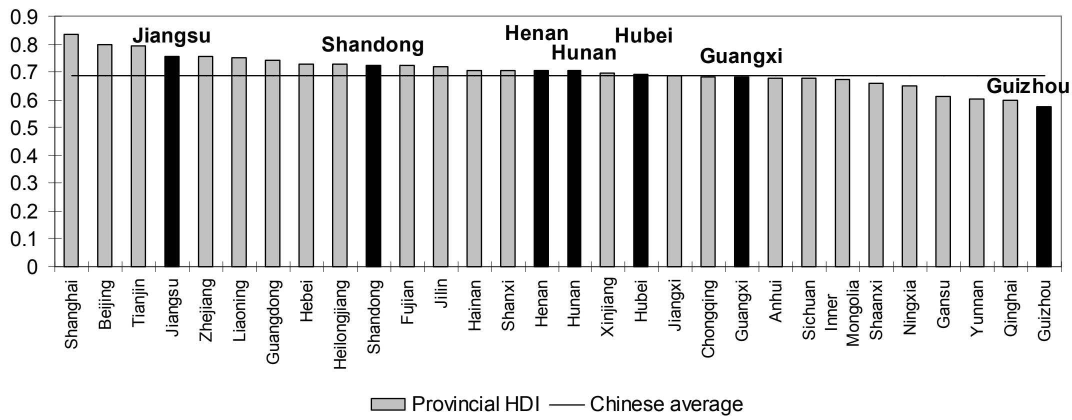


Source: Author's calculations based on data from various issues of China Statistical Yearbook.

Note: The study provinces are highlighted by black bars.

The wide regional variation between coastal and inland provinces also exists in human development, such as education and health care. This can be seen from regional HDI. As shown in Fig. 2.3, Guizhou again fell far behind other provinces.

Figure 2.3 Human Development Index in 2003, by province



Source: National Human Development Report (2005).

Note: The study provinces are highlighted by black bars.

[6] Figures in this and the previous sentences are the author's calculations based on various issues of the China Statistical Yearbook.

From the above statistics, it could be argued that our data set adequately reflects the variation in China due to its regional, economic and social coverage. One may reasonably expect the empirical results based on it to be representative of China overall.

2.2.3 Panel construction

A balanced panel is extracted from original CHNS surveys. Rural households in our sample are those having rural registration records and living in the countryside in the 1989 survey. To build a tractable panel over 18 years, we trim off all newly formed households from the subsequent six rounds. That is, we pick up rural households who not only appeared in the 1989 survey, but were also re-interviewed in the six follow-up rounds. A small number of them obtained urban registration after 1993, but continued to dwell in the survey villages regularly (longer than half of a year in the survey year). They are still, following Benjamin *et al.* (2005), deemed to be rural households.[7] As a result, 1446 rural households appear in our balanced panel.[8]

A typical concern over such a balanced panel in a long period is aging households. Households would retired or unable to do farming because of the age, and therefore, have less income and become poor. Although we control for age in the estimation of the following empirical chapters, the aging problem cannot be obviated completely.

[7] In our sample, households becoming urban registered account for 10-14 percent in surveys after 1993. The overwhelming majority of them are farmers or labourers. Excluding them pushes down the mean per capita household's income/consumption by 0.1-2.5 percent. This downward adjustment of income and consumption has trivial impact on our main results in the following chapters. For example, in Chapter 3, it raises the household average welfare loss due to increasing uncertainties by 0.1 percent.

[8] Households reporting zero food consumption are all excluded, as this may signal measurement errors in household consumption.

Another problem, as noted by Zhang and Wan (2009) particularly for the CHNS in the early 1990s, is the attrition of households. To improve the accuracy and reliability of empirical estimation, Dercon and Shapiro (2007) suggest controlling for the attrition of household members in panels.[9] The attrition of original household members in our sample is within the normal range. The share of households reporting disappearance of original members is 20 percent prior to 2006 and no more than two persons in such a household. Approximately 1.14 percent of study households in our sample have members participating in different households in different surveys (i.e. having multiple IDs). If a person has a multiple ID, the most recent household is assigned to that person. In cases where a death has been reported more than once, the first reported date is assumed to be the most accurate. The dates of household members' deaths are also recorded by the CHNS. For those households who report the member's death more than once, the earliest date is maintained since it is assumed to be the closest one to the real time of death. About 2.4 percent of household heads in our sample died after the 2000 survey. In every sample year from 1991, over 92 percent of households on average do not report any death or only one death. With regard to nationalities, over 97 percent of the responses regarding nationalities were consistent across surveys. In cases of inconsistent nationalities, we assume that they belong to Han if they were coded as Han at one time. Other individuals having different variables across surveys were coded as 'other' and their specific nationality was used.

[9] More detailed discussion on the impact of household attrition on our empirical estimations will be given Chapter 4.

As mentioned at the outset of Section 2.2.1, the CHNS draws samples from every income layer from the very poor county and village to the richest. Our selected samples bear this feature as well. A brief description of geographic and demographic distributions is shown in Table 2.1. Households are equally spread across three villages in each county and four counties in each province, which permits representativeness of the whole wealth distribution. Demographically, the share of ethnic minorities in Guangxi is the largest as it is an ethnic autonomous province. The average share of ethnic minorities in sample provinces in our panel is 8.69 percent, which is close to the 8.41 percent suggested by the 5th National Census published in the China Statistical Yearbook (2007). The proportion of households belonging to the ethnic groups is higher in two south-western provinces which are widely recognised as the most diversified regions of China.

Table 2.1 Geographic and demographic distributions of the study population

Region	Province	No. of hh.	Share, %	No. of ethnic minority	Share, %
Coastal	Jiangsu	211	14.59	9	4.27
	Shandong	193	13.35	6	3.11
Central	Henan	181	12.52	14	7.73
	Hubei	224	15.49	16	7.14
	Hunan	181	12.52	16	7.14
Western	Guangxi	239	16.53	28	11.72
	Guizhou	217	15.01	18	8.29

2.2.4 Constructed variables and justification

This section describes how we construct three key variables in our empirical research. These variables are the spatial price deflators which are used to compute real terms of all monetary variables, household income and consumption.

2.2.4.1 Spatial deflators

The deflators used to compute the real monetary terms play a pivotal role in forming a picture of households' consumption/income and therefore of constructing poverty profiles. Notwithstanding the rural and urban consumer price indices at national and provincial levels published by the NBS, one cannot compare directly real price levels between different areas at a given point in time otherwise, as Chen and Ravallion (1996, p. 30) point out, 'poverty will be overestimated in some regions and underestimated in others'. As a result, 'the effect on changes over time is unclear'. Moreover, the consumer basket used by the NBS to derive the CPI also changes in urban and rural areas, across different provinces and over time. All of these variations may cause serious problems of inconsistency and inaccuracy in transformed real terms. As there is no comparable absolute CPI officially published in China, the CHNS used its community surveys of prices of basket goods to build its own rural and urban consumer price indices differing from the rural CPI published by the NBS. This new index contains the same consumer baskets in rural/urban divide, across provinces and different rounds of surveys.

Firstly, they set the consumer basket in urban areas in 1989 supplied by the NBS (Ren *et al.*, 1989) and calculated the cost of this consumer basket. It contains 57 food and non-food items. Secondly, they calculated the average urban-rural price ratio using CHNS price data collected in 1991.[10] The items used to compute the ratio are a sub-group containing 19 items drawn from the above consumer basket given by the NBS. Thirdly, the cost of the consumer basket (equal to the basket in urban areas) was calculated in rural areas in 1989 by dividing the cost in urban areas by the urban-

[10] As there is no data available for 1989, we use the ratio of 1991 to proxy the ratio in 1989.

rural price ratio obtained in step 2. Fourthly, they calculated the cost of the consumer basket for both rural and urban areas in 1989 by using corresponding costs in 1989 divided by relevant CPI in 1989 obtained from the China Statistical Yearbook (1989).

CHNS inflates the 1989 price for each survey year thereafter by urban and rural CPI from NBS respectively to form rural and urban consumer price indices at the relevant year's prices. Then they set the cost in urban areas in Liaoning province in 2006 at 1 and made all other costs relative to that. This can be used to deflate monetary variables to 2006 *yuan*.

This consumer price index has two attractive characteristics which the published NBS consumer price index cannot parallel. It is based on the same consumer basket for both rural and urban areas in all sample provinces over time[11] and the deflated variables are comparable across provinces, rural and urban areas and in different rounds of surveys as well.

2.2.4.2 Household net income

Rural households' net income is the sum of all possible sources of income, subsidies and other revenue gathered by the CHNS minus expenditure related to these sources. Specifically, there are seven sources of households' income, including businesses operated by households, farming, gardening, fishing, raising livestock, non-retirement and retirement wages. Subsidies at household level contain one-child and child-care subsidies, gas, coal and electricity subsidies, food, gift and reduced prices

[11] The rural and urban CPI published by NBS have their own series over time, but cannot be compared with each other. In addition, NBS changed the components in the basket from time to time.

from work units. Individual subsidies are annualized and added to the household's subsidies. They include food subsidies, health subsidies, bath and hair cut subsidies, average monthly subsidies from jobs and other non-categorised subsidies. Other revenue includes income from leased land, rent from non-land assets, lodgers or boarders, poverty or disability remittances, money and value of in-kind gifts from children, parents, relatives or friends, value of in-kind gifts of food and clothing, and value of gifts from local enterprises and other unspecified sources. All monetary terms are finally deflated into 2006 prices by the spatial rural consumer price index.

Among various components, agricultural production serves as the mainstay of rural households' income (Table 2.2). The rich rural households' income relies relatively less on agricultural production but more on wages, including both non-retirement and retirement, from non-agricultural sectors.

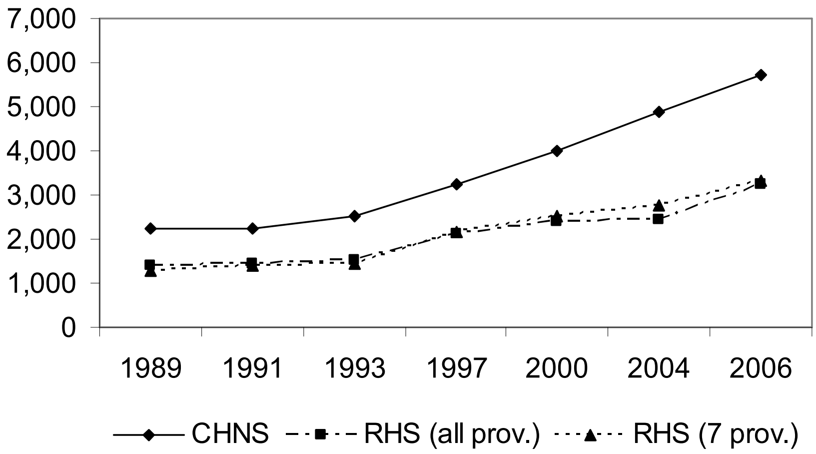
Table 2.2 Components of household income, by the intertemporal mean (%)

Components of the household's gross income	Intertemporal mean per capita cons. quartiles			
	1 (poor)	2	3	4 (rich)
Agricultural production	58.19	55.12	52.67	55.05
Non-retirement wages	17.49	20.78	21.88	19.63
Small handicraft & household business	10.87	10.85	8.35	8.36
Income from retirement pensions & wages	1.14	1.20	2.85	3.02
Subsidies	1.27	2.10	2.49	2.05
Others	11.05	9.96	11.78	11.93

Fig. 2.4 compares mean per capita rural household's net income drawn from our sample and RHS. Income/consumption streams drawn from them are expected to suggest same trends if our constructed panel based on CHNS shares similar features with the government's official survey, RHS. Fig. 2.4 basically meets this expectation.

The distance between them was relatively stable before 1997, but tended to be enlarged thereafter.

Figure 2.4 Comparison of mean per capita rural household's net income in CHNS and RHS



Several factors could account for this phenomenon. One might be lower imputation prices used by the NBS. Prior to 1997, the NBS used government determined prices to impute in-kind income/consumption, which was about 50 percent of the market price (Benjamin *et al.*, 2005). This imputation price was raised to 85-90 percent of the market price level after 1997. In contrast, CHNS consistently uses market prices to measure income. Another possible reason would be the low representativeness of RHS. As we stated earlier, CHNS draws sample households randomly from every quartile of the output distribution, while RHS misses the extremely rich and poor groups. This is reflected by the underestimate of income from family-run businesses which has been a more substantial and important income source during the period of reform. The third reason may lie in the rural-urban division in CHNS. As mentioned earlier, some villages/towns may be urbanised more or less over the sample period of 18 years. Nevertheless, the CHNS consistently regards them as rural areas as samples from the second round were drawn from the first round of the surveys in 1989.[12] The derived households' income may therefore be higher than that of the RHS which actually drops these somewhat urbanized areas. Fourthly, it is notable that the CHNS does not subtract taxes and depreciation of assets owned by the household as the NBS has done to the rural household's net income in RHS, because there is always a nagging worry about the arbitrary recorded depreciation expenses and taxes would confound the household's earning ability (Benjamin *et al.*, 2005). Consequently, the average per capita rural household's net income in the CHNS data is higher than that of the RHS in all survey years. The different treatment of fees, taxes, imputation prices and deflators between CHNS and RHS can account for 81 percent of the gap prior to 1997 and 50 percent thereafter when the government dramatically raises the price of agricultural product and NBS applies for a higher imputation price close to the market price.

2.2.4.3 Household consumption expenditure

Households' total consumption is composed of five components: households' food consumption, expenditure on durable goods, medical care, insurance and the discounted value of housing. CHNS only gives households' annual insurance premium directly. Specifically, we construct the rest of the variables as follows.

i. Food consumption

To obtain the rural household's food consumption, we first calculate the rural household's actual food consumption per year according to the nutrition surveys of

[12] Evidence may be seen from the differences of cost-of-living between urban and rural areas. In 2005, the general consumer price in urban areas is 37 percent higher than that in rural areas on the basis of RHS (Ravallion and Chen, 2007), while it is 17 percent in CHNS.

households' three-day food consumption in *jin*.[13] It is derived by subtracting the final amount remaining at the end of the 3rd day from the initial amount on hand at the beginning of this period. By doing so, our measure of actual food consumption contains the food purchased from the state market and free markets as well as those produced by the households themselves. Secondly, we get the nominal implicit food price[14] at each surveyed year (*yuan* per *jin*) from various issues of China Statistical Yearbook as the imputation price to calculate food consumption expenditures. Specifically, this is calculated by dividing rural household per capita food expenditure by the quantity of household per capita food consumption. However the NBS only published per capita quantity of staples consumed by rural households. We get per capita quantity of total food by dividing staples consumption by an adjustment factor 0.4, which is the average share of per capita rural household's staples consumed in per capita quantity of food during 1990-1999.[15] Thirdly, we deflate the above nominal implicit food prices to real terms in 2006 prices by CHNS rural CPI index. Fourthly, the quantity of food consumed by the household is calculated using Ligon and Schechter's (2002) method. Specifically, we subtract the stock at the end of the 3-day interview period from the initial stock and multiply them by the implicit price used by the NBS. The quantity of food constructed in this way includes both stock variation and the new purchases and therefore, can overcome the commonly criticized measurement error of underreporting family

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[13] A Chinese unit of measuring food quantity which is equivalent to 500 gm.

[14] This is consistent with the prices that NBS used to obtain the in-kind consumption and income, but lower than the market prices. NBS used the state-determined procurement price till 1996, which was much lower than the market price. For example, in 1990, the implicit price per kg of staples was 0.5169 *yuan* while the market price at that time was around one. The government applied an average price between procurement and contract prices from 1997 and since 1999, the NBS add a 10 percent or 15 percent discount to market prices and formed the new imputation prices while calculating rural households' consumption and income. This discount is held to represent the transaction fees, such as marketing and transportation costs. In sum, the imputed income and consumption in the RHS are underestimated prior to 1997. Brandt and Holz (2006) give a detailed review of the evolution of the imputation prices used by the NBS.

[15] We take the average in the 1990s as NBS published only these two indicators until 1999.

consumption of crops (Ravallion and Chaudhuri, 1997). Finally we multiply the quantity of food actually consumed by the households which has been derived in the first step and the average price to obtain real households' food consumption expenditures.

ii. Consumer durables

The expenditure on durable goods is the sum of household's expenditure on 20 items.[16] They are discounted with an assumed life of use of 7 years.[17] The nominal total expenditure on durable goods is also deflated by CHNS rural CPI and transformed into 2006 prices.

iii. Medical and health care

The rural household's annual medical expenditure is derived by summarizing costs on immunization which are not covered by insurance and total costs of treatment for illness and injuries including all registration fees, medicines, treatment fees and bed fees.

[16] They are tricycles, bicycles, motorcycles, automobiles, living room furniture including sofa, table, chairs, etc., bedroom furniture including beds, dressers, etc., radio cassette players, picture recording machines, black and white televisions, colour televisions, washing machines, refrigerators, air conditioners, sewing machines, electric fans, big wall clocks and cameras.

[17] We also tried 5 and 10 years alternatively. The consumption poverty incidence is not sensitive to the choice of the life of use.

iv. Housing

Between 88 and 96 percent of rural households in each round of surveys own their houses. The current flow consumption of housing is defined as one-twentieth of the current value of the house, assuming a 20-year life of use.[18]

Table 2.3 summarises the proportions of different components of rural households' total consumption expenditures. More affluent households tend to consume less food and more durable goods and spend more on housing and medical services.

Table 2.3 Components of household consumption expenditure, by the intertemporal mean (%)

Component	Intertemporal mean per capita consumption quintiles				
	1 (poor)	2	3	4	5 (rich)
Food	79.82	74.75	69.74	62.54	46.08
Durable goods	5.05	6.83	7.63	8.48	8.57
Housing	12.95	16.12	19.82	25.12	40.00
Medical care and insurance	2.19	2.30	2.81	3.85	5.35

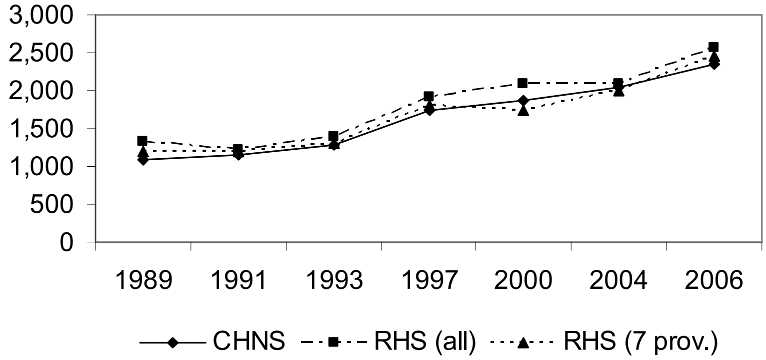
Due to the design of surveys on households' consumption and data limitations, we cannot obtain other reliable sources of consumption expenditures as the RHS. The RHS is more comprehensive which, in addition, surveys transport costs, various services bought by rural households, entertainment, etc. This results a lower mean per capita rural household's consumption in CHNS than that of the RHS (the same 7 provinces) in most of the survey years.[19] Nevertheless, in general, both income and consumption streams derived form CHNS and RHS remain similar (Fig. 2.5a).

[18] Benjamin *et al.* (2005) also use this method to construct rural households' consumption on the basis of RCRE data set. We do not know whether NBS gets the consumption of housing in the same way, but their per capita values are similar to our calculations.

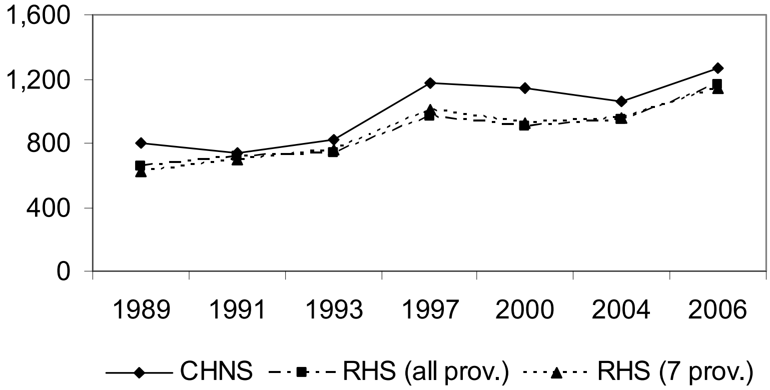
[19] In 2000 and 2004, per capita consumption in CHNS is higher than that of the RHS if we look at the same provinces. This is a joint effect of more increment of per capita non-food consumption in CHNS than RHS from 1997 and a significant fall in food consumption in RHS. After 2004, the non-food

Figure 2.5 Comparison of rural household mean per capita consumption expenditure in CHNS and RHS

(a) Total consumption



(b) Food consumption



However the proportion of the food component in total living expenditure is much higher in CHNS (Fig. 2.5b). It decreased from 76.3 percent in 1989 to 63.7 percent in 2006 but from 58.8 percent in 1990 to 43 percent in 2006 in the RHS.[20] The quintile shares of food and housing listed in Table 2.4 are also lower in the RHS. The main cause for this change is ascribable to our way of constructing rural households' consumption expenditure. As stated earlier, household consumption in our data is

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consumption in CHNS more and more lagged behind that in RHS; therefore the per capita total consumption of CHNS is smaller again.

[20] However the relative changes in two data sets are similar. The RHS figures are calculated based on China Statistical Yearbook (2007).

smaller than that in the RHS figures by construction. Together with greater food expenditure in CHNS, the shares of food are made greater than those of the RHS.

2.2.4.4 Imputed agricultural fixed assets

The CHNS surveys the quantity of agricultural equipment owned by the rural household, including large or medium sized tractors, walking tractors, animal carts, irrigation equipment, power threshers and household water pumps. Similar to the calculation of food consumption, we impute the value of these agricultural fixed assets by the implicit price on the basis of RHS statistics. The NBS reports annually the initial value of agricultural fixed assets used in production for the average rural household as well as the quantity of every kind of these assets in the China Statistical Yearbook. We calculated the implicit price (*yuan*/unit) accordingly for every survey year and deflated them to 2006 prices by the rural CPI given by the NBS. The value of agricultural fixed assets is gathered by multiplying the implicit price and the quantity owned per rural household in CHNS.

2.3 Summary statistics

2.3.1 Constructed variables

2.3.1.1 Spatial price deflators for rural areas

The rural CPI in 2005 was about 2.6 times that in 1988 in real terms at the national level.[21] Specifically for seven sample provinces using the CHNS basket (Table 2.4), rural Guizhou had the lowest price level in 1989 but the highest one in 2006,

[21] Author's calculation based on data from the China Statistical Yearbook (2007) and (1996) in 1985 prices.

growing 1.5 times. By contrast, coastal provinces had relatively smaller proportionate growth rates in prices (about 1.1 times). As usually claimed, more affluent provinces are more powerful in smoothing prices than poorer ones. Another important implication of price differences across provinces lies in the measured inequalities, which we will discuss in Section 2.3.2.2. During 1993-1997, the prices increased sharply in all provinces, reflecting the policy adjustment on raising prices of agricultural goods.

Table 2.4 Spatial rural consumer price index by province and year

Year	Coastal			Central		Western	
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou
1989	0.373	0.398	0.374	0.363	0.377	0.403	0.357
1991	0.387	0.421	0.372	0.386	0.387	0.423	0.378
1993	0.468	0.480	0.418	0.476	0.480	0.523	0.469
1997	0.718	0.769	0.692	0.791	0.799	0.850	0.805
2000	0.703	0.745	0.647	0.756	0.822	0.804	0.801
2004	0.757	0.809	0.701	0.815	0.893	0.845	0.864
2006	0.788	0.837	0.726	0.858	0.929	0.866	0.899

Note: CPI in urban Liaoning province in 2006=1.

The spatial price deflators indicate a differential of 17 percent in urban-rural cost-of-living in 2005, while the figure is 37 percent according to Chen and Ravallion (2008). The large difference between them may stem from the rural-urban price ratio in 1989, which is calculated in the second step in constructing the CHNS price index. As described above, the CHNS team used a sub bundle of goods to construct the ratio, in which only four durable goods were included. 28 items with higher prices were excluded, such as televisions, bicycles, refrigerators and furniture. Therefore, the derived rural price level in 1989 was lower than the real one. Then the price in rural areas inflated, according to rural CPI, in the following years based on its 1989 level.

The measured rural urban price ratio therefore in the 1989 round as well as the following rounds may be underestimated in the CHNS data set.

In the empirical work, we use these spatial deflators to translate all monetary values into real terms. For the poverty line, we use the differential of 37 percent rural-urban cost-of-living to adjust US$1.25 and US$2 per person per day, following Chen and Ravallion's (2008) treatment. This also eases the comparison between our static poverty estimates and their results.

2.3.1.2 Per capita rural household net income and total consumption

The mean per capita rural household's net income and consumption for all sample provinces consistently increased over time (Fig. 2.6-2.7). In general, coastal provinces outperformed their inland counterparts. Guizhou had the lowest income level among all provinces and the smallest per capita consumption happened in the other western province Guangxi. The per capita income gap between Jiangsu and Guizhou is about 1,500 *yuan* in 1989. However in 2006, it became much greater and registered at 5,000 *yuan*. There is obviously no absolute convergence. The prevailing convergence regressions (MRW) do not suggest conditional convergence for rural households' net income.[22] The coefficients of initial mean per capita net income in 1989 is positive and insignificant at three traditional levels. Even though the coefficient of the initial level of consumption is significantly negative, the value is extremely close to zero so this cannot indicate a convergence between provinces.

[22] We regress the log difference mean net income (or consumption) per household during 1989-2006 with the log value of the mean net income (or consumption) in 1989 according to Mankiw *et al.* (1992).

Figure 2.6 Mean per capita rural household net income, by province

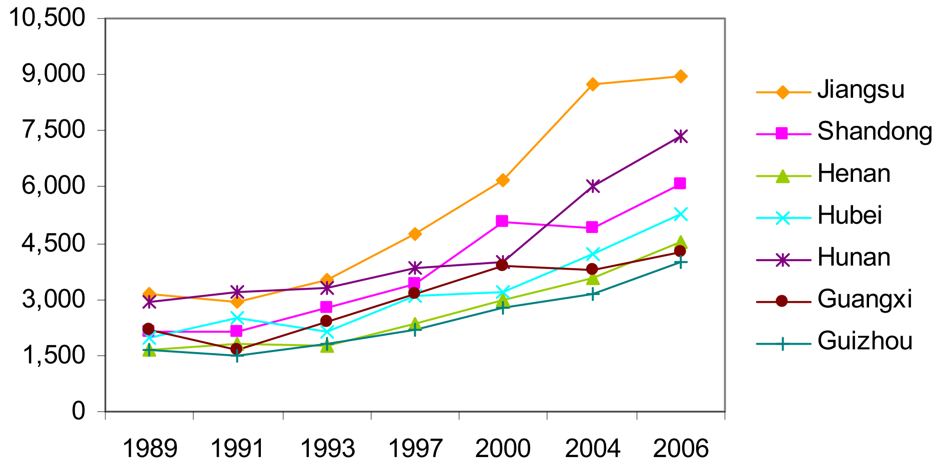
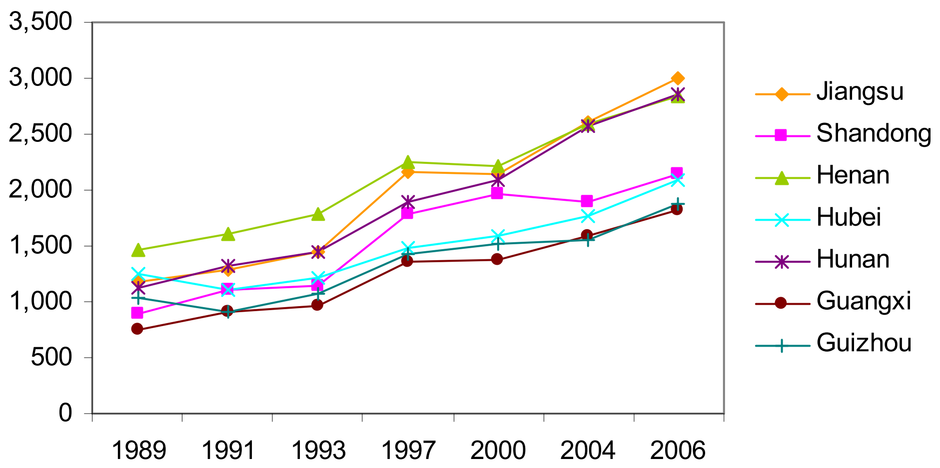


Figure 2.7 Mean per capita rural household consumption, by province



With respect to geographic distribution of household intertemporal mean consumption (Table 2.5), not surprisingly, rural households in western provinces, which are less developed, have lower consumption level in the long-run. By contrast, in coastal regions, about 57 percent of coastal rural residents' mean consumption in 1989-2006 lies in the top half.

Table 2.5 Geographic distribution of household by the intertemporal mean consumption

Region	Intertemporal mean per capita consumption quartiles				Total
	1 (poor)	2	3	4 (rich)	
Coastal	61	111	136	96	404
Central	75	138	150	223	586
Western	225	113	75	43	456
Total	361	362	361	362	1446

Based on the constructed income and consumption, the next sub-section shows some preliminary evidence on household welfare, inequality and poverty status during 1989-2006.

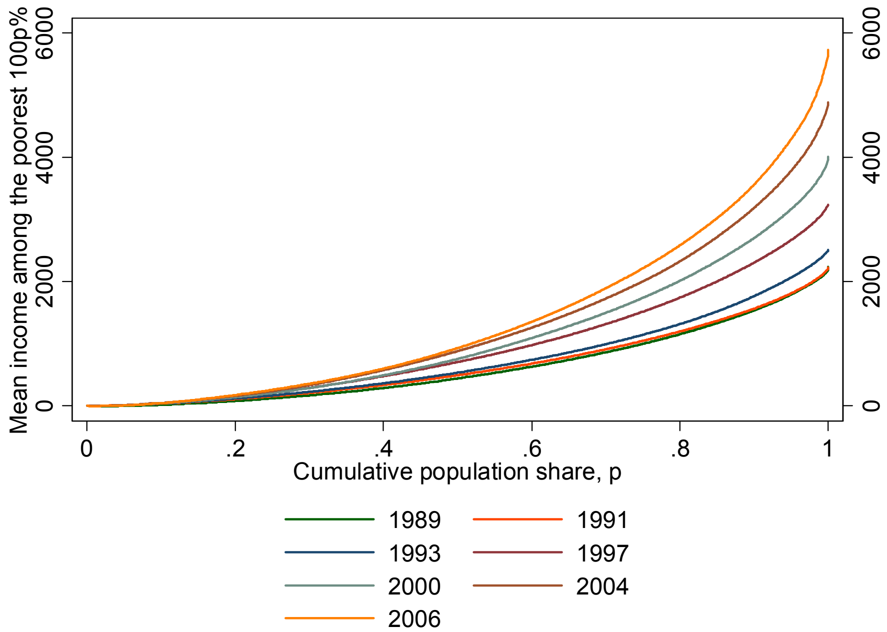
2.3.2 Preliminary exploration of rural households' livelihood

2.3.2.1 Social welfare

Fig. 2.5 has shown that some fluctuations in a few provinces notwithstanding, there have been overall increasing trends for both consumption and income. This lifts the welfare of rural society as a whole. As demonstrated by the Generalized Lorenz Curve (GLC) of income in Fig. 2.8,[23] the 1989 and 1991 curves are close to and sometimes cross each other, but for the upper 50 percent of the population, the GLC of one year strictly dominates that of the previous year. According to the second order welfare dominance result (Shorrocks, 1983), social welfare in terms of household per capita net income has improved, especially since 1991.

[23] The graph of household per capita consumption is not reported here, but it shares similar characteristics.

Figure 2.8 Generalized Lorenz curves of rural household per capita net income



Along with this welfare improvement, there has been greater dispersal of income. As can be seen from Table 2.6, although the GL(p) rose considerably, the income shares for poorer households fell. For the poorest 10 percent of population in particular, their welfare declined in the periods 1997-2000 and 2004-2006. Life is much harder for 0.8 percent of the population distributed at the bottom in terms of per capita income. Their welfare in 2006 was even lower than in 1989. Things do not get less severe in the case of per capita consumption: the poorest 10 percent of the population suffered decreasing welfare during 1997-2004.

Table 2.6 Per capita income shares, by quintile

Quintile group	1989				2006			
	Quintile max	% of median	% of total	GL(p)	Quintile max	% of median	% of total	GL(p)
1 (poor)	775.82	44.67	3.36	75.07	1610.32	42.95	2.99	171.32
2	1370.12	78.90	9.35	284.19	2778.10	74.09	7.44	597.65
3	2054.83	118.33	15.37	627.78	4741.81	126.47	13.14	1350.98
4	3306.52	190.40	23.40	1150.89	8011.33	213.67	21.52	2584.14
5 (rich)			48.52	2235.43			54.91	5731.19

Note: The generalised lorenz ordinates GL(p)=mean(household per capita income)×L(p), where p=F(quintile maximum).

2.3.2.2 Inequality

Fig. 2.9-2.10 show the distribution of per capita rural household's consumption and net income in each of the sample periods. Although mean consumption and income increased over time, their distributions skew heavily to the right over time.[24] This suggests that during 1989-2006, most rural households have relatively modest consumption or income while a small number of the study population show higher values. In the consumption regressions, we use the logarithmic transformations of income and consumption instead of their levels to shrink the right tail. In addition, massive outliers do not seem to exist in the dataset.

[24] The same pattern holds for every study province.

Figure 2.9 Kernel distribution of per capita rural household consumption, by year

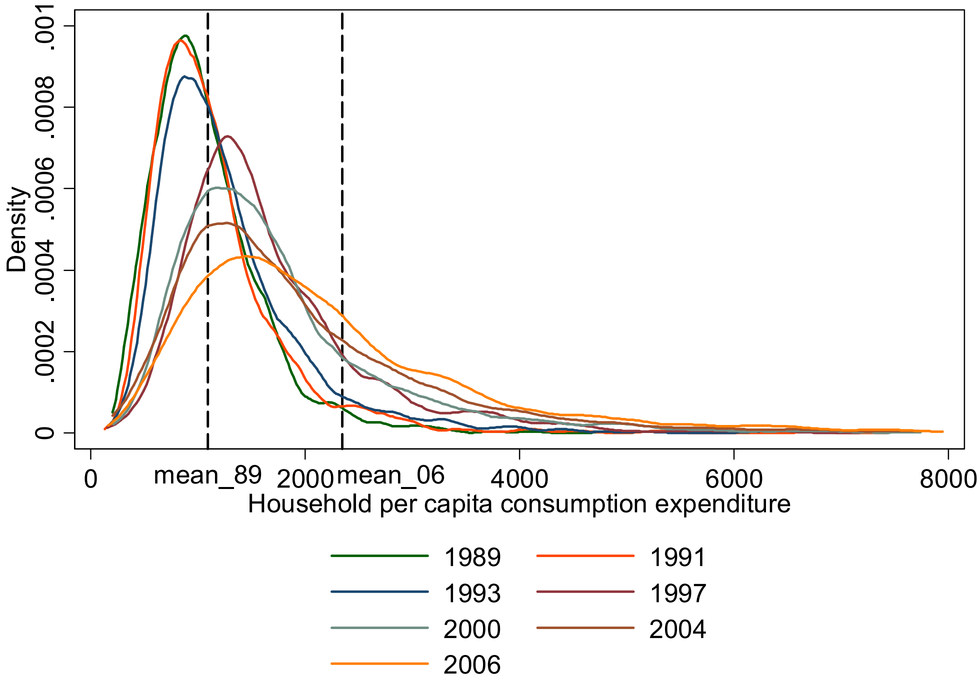
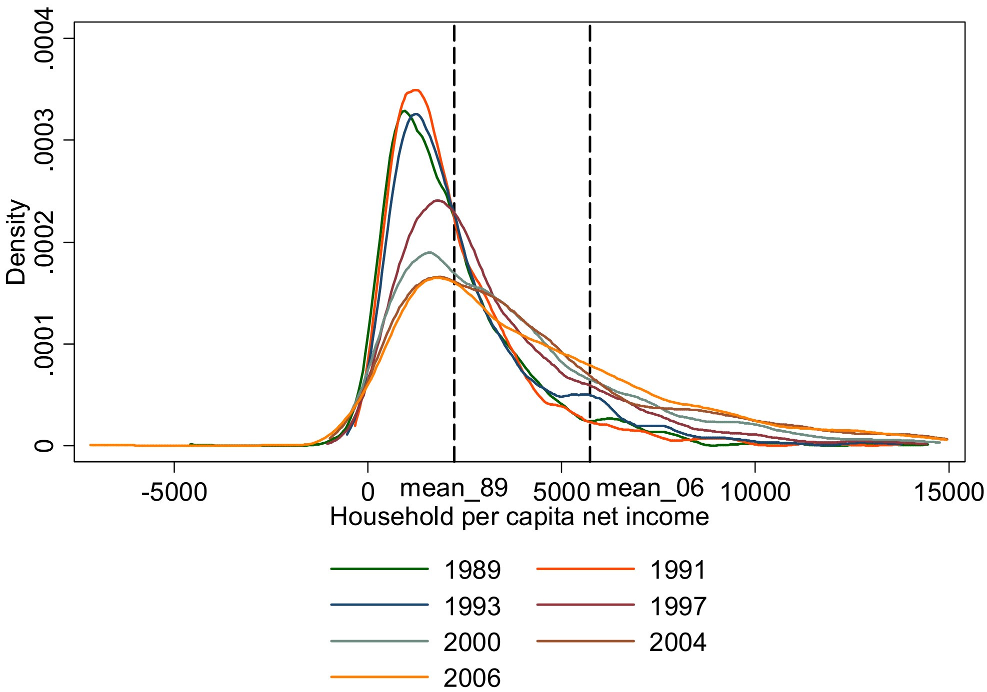


Figure 2.10 Kernel distribution of per capita rural household net income, by year



Moreover, the inequality in terms of rural households' per capita consumption and net income is directly measured by three indices in Table 2.7. The net income witnessed decreasing inequality in the late 1980s and mid 1990s, while consumption inequality went up in almost all periods (only a tiny decrease between 1991 and 1993). During the late 1980s, both income and consumption showed a pro-poor growth (except for those who were ultra poor). In the mid 1990s, rural households' income and consumption increased dramatically, as the government substantially raised the price of agricultural products. We further calculate the growth rates of income and consumption for each percentile in the income/consumption distribution and find this rapid growth is especially true for those between 20-40 percent: their income/consumption approached and sometimes was even slightly higher than that of the rich. However, the consumption inequality did not benefit from this policy. Income inequality consistently experienced an increase in the following periods. Compared with consumption, income inequality is particularly intensified.

Table 2.7 Consumption and income inequalities in rural China during 1989-2006

Year	Household per capita consumption			Household per capita income		
	Gini	Theil-L	Theil-T	Gini	Theil-L	Theil-T
1989	0.257	0.118	0.111	0.450	0.381	0.325
1991	0.272	0.139	0.123	0.414	0.298	0.296
1993	0.271	0.128	0.119	0.424	0.302	0.313
1997	0.288	0.176	0.142	0.416	0.295	0.297
2000	0.335	0.257	0.192	0.463	0.389	0.379
2004	0.356	0.249	0.213	0.483	0.417	0.400
2006	0.354	0.232	0.208	0.513	0.489	0.469

The Gini coefficient of income on the basis of CHNS is on average about 32 percent higher than that of the RHS[25] over the sample period. As we have discussed before, this is on the grounds that the RHS excludes many of the extremely rich and the ultra poor. The RHS's view is that these groups are less representative of rural China as a whole. The other important reason lies in the spatial deflators we use to translate income and consumption. The spatial rural price index in Table 2.4 suggests relatively lower price level in richer regions (coastal provinces) and higher price level in poorer regions (western provinces). Therefore, the Gini coefficients on the basis of RHS, failing to account for spatial cost-of-living differences, tend to understate the income inequality, as do the consumption inequality measures. Measuring welfare either way, the inequality deteriorates over time. Over the sample period 1989-2006, consumption inequality rises 38 percent by percentage growth, which is more pronounced than that of the net income (14 percent).

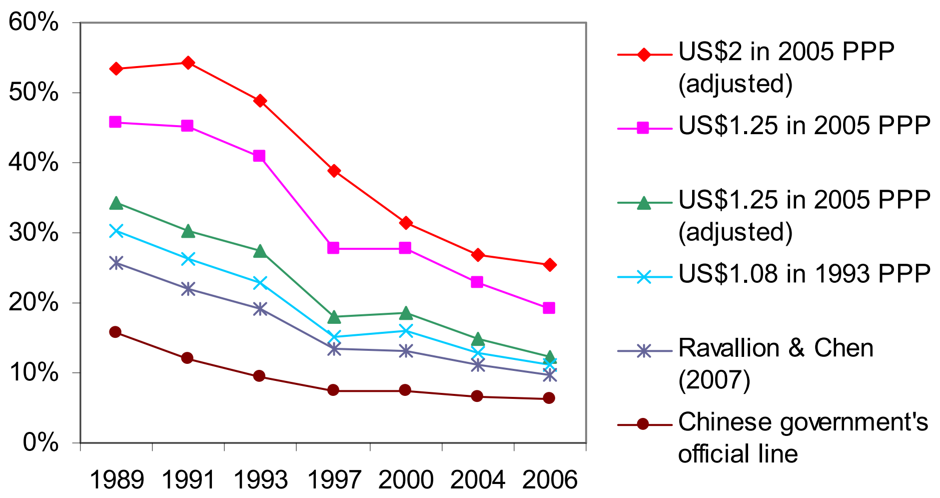
2.3.2.3 Static poverty

Both income and consumption poverty incidences decline dramatically. We include income poverty incidence under six poverty lines in Fig. 2.11. The official poverty line in China has not been updated for nearly twenty years, and has remained at 300 *yuan* in 1990 prices regardless of the considerable economic development the country has achieved. This very low poverty line clearly cannot coincide with China's fast economic growth. In general, consistent with Zhang and Wan's (2006a) estimates using CHNS, the rural income poverty fell sharply under most poverty lines during 1989-2006 as a result of fast growing income. In terms of proportionate

[25] The Gini coefficients on the basis of RHS are offered in Bramall (2001) and Ravallion and Chen (2007).

changes, income poverty incidence decreased by 76-77 percent in Chen and Ravallion's (2008) study during 1987-2005 and 53-64 percent according to our estimation at different poverty lines during 1989-2006. However the incidence in our panel slightly increased by 0.7 percent under the highest poverty line in the period 1989-1991. The reason lies in the very small decrease in net income for the upper half of the population (very close to zero) while those at the bottom half had an average positive growth rate of per capita household income.[26] Additionally, in affinity with Zhang and Wan's (2006a) outcome, over the entire sample period 1989-2006, the percentage changes tend to be greater at lower poverty lines, 'suggesting concentration of per capita income at the lower end of the income spectrum'.

Figure 2.11 Income poverty incidence



Note: a. The Chinese official poverty line is 530 *yuan* in 1995 prices.

b. Ravallion and Chen (2007) set an adjusted poverty line for rural China at 850 *yuan* in 2002 prices.

c. US$ 1.08/day in 1993 PPP is equivalent to 1,051 *yuan* in 2005 prices.

d. US$1.25/day in 2005 PPP (adjusted) is allow for a 37 percent difference in cost-of-living between rural and urban areas in 2005, according to Ravallion and Chen (2008).

e. US$1.25/day is the new international poverty line suggested by the World Bank.

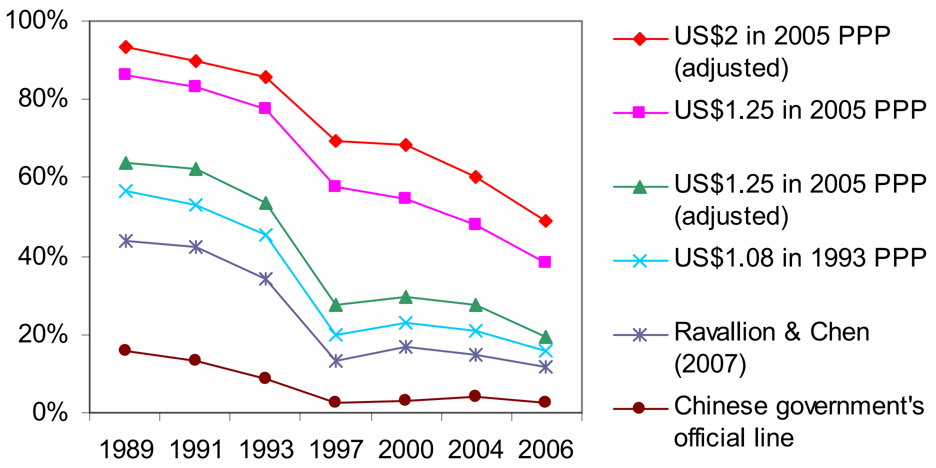
[26] When trimming off the top 5 percent of households in the per capita income distribution during 1989-1991, the poverty incidence turns to decline at the adjusted US$2 poverty line.

f. US$2/day is about the median of 75 countries' national poverty lines used by Ravallion *et al.* (2008).

Income poverty reduction suffered a period of stagnation between 1997 and 2000, which echoes estimates from the World Bank and UNU-WIDER. Particularly, at the value level, using the Rural Household Survey conducted by the National Bureau of Statistics annually and the poverty line of US$1.08 in 1993 PPP terms, Chen and Ravallion (2008) find income poverty incidence increased by 2.4 percent among rural households between 1996 and 1999. Benjamin *et al.* (2005) find absolute decrease in rural households' income based on RCRE survey. Zhang and Wan (2006a), who also use CHNS data, obtain an increase of 5.55 percent, while our data suggest 0.7 percent. Using a growth-inequality decomposition, this increment can be seen to be a joint outcome of large negative redistribution effect and relatively smaller positive growth impact as China weathered the financial crisis in that period (Chen and Wang, 2001). However the incidence goes down at the highest poverty line of US$2, indicating that the poor are hurt most compared with those at the top.

The consumption poverty incidence also suggests an overall downward trend (Fig. 2.12). However, this increased in 1997-2000 under all poverty lines except the highest two, which is consistent with Chen and Ravallion's (2008) finding. During 1991 and 1997, the poverty population consistently declined in rural areas due to the positive growth effect. Particularly during 1993 and 1997, there was a sharp decrease in consumption poverty incidence, from 6.2 to 25.8 percent at five poverty lines. This is mainly a result of the rising prices of agricultural goods. According to Chen and Wang (2001), the Chinese government raised the official purchasing prices of agricultural product by 75 percent, particularly for grain which was doubled. This benefited the poor and near poor (the adjusted US$1.25 and 1.08 poverty lines) most, since the share of food expenditure declines as households get rich. Similar to the case of net income, the lower the poverty line, the greater the percentage decrease in the whole sample period (82.7-47.6 percent for poverty lines from the lowest to the highest), implying that per capita consumption also concentrates at the lower end of the consumption spectrum.

Figure 2.12 Consumption poverty incidence



Note: a. The Chinese official poverty line is 530 *yuan* in 1995 prices.

b. Ravallion and Chen (2007) set an adjusted poverty line for rural China at 850 *yuan* in 2002 prices.

c. US$ 1.08/day in 1993 PPP is equivalent to 1,051 *yuan* in 2005 prices.

d. US$1.25/day in 2005 PPP (adjusted) is allow for a 37 percent difference in cost-of-living between rural and urban areas in 2005, according to Ravallion and Chen (2008).

e. US$1.25/day is the new international poverty line suggested by the World Bank.

f. US$2/day is about the median of 75 countries' national poverty lines used by Ravallion *et al.* (2008).

It is worth noting that in 2000-2004, consumption poverty incidence decreased at the four higher poverty lines, which is as same as Chen and Ravallion's (2008) estimation, but increased at the official Chinese poverty line. This indicates that the aftermath of the economic slowdown in the late 1990s still influences the ultra poor's life. In effect, the rural population in poverty announced by the State Council increased by 0.8 million from 2002 to 2003 (Wang, 2005). This can also be confirmed by the pro-poor growth rates formulated by Ravallion and Chen (2003). Applying their method to every sub-period in our sample, the growth rates for the poorest 16-17 percent of households were found to remain negative during 2000-2004. In contrast, the rest of the population started to see increasing consumption after 2000. For the whole sample, the annual growth rate of per capita consumption in mean was 2.54 percent.

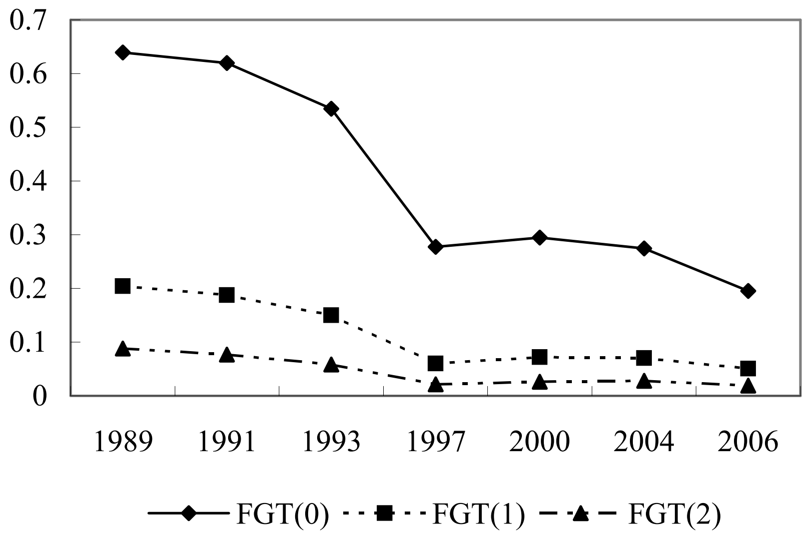
At the level of consumption poverty incidence, our estimates are generally higher than those in Chen and Ravallion's (2008) study, but income poverty incidence is lower. These differences reflect the distinct characteristics of the two datasets. As we have stated in Section 2.2.4, per capita rural households' consumption is lower in the CHNS than that in the RHS and income is higher than their data. However, when comparing income and consumption poverty incidence, in parallel with Chen and Ravallion (2008), the rural income poverty incidence is nearly half those figures of consumption poverty at different poverty lines, except at the Chinese official line.

The other source of the upward biased consumption poverty incidence may come from the relatively large share of food component in total consumption expenditure. The above estimates are obtained by the poverty line based on food bundles as well as on the non-food component. The cost of the former component accounts for 65 percent in the Chinese official poverty line and 60-75 percent in Chen and Ravallion's (1996) re-estimation of two new poverty lines. Considering the dominating share of food expenditure in our consumption data, the estimates of consumption poverty incidence would be more accurate if one used the food poverty line.

Besides the poverty incidence, we also check the severity of poverty by the poverty gap (FGT(1)) and squared poverty gap (FGT(2)). On the one hand, the higher order FGT-class measures (Forster, *et al.* 1984) for the entire study population declined during 1989-2006 under all poverty lines. This is similar to the trend in poverty incidence (FGT(0)), but the percentage changes for higher order FGT indicators are greater than that of the FGT(0) in cases of both consumption and income poverty.[27] This confirms the finding drawn from RHS, RCRE and CHNS data by Ravallion and Chen (2007) and Zhang and Wan (2006a) and implies that per capita consumption/income for the ultra-poor and those around the poverty line are positively correlated. On the other hand, poverty appears to have been concentrated. As illustrated by Fig. 2.13, persistence of poverty for those existing on less than price-adjusted US$1.25/day seems to have been accentuated. The poverty gap and squared poverty gap have also become more and more stagnant since 1997 and even increase from 1997 to 2000, indicating the increasing difficulty in lifting these people out of poverty.

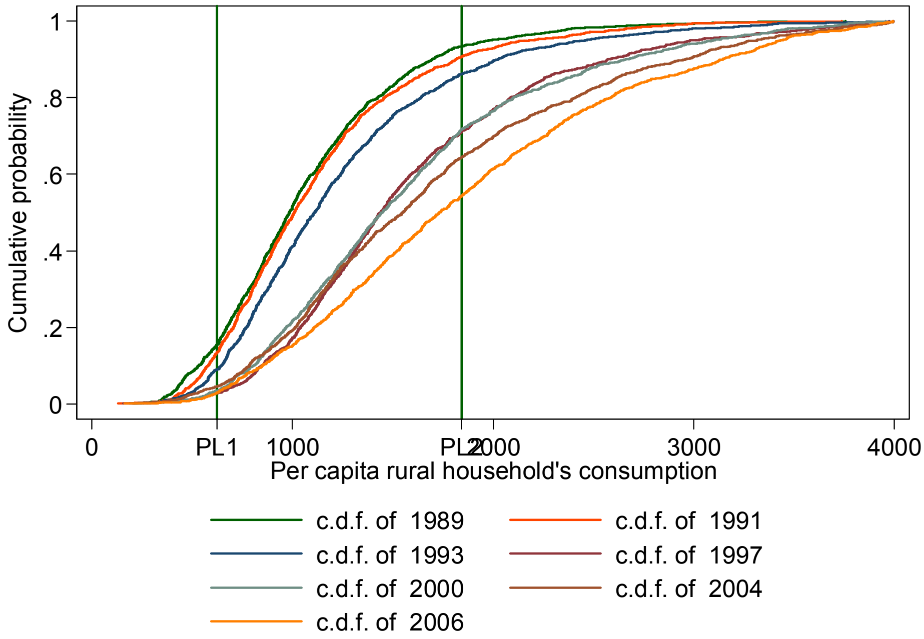
[27] The only exception is the consumption poverty measured by the Chinese government's official poverty line.

Figure 2.13 Incidence and intensity of consumption poverty



In order to check the sensitivity of the above results to the choice of poverty lines, Fig. 2.14 draws the cumulative distribution functions (CDFs) for per capita rural household's consumption expenditure during 1989-2006. The CDF curves of 1989, 1991 and 1993 are strictly below each other in turn between the Chinese official poverty line (lower limit) and the adjusted US$2 (upper limit) which is a median poverty line among developing countries. This implies a reduction in consumption poverty incidence regardless of which poverty lines and measures are used in this domain. However, the CDFs of other years are close to and sometimes intersect with each other. In the range of 1,500 *yuan* and the line of adjusted US$2, the CDF of 2006 is well below the rest which indicates that the poverty incidence declined during 1997-2006 whichever the poverty lines is referred to. Nevertheless, the CDF of year 1997 lies above the 2000 curve, pointing to an increase in the poor population.

Figure 2.14 Cumulative distribution function of per capita rural household consumption



Note: The lower and upper limits (PL1 and PL2) are the Chinese government's official poverty line and the adjusted US$2/day, respectively.

2.3.2.4 Poverty dynamics

Former studies identify a significant transient component in rural China's poverty reduction. Jalan and Ravallion (1998a, b) and McCulloch and Calandrino (2003) find that households frequently moved in and out of poverty. Our data also suggest the same feature.

Table 2.8 gives the consumption poverty dynamics over time, using McCulloch and Calandrino's (2003) categorisation. They attribute the observed consumption poverty in each year into chronic and transient components according to household intertemporal mean consumption within a certain time period. The 'Row %' is the proportion of the (non)chronically poor among the observed (non)poor. The

'Column %' is the proportion of the observed (non)poor among the (non)chronically poor. In our sample, 37.4 percent of the poor in 1989 were chronically poor in terms of having lower intertemporal mean consumption than the poverty line. This proportion increased to 68.4 percent in 2006, indicating more significant feature of persistence in observed poverty. Meanwhile, 88.7 percent of the chronically poor were also observed as consumption poor in 1989. This proportion decreased as household consumption increased over time. Analogically, 54.7 percent of the non-chronically poor had lower consumption than the poverty line in 1989. This proportion dropped sharply, but still registered at 8.4 percent in 2006. These two phenomena reveal that whether households are chronically or non-chronically poor, they escape and suffer poverty from time to time.[28]

[28] It should be noted that we may have over-stated the transitory poverty under McCulloch and Calandrino's (2003) framework. The limitation of their method is that their transitory poverty calculations do not reflect the case that many households may escape as a result of increasing mean consumption. Even if these increases were perfectly linear and steady, they would show up as transitory poverty.

Table 2.8 Household decomposition by intertemporal mean consumption and poverty status

	1989		2006	
	No. of households with intertemporal mean consumption...		No. of households with intertemporal mean consumption…	
	below the poverty line	above the poverty line	below the poverty line	above the poverty line
Poor	346	578	193	89
Row %	37.4	62.6	68.4	31.6
Column %	88.7	54.7	49.5	8.4
Non-poor	44	478	197	967
Row %	8.4	91.6	16.9	83.1
Column %	11.3	45.3	50.5	91.6
Total	390	1056	390	1056
Row %	27.0	73.0	27.0	73.0

Note: a The poverty line is the adjusted US$1.25/day.

The high proportion of transient poverty would, as argued by Jalan and Ravallion (1998a) and McCulloch and Calandrino (2003), tend to provide misleading signals to policy designers. Specifically, if the government targets aid towards static poverty from one year, 62.6 and 31.6 percent of the poor in 1989 and 2006 respectively might be inappropriately included, since their intertemporal mean consumption in the long-run is higher than the poverty line and being in poverty is only an occasional situation for them. However, should the aid be allocated based on the intertemporal mean, 54.7 percent and 8.4 percent of the non-chronically poor in 1989 and 2006 respectively would not be able to benefit from the plan, although they did suffer some degree of poverty in that year.

2.3.3 Other variables

This sub-section briefly describes the main features of household characteristics, including the household head's age and education, off-farm employment within the household and the demographic structure of the household.

2.3.3.1 The household head's age

As shown in Fig. 2.15, the mode (or peak) of the distribution is around 40 years old. The proportion of households changing the head ranged from 2.97 to 4.08 percent in each survey year. The distribution of age does not change much across surveys. Geographically, as shown in Table 2.9, household heads in western provinces appear older than the rest.

Figure 2.15 Distribution of surveyed rural household heads

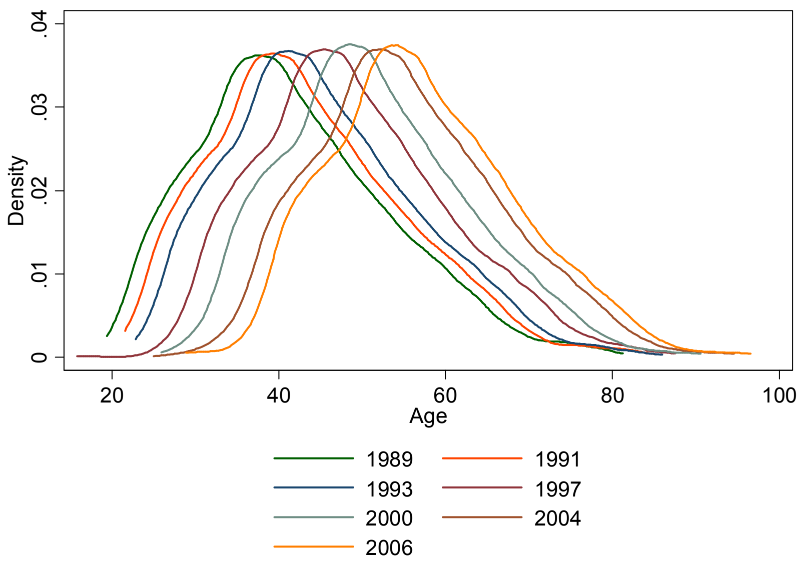


Table 2.9 Average age of rural household heads

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	41.1	40.5	42.5	38.1	41.2	44.0	44.7	41.8
1991	43.2	42.6	44.4	40.2	42.5	45.4	46.4	43.6
1993	45.0	43.8	45.9	42.2	44.7	47.6	48.1	45.4
1997	49.4	48.0	49.8	45.6	48.5	50.7	51.0	49.0
2000	51.9	51.0	52.3	48.7	51.0	53.1	53.5	51.7
2004	55.7	54.8	56.3	51.8	54.9	57.7	57.5	55.6
2006	57.8	56.8	57.3	53.7	57.2	59.9	60.1	57.6

2.3.3.2 Household size and structure

Table 2.10 shows that western provinces had the largest household size, while coastal provinces had the smallest. The average household size for all provinces decreased before 2004, but increased slightly during 2004-2006. The mass of households had 4 members, and the second biggest proportion was households having 5 members. Rural households in coastal provinces have smaller sizes than those residing in inland areas. Western provinces have the largest average rural household sizes.

Table 2.10 Average household size

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	3.98	4.21	4.95	4.58	4.36	5.10	4.99	4.61
1991	3.97	4.15	4.71	4.50	4.29	4.84	4.84	4.48
1993	3.94	4.11	4.66	4.55	4.18	4.71	4.83	4.44
1997	3.92	3.89	4.31	4.33	3.94	4.68	4.59	4.26
2000	3.76	3.71	4.36	4.21	3.75	4.58	4.41	4.13
2004	3.46	3.30	4.15	3.98	3.25	4.36	4.00	3.81
2006	3.65	3.45	4.09	3.92	3.67	4.42	4.12	3.92

Because of the implementation of the One-Child Policy in China and the fact that we are tracking the same households in all seven rounds of surveys, the number of children should go down. Table 2.11 illustrates that the average number of children per household sharply decreased. Rural households in Guizhou province had the highest number of children, which might be the result of a more relaxed family planning policy for ethnic minorities, while those in coastal provinces had smallest number.

Table 2.11 Average number of children under 18 per rural household

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	0.89	1.05	1.34	1.29	1.38	1.29	1.84	1.30
1991	0.89	1.09	1.30	1.46	1.29	1.34	1.69	1.30
1993	0.92	1.20	1.40	1.50	1.31	1.59	1.51	1.36
1997	0.71	0.95	1.16	1.30	1.01	1.30	1.25	1.11
2000	0.58	0.74	1.01	1.05	0.67	1.07	1.01	0.89
2004	0.29	0.26	0.60	0.43	0.27	0.47	0.50	0.41
2006	0.30	0.30	0.56	0.34	0.35	0.54	0.64	0.44

2.3.3.3 Occupation, employment and labour supply

Table 2.12 summarises the occupation components in our panel. Farm households, whose household heads are farmers, accounted for 73.4 on average. About 43.6 percent of the study households were farm households in all rounds of the surveys. The next biggest category is the non-skilled worker and its proportion increased with an annual growth rate of 3.7 percent. The proportion of non-skilled workers fluctuated across years, with the highest and lowest growth rate being 12.46 percent along with the prosperity of TVEs during 1991-1993 and -3.8 percent during 1993-1997 when the financial crisis hit many south-eastern Asian countries. On average, it grew 2.2 percent per annum.

Table 2.12 Occupation of the household head (%)

Year	Farmer	Non-skilled worker	Skilled worker	Professional
1989	77.41	7.24	6.37	6.30
1991	74.93	7.02	7.02	6.81
1993	73.82	8.77	7.51	8.06
1997	71.98	7.44	8.29	8.92
2000	73.63	7.03	9.43	7.03
2004	69.48	8.37	11.11	6.97
2006	67.68	8.87	11.90	6.56
Average	73.42	7.66	8.81	7.24

Note: a. Non-skilled workers include labourer and homemakers.

b. Skilled workers include technical skilled workers (foremen, craftsmen, drivers, etc.) and service workers (housekeepers, cook, waiters/waitresses, doorkeepers, barbers/beauticians, counter sales, launderers, childcare, etc.).

c. Professionals include doctors, nurses, lawyers, teachers, engineers, managers and government officials.

The number of household members currently employed in non-agricultural sectors decreases over time (Table 2.13) as more and more members' ages reach the retirement line at 55 years old. Nevertheless it should be noted that Guangxi and Guizhou provinces, which used to have the highest employment levels in 1989 on account of their large household sizes, show a relatively lower profile in 2006 than in Jiangsu where the household size is the second smallest. This might be a hint of less developed labour markets in western provinces.[29]

[29] However we cannot make firm conclusions on this since the average age in western rural households is higher than that in coastal provinces. It could be the case that the relatively larger reduction in employment in the west is a result of their being more retired members in the household and that this is therefore irrelevant to the development of the labour market.

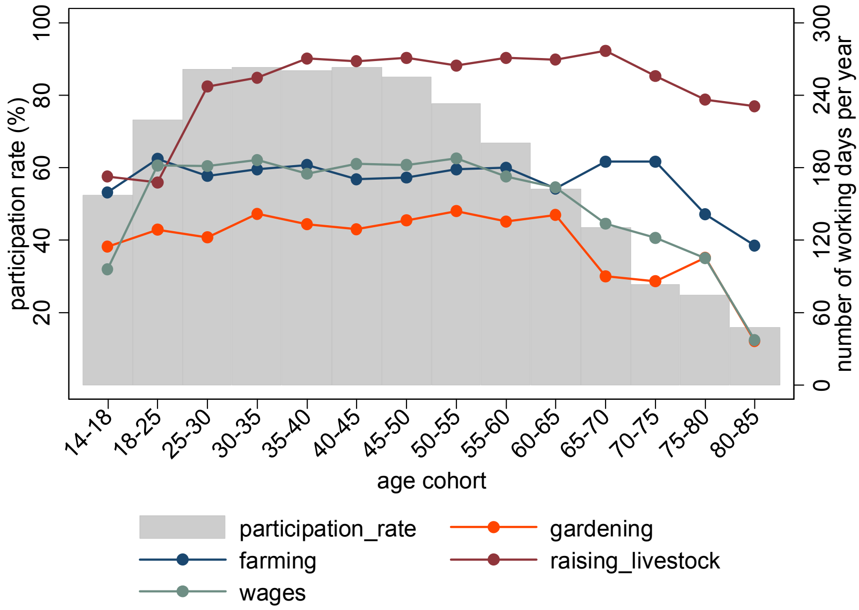
Table 2.13 Average number of members currently employed per rural household

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	3.28	2.94	3.95	3.45	3.34	3.81	4.13	3.57
1991	2.61	2.43	2.80	2.50	2.27	2.79	2.92	2.63
1993	2.62	2.30	2.90	2.57	2.16	2.78	3.04	2.63
1997	2.56	2.06	2.79	2.53	1.84	2.88	2.98	2.54
2000	2.53	1.94	2.75	2.59	1.93	2.77	2.83	2.54
2004	1.83	1.69	1.96	1.57	1.02	1.87	1.99	2.50
2006	1.80	1.53	1.76	1.34	1.25	1.77	1.75	1.72

It is often argued that the Chinese rural labour supply is abundant. It is usually the case in rural China that not only adults of working age are in the household labour force, but also children and the elderly who help with some production activities. Our data suggest that half of the children between 14 and 18 were engaged in earning wages and general farming activities.[30] As a natural result of more than three decades of one-child policy, the elderly have become dominant in the observed dependency ratio – the share increases from 46 to 94 percent. The term 'ceaseless toil' has been widely used to describe the large numbers of elderly working in rural China (Benjamin *et al.*, 2000, 2003; Cai, 2004; Pang *et al.*, 2004). The elder groups, especially those aged between 60 and 65, worked more in agriculture even though their involvement in formal wage-earning sectors dramatically shrank. This is probably due to the enforcement of a retirement age in the formal labour market (Fig. 2.16).

[30] In rural China, children usually help their families with farming, gardening, raising livestock and other agriculture activities after class.

Figure 2.16 Average labour input, by age cohort (1989-2006)



Several reasons could account for this strong propensity towards work. The most important source is their social insecurity. A significant delimitation on social protection systems after the reform and pro-urban policy design is comprehensive guarantees for urban residents (such as minimum living standard, health and unemployment insurance, pension and various subsidies) and partial, or no, assistance for those having rural *Hukou*[31] The coverage and extent of social assistance in rural areas is extraordinarily limited. Only 6.8 percent of rural residents enjoyed at least one kind of social assistance in 2008, which only registered at one sixth of the coverage among urban residents. In addition, most of the social assistance going to rural residents is temporally provided. In general, after the 1978 reforms, social security in rural areas was almost non-existent until 2000. Another possible reason revealed by nation-wide interviews says that traditionally Chinese

[31] Every household in China has to register as either an urban or rural household. The household registration is called *Hukou*. A household's rural *Hukou* endows it with some resources (e.g., land for farming and building its own house), and at the same time, restricts it from out-migrating from its original place of residence and enjoying many social protections which are solely provided to urban residents (e.g., the minimum livelihood guarantee system, health insurance, pension).

filial piety may collapse more or less in both poor and rich regions, which drives the rural elderly to protect themselves by prolonging work (Cai, 2004; Pang, *et al.*, 2004). Last but not least, rural households' living arrangement varies in accordance with the reform.

2.3.3.4 Education

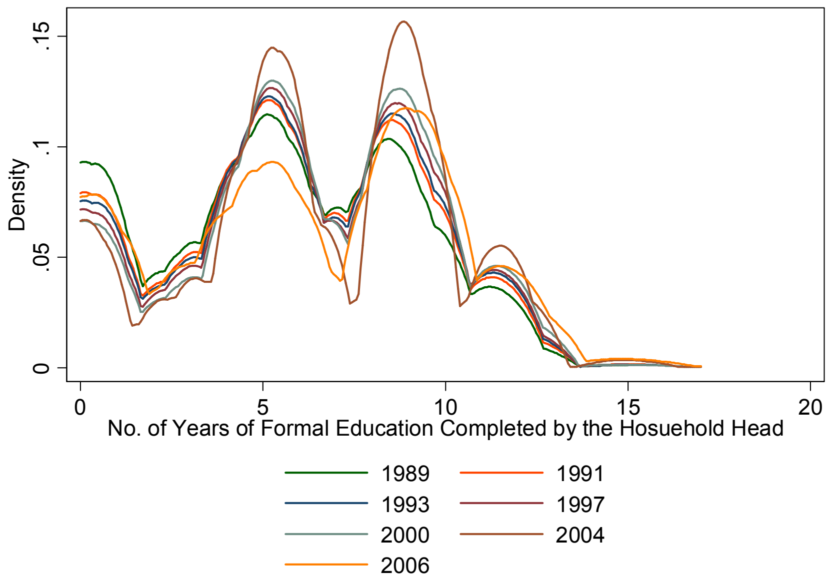
Table 2.14 summarises the number of years in formal education that an average rural household head has completed. Hubei showed the highest education level in most periods. Central and coastal provinces have higher education level on average, while rural households in Guizhou always obtained the least formal education.

Table 2.14 Average years of formal education completed by rural household heads

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	5.32	5.88	5.18	6.06	5.45	5.27	3.73	5.26
1991	5.60	6.18	5.50	6.39	6.06	5.75	4.02	5.63
1993	5.70	6.34	5.61	6.44	6.13	5.78	4.26	5.82
1997	5.77	6.57	5.69	6.62	6.41	5.90	4.37	5.89
2000	6.00	6.67	5.93	6.66	6.55	6.19	4.73	6.09
2004	6.20	7.04	6.09	7.12	7.07	6.28	4.98	6.38
2006	6.07	6.22	6.02	6.71	6.50	6.03	4.48	5.99

The mean education level for all provinces increased over time. The number of rural household heads never receiving formal education dramatically shrank. As Fig. 2.17 illustrates, there were two peaks in the distribution of the household head's education level, around 5.5 and 8.5 years respectively in every survey year. The first peak indicates that the mass of household heads had completed primary school. The second peak indicates household heads having completed elementary school (i.e. nine-year compulsory education), and this frequency has increased significantly since 2004. However, a very limited number of rural household heads completed high school education or higher education.

Figure 2.17 Distribution of education level in rural households



2.3.3.5 Assets owned by rural households

Table 2.15 shows that the number of motorcycles owned by the average rural household decreased in the late 1980s and during the period of financial crisis in the late 1990s. It is not surprising that the smallest average number of motorcycles appeared in Guizhou province. More motorcycles are owned by rural households in Jiangsu and Hubei provinces.

Table 2.15 Average number of motorcycles owned by the rural household

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	1.00	1.33	1.00	1.50	1.67	1.00	1.00	1.26
1991	1.00	1.00	1.00		2.00	1.00		1.08
1993	1.00	1.13	1.00		1.22	1.00	1.00	1.09
1997	1.00	1.06	1.00	1.08	1.08	1.29	1.08	1.11
2000	1.11	1.12	1.03	1.07	1.11	1.14	1.08	1.10
2004	1.17	1.09	1.19	1.06	1.23	1.13	1.02	1.12
2006	1.18	1.15	1.09	1.26	1.06	1.24	1.00	1.17

Table 2.16 suggests that the average rural household owned more agricultural equipment during 1989-2006, except for a period of decline in the mid 1990s. Costal and most central provinces have more equipment, while the figure in Guizhou province only accounts for 8.86 percent of that in Henan in 2006. Agricultural development and modernisation in Guizhou lag far behind the coastal and central regions and is even much less than its neighbouring Guangxi province.

Table 2.16 Average number of items of agricultural equipment owned by the rural household

Year	Coastal		Central			Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	0.30	0.65	1.16	0.23	0.13	0.25	0.12	0.39
1991	0.28	0.77	0.87	0.36	0.14	0.24	0.13	0.39
1993	0.35	0.80	0.86	0.23	0.20	0.29	0.12	0.39
1997	0.24	0.55	0.60	0.17	0.10	0.18	0.05	0.26
2000	0.30	0.64	0.59	0.23	0.12	0.28	0.07	0.31
2004	0.50	0.68	0.82	0.38	0.21	0.40	0.09	0.43
2006	0.46	0.68	0.93	0.47	0.30	0.61	0.08	0.50

2.3.3.6 Farmland

Per capita cultivated land owned by the household in sample provinces fluctuated around their own provincial mean, as shown in Table 2.17. The mean for all sample provinces increased prior to 1993 but suggested a lot of fluctuation after that. Per capita farmland owned by rural households in 2006 is basically the same as the 1989 figure.

Table 2.17 Average household per capita cultivated land (acres)

Year	Coastal			Central		Western		All
	Jiangsu	Shandong	Henan	Hubei	Hunan	Guangxi	Guizhou	
1989	1.22	0.77	1.20	0.77	0.62	0.58	0.82	0.85
1991	1.19	0.98	1.25	0.87	0.63	0.71	0.82	0.91
1993	1.23	0.88	1.31	0.89	0.78	0.72	0.95	0.96
1997	0.99	0.85	1.27	0.87	0.65	0.66	0.73	0.85
2000	0.98	1.29	1.07	0.64	0.27	0.56	0.73	0.79
2004	1.28	0.98	1.45	0.88	0.52	0.59	0.65	0.90
2006	1.13	1.32	1.22	0.73	0.39	0.68	0.71	0.88

2.3.4 Cross-tabulation of variables

The intertemporal mean per capita household's net income increases as the households become richer (Table 2.18). The mean per capita agricultural fixed assets, motorcycles and farmland owned by the rural household also go up with consumption. The smallest household sizes and the highest education level are found in the richest group. The household heads belonging to the poorest group are relatively older than others.

Table 2.18 Cross-tabulation of the rural household's intertemporal mean

Variables	Intertemporal mean per capita consumption quartiles			
	1 (poor)	2	3	4 (rich)
per capita consumption	942.80	1,126.94	1,651.84	2,720.58
per capita net income	2,480.98	3,008.13	3,532.47	5,166.18
per capita agricultural fixed assets	263.79	340.80	363.62	330.25
per capita motorcycles	0.02	0.03	0.05	0.06
per capita farmland (acres)	0.80	0.92	1.03	0.76
household head's age	50.40	49.54	49.64	50.34
household head's education (years)	5.58	5.73	5.93	6.18
household size	4.68	4.19	4.11	3.97
current employment	2.61	2.39	2.43	2.39

2.4 Some concluding comments

In this chapter, we have discussed the construction of the panel and some key variables to be used in the following three substantive chapters. This discussion has shown that the panel yields comparable statistics for household poverty and inequality. Support for this is given by similar findings of two other nation-wide household surveys. There are grounds therefore for a reasonable belief in the reliability and precision of the empirical analyses undertaken in the following substantive chapters.

CHAPTER 3

VOLATILITY AND INEQUALITY:

RURAL HOUSEHOLDS□UNCERTAIN WELFARE

3.1 Introduction

China has been experiencing significant economic growth since the economic reforms that began in 1978. Rural households’ real per capita income and consumption increased by 6 and 5 percent per annum respectively in the period 1986-2009.[32] Poverty reduction in rural areas has been remarkably successful, with poverty incidence shrinking from 30.7 percent in 1978 to 2.3 percent in 2006 according to the Chinese government’s official poverty line (State Council, 2007). That is, nearly 230 million people grew out of from deprivation, which means China accounted for more than 70 percent of the world’s poor who escaped poverty in this period (State Council, 2007).

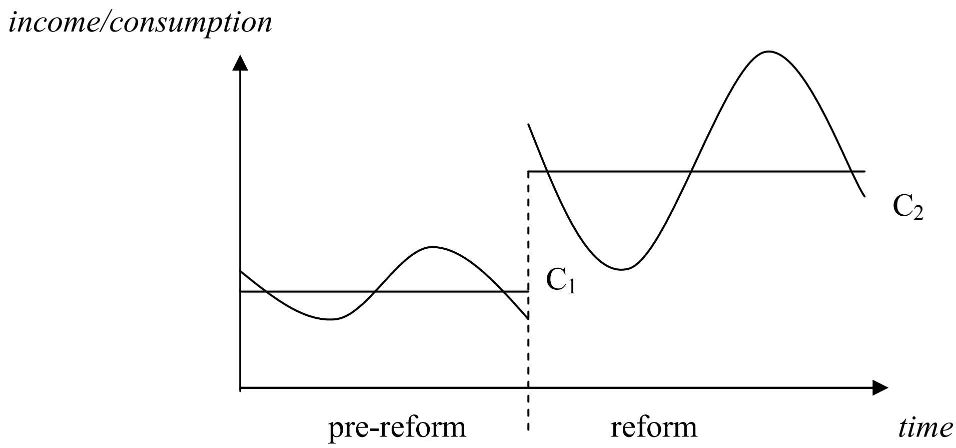
While their livelihoods have been dramatically improved, rural households continue to confront many uncertainties as they live through the radical economic transition and social changes China is undergoing (Whalley and Yue, 2009). This increased uncertainty can be seen as a result of increased volatility and inequality in rural

[32] Author’s calculations based on data from All China Data, University of Michigan.

households' income and consumption streams, which are discussed over the following pages and in Figures 3.1 and 3.2 respectively.

In Fig. 3.1(a), the mean consumption, represented by the horizontal lines C_1 and C_2, is higher in the reform period than in the pre-reform period, but there is more fluctuation in household income and consumption flows in the reform period (Ho *et al.*, 2010). The market-oriented economic reforms have taken over the socialist egalitarian distribution system since 1978. Collective farms were replaced by the Household Responsibility System in the mid 1980s. Farmers began to be responsible for their own profits and losses during the agricultural production and were allowed to sell their products in excess of the quota in markets. As rural households become increasingly integrated into the market economy compared with being allocated with everything in the pre-reform era, greater volatility also appears in their income and consumption. More specifically, several explanations have been advanced in the literature to account for this phenomenon.

Figure 3.1(a) Greater volatility in reform period



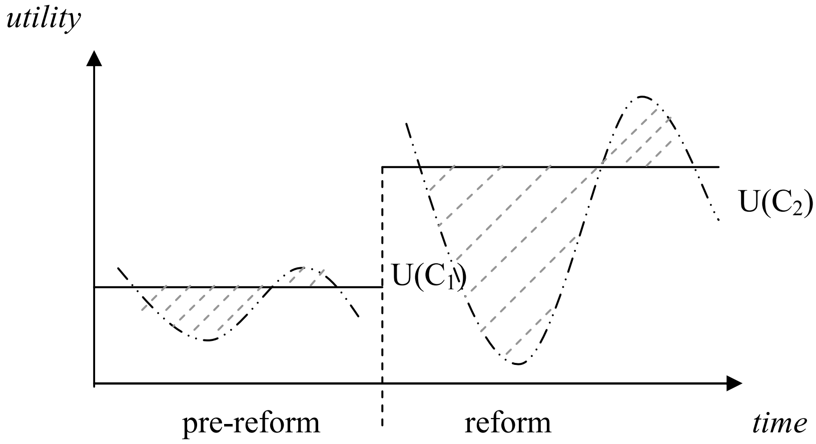
With respect to income volatility, farmers' production activities (and hence income) are not efficiently protected by either formal or informal microinsurance mechanisms

(Cai *et al*., 2009). Moreover, income fluctuations could be intensified by exposure to uninsured risk, such as unforeseeable agricultural production related risk (Yang, 2007) and unstable employment opportunities in non-agricultural sectors, typically the private enterprises in coastal regions (Cai *et al.*, 2008).

Consumption is variable due to shocks as well. At the household level, Jalan and Ravallion (1999) find no evidence supporting full risk-sharing. Their analysis reveals that around 40 percent of any income shock is passed on to the poorest rural household's current consumption, and that a rural household's consumption is only partially insured, whatever its position is in the wealth distribution. At province level, Ho *et al.*'s (2010) estimates indicate decreasing degrees of consumption risk-sharing across provinces over time. In addition, unexpected large-scale consumption expenditure may occur when there are ill health family members (Liu *et al.*, 1999, Wagstaff and Lindelow, 2008). Large-scale medical expenditure reduced households' investment in human capital and physical capital for farm production, especially for the poor (Wang *et al.*, 2006). More vitally, restricted access to financial credit (Rui and Xi, 2010) can leave rural households with very limited ability to cope with negative shocks *ex post* and smooth their consumption.

In the presence of more volatile income and consumption, Whalley and Yue (2009) find that the increasing volatility also intensifies the real rural-urban income gap by around 20 percent. Another immediate consequence of volatile income and consumption is that those who have recently escaped poverty, but are still 'near-poor' may easily slide back into poverty (Jalan and Ravallion, 1998a,b; McCulloch and Calandrino, 2003; Duclos *et al.*, 2010). Most importantly, the utility gained from the growth of income and consumption may be partially off-set by the utility loss brought by the greater volatility (Ho *et al.*, 2010). As illustrated in Fig. 3.1(a), we suppose that households have regular income or consumption fluctuations in both pre-reform and reform periods.[33] Under a concave utility function assuming decreasing marginal returns of income or consumption, the utility loss due to a shortfall is greater than the gain from an equivalent income or consumption above the intertemporal mean (Thorbecke, 2004). In this sense, volatility could generate utility loss to households, regardless of its magnitude. This is illustrated in Fig. 3.1(b), where the utility losses due to volatility in pre-reform and reform periods are derived by subtracting the shaded areas below $U(C_1)$ and $U(C_2)$ by the shaded areas above each of them. Moreover, as Fig. 3.1(a) and (b) assume greater volatility in the reform period, the utility loss due to volatility is greater in this era. Given these potential utility losses generated by volatility, 'a household with very low expected consumption expenditures but with no chance of starving may well be poor, but it still might not wish to trade places with a household having a higher expected consumption but greater consumption risk' (Ligon and Schechter, 2003).

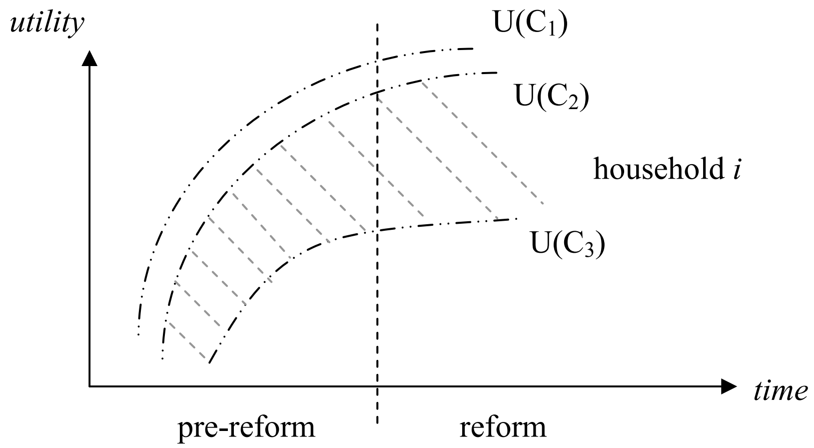
Figure 3.1(b) Welfare loss associated with greater volatility



[33] Following Thorbecke (2004), 'regular fluctuations' mean that in each period, the excess income or consumption above the intertemporal mean is exactly compensated by an equivalent shortfall.

Relative inequality also increased after the reform. This increasing disparity relative to other households may lead to household *i* perceiving that it is not as happy as it could have been if its mean consumption synchronised with that of the average household. In other words, rural households' perceptions of their relative position in the economy and aspirations for an urban and hedonistic lifestyle may also play a role in forming their welfare (Knight *et al.*, 2009b). As seen in Fig. 3.2, the reference household's consumption is C_1 and the lowest consumption is C_3 among all households. Under an increasing and concave utility function, household *i*'s utility in the shaded area grows over time due to its higher income or consumption. Nevertheless, its utility is below the reference household and the utility gap between them becomes larger as income or consumption inequality increases. The household *i* becomes increasingly worse-off compared with the reference household. In comparison, although the utility of those having C_2 is lower than the reference level, the gap between them remains constant, as these households' income or consumption increases proportionately with the reference household.

Figure 3.2 Welfare loss associated with greater relative inequality



This reference-point hypothesis has been widely examined in the literature on subjective well-being in developed countries. For developing countries, Chinese rural households' subjective well-being is found to be positively affected by increased absolute income but off-set by decreased relative income (Knight *et al.*, 2009b) and poorer households are more concerned with their relative positions within the village (Brown *et al.*, 2010). Fafchamps and Shilpi (2008) and Akay *et al.* (2010) also observe a similar relationship between households' subjective well-being and relative income in Nepal and rural Ethiopia.

The above evidence on heightened volatility and inequality in household income and consumption opens up the question: what are the welfare consequences of the simultaneous increases in mean income and consumption, and volatility and inequality? It is therefore worthwhile performing an assessment from a utilitarian stance on rural China's development: one which not only reflects the benefit of growing income and consumption but also reveals potential welfare losses brought about by uncertainties associated with greater volatility and inequality. However, the empirical examination of welfare consequence of income or consumption volatility at the household level in rural China is surprisingly thin. As far as we know, the only exception is Whalley and Yue (2009), who studied the impact of the income volatility on inequality. Additionally, Ho *et al.* (2010) quantify the welfare loss caused by consumption fluctuations, but their analysis is at the provincial level and is therefore susceptible to larger measurement errors. Knight *et al.* (2009b) provide the first attempt to study subjective well-being for Chinese rural households. Although useful for identifying the correlates of households' happiness, it has two shortcomings: it is subject to possibly substantial measurement errors due to self-reported satisfaction, and cannot measure to what extent households' perceptions of their relative status may effectively change their welfare.

This chapter attempts to overcome the above problems and extend understanding of rural China's development through a utilitarian lens. It employs Ligon and Schecter's (2003) methodology and enlarges traditionally semantic sphere of development following the notion of households' vulnerability as uncertain welfare (VUW) introduced by Thorbecke (2004). Specifically, this chapter attempts to address two questions: (1) To what extent are rural households vulnerable in terms of suffering from welfare losses due to increasingly uncertain livelihoods? (2) What are the components of this welfare loss and their own correlates?

The analysis finds that in the period of 1989-2006, the welfare improvement and the increase in consumption follow different trends. More than half of the sample households' welfare was less than it would have been if resources could have been costlessly redistributed so as to eliminate all volatility and inequality in consumption. Furthermore, these welfare losses, measured as household vulnerability, have increased over time. When decomposed, the inequality component accounted for around 80 percent of vulnerability, while the share of the risk component was around 20 percent.

The rest of this chapter is organised as follows. The next section sketches the measure of vulnerability and its decomposition. Section 3.3 scrutinises the data set. Empirical results are elaborated in Section 3.4. Section 3.5 concludes.

3.2 Analytical framework

This chapter defines household vulnerability as a situation where expected utility is low compared with a reference level, in line with Ligon and Schechter (2003). This definition requires calculations of household utility based on their expected consumption. Therefore, we first estimate household consumption in Section 3.2.1. The estimates allow us to compute each household's expected consumption, which is then used to derive household vulnerability in Section 3.2.2, while, Section 3.3.3 decomposes household vulnerability into its different sources.

3.2.1 Consumption regression

Following Zhang and Wan (2006b), who employ the permanent income hypothesis, household *h*'s consumption at time *t* is defined by the following equation:

$$\ln c_{ht} = \sum_{m=1}^{M} \beta_{1m} x_{hmt}^{P} + \sum_{n=1}^{N} \beta_{2n} x_{hnt}^{TS} + \alpha_h + \eta_t + \varepsilon_{ht} \tag{3.1}$$

where x_{hmt}^{P} denotes $m \in \{1,2,\ldots,M\}$ factors which may influence the permanent component of the household's consumption; x_{hnt}^{TS} represents $n \in \{1,2,\ldots,N\}$ factors which only influence the transitory part of households' consumption; α_h are time-invariant household-specific fixed effects; η_t are time fixed effects representing covariate shocks facing all households within the same period; and ε_{ht} is a white noise error. According to Schechter (2006), Eq. (3.1) is appropriately specified as the underlying assumption, that households' consumption is stationary over the sample periods, holds.[34] The estimated coefficients of Eq. (3.1) are used to calculate different conditional expectations of household consumption, which will be used in the following sub-section.[35]

[34] We examine the panel unit root in per capita log of household consumption by using LLC, IPS, Harris-Tzavalis and Hadri LM stationarity tests allowing for cross-sectional dependence. All tests support stationarity.

[35] Gaiha and Imai (2008) are concerned with the endogeneity of household income and possible measurement errors on the right hand side of the equation. They suggest a two-stage generalized least square (G2SLS) procedure which 'instruments' income by both a set of fixed assets owned by the

3.2.2 Measuring households' vulnerability as uncertain welfare

The method used for computing household vulnerability is in the spirit of Ligon and Schechter (2003) (LS henceforth). In general, rural households are assumed to follow an HARA family of utility functions.[36] In particular, we assign a strictly increasing and weakly concave utility function $\{U_{ht}\}$ in the HARA family to each rural household, considering the decreasing marginal utility brought by any additional unit of consumption as the consumption level increases. Household *h*'s utility may take any shape from $\{U_{ht}\}$. In order to evaluate the welfare consequences, we assume that *h*'s instantaneous utility takes the form:

$$U(c_{ht}) = \frac{c_{ht}^{1-\gamma}}{1-\gamma} \tag{3.2}$$

Furthermore, *h* is assumed to be risk averse. In order to calculate the utility loss, we assume $\gamma = 2$.[37] The household's vulnerability as uncertain welfare (from *t* to *t+1*) is defined as the gap between the utility derived from mean consumption across all households over time and household *h*'s expected utility,

$$V_{ht} = U(z_t) - EU(c_h) \tag{3.3}$$

household and demographic characteristics. They do so in order to generate consistent estimates of the coefficients. This chapter does not adopt this technique since the Hausman specification test rejected the endogeneity in income.

[36] Ligon and Schechter (2004, p. 4) argue that 'since the class of von Neumann-Morgenstern utility functions was originally designed to capture risk preferences, and since these functions are widely estimated and used in actual applications, it seems sensible to adopt these functions to measure the welfare loss associated with risk'.

[37] There is no reliable estimate of risk-aversion coefficient for rural Chinese households in the existing literature. Xu (2008) and Ho *et al.* (2010) arbitrarily assume 4 when calibrating their models. Whalley and Yue (2009) employ a set of values from 0.9 to 10. LS argue that the magnitude of vulnerability and its components are sensitive to the shape of utility function and the value of γ, but the share of components in vulnerability are less sensitive. We therefore follow LS's suggestion and assign 2 to household risk-aversion in the estimation, but follow Whalley and Yue (2009) and use a set of alternative values to check the robustness of our estimates in Section 3.4.5.

where z_t denotes the average intertemporal mean consumption across all households in the period of $[t, t+1]$, i.e. $z_t = \frac{1}{N}\sum_{h=1}^{N}\frac{c_{ht} + c_{h(t+1)}}{2}$;[38] h's expected utility is calculated as its intertemporal mean utility between t and $t+1$, i.e., $EU(c_h) = \frac{1}{2}\left[U(c_{ht}) + U(c_{h(t+1)})\right]$. In practice, we use z_t to normalise c_{ht}, in order to translate V_{ht} from the utiles into a percentage of the utility for the reference household whose consumption is z_t. Given the assumptions of our utility function (Eq. 3.2) and the definition of vulnerability (Eq. 3.3), increasing relative consumption inequality will always increase household vulnerability.

Before continuing, it should be noted that the benchmark z_t against which the vulnerability is measured is different from that used by LS, who calculate a unique z as the mean intertemporal consumption for all households within the entire sample period, since their panel only covers 12 consecutive months. The approach used here differs because, it is argued, while one z might be appropriate for short panels, a constant z may be less reliable for a longer time span (as in this work) for two reasons.

First, Elbers and Gunning (2003) argue that z_t measured by the intertemporal mean consumption is actually an 'average under risk' value rather than the real 'deterministic long-run value'. The LS estimator utilises observed consumption data and is essentially *ex post*. It implicitly assumes that there are no behavioural

[38] In the LS method, it is called 'certainty-equivalent consumption'. However, Elbers and Gunning (2003) argue that it is essentially the 'average under risk' as LS use observed consumption data to calculate the mean without taking the impact of household behavioural response to risk. In this chapter, we follow Elbers and Gunning's (2003) argument and view z_t the average consumption.

responses to risk and, therefore, that risk only 'affects the volatility around the mean Ec_h but not the mean itself'. However, both *ex ante* and *ex post* effects of risk can reduce growth in the long term (Elbers and Gunning, 2003). Households may try to avoid risk by choosing to remain at a consumption level with lower mean but less variation, and thus smooth consumption under negative shocks. Therefore, using intertemporal mean consumption as the riskless counterfactual to measure vulnerability can mistake the risk component as the observed poverty component. Elbers and Gunning's (2003) simulation shows that this bias increases as the sample covers a longer time, because the deterministic long-run value and the intertemporal mean under risk and shocks converge to different steady states. Difficulties also arise in the interpretation of the risk component itself: low utility may be caused by households' exposure to risk and/or their inability to handle risk.

Second, an identical z for a long time period might artificially exaggerate household consumption variations relative to the reference level, especially for the beginning and end of the survey years. Consequently, the mean vulnerability might be overestimated.[39]

In order to accommodate the estimated VUW to the above problems, the present study calculates mean intertemporal household consumption for each sub-period containing two consecutive rounds of surveys. In other words, we construct different benchmarks and calculate per-period utility loss instead of using a sole household's intertemporal mean consumption over 18 years. This time-varying z_t not only reflects the changing mean consumption as a result of households' risk

[39] Applying Eq. (3.3) to the full panel, the average vulnerability in rural China during the period 1989-2006 is 9.2 percent higher than the value which is derived when treating sub-periods separately.

management, [40] but also mitigates the impact of exaggerated fluctuations of consumption at two tails of the sample period.

3.2.3 Decomposition

As introduced in Section 3.1, household vulnerability could stem from inequality and volatility in household consumption. Correspondingly, Ligon and Schechter (2003) decompose households' VUW into inequality and risk components:

$$\begin{aligned} V_{ht} &= [U(z_t) - U(Ec_h)] && \textit{inequality} \\ &\quad + [U(Ec_h) - EU(c_h)] && \textit{risk} \end{aligned} \tag{3.4}$$

where Ec_h denotes the expected consumption for the household h between t and $t+1$, which is calculated as h's intertemporal mean consumption in this period, $Ec_h = \bar{c}_h = \frac{1}{2}\left(c_{ht} + c_{h(t+1)}\right)$; $U(Ec_h)$ is the corresponding utility obtained from this expected consumption; and the expected utility $EU(c_h)$ is defined as for Eq. (3.3). The inequality component measures the utility loss due to the gap between the household's own intertemporal mean consumption and the average intertemporal mean consumption for all households within the same time period. [41] The risk component measures the utility loss caused by households' risk aversion, as the expected utility $EU(c_h)$ falls below $UE(c_h)$ for risk averse households.

[40] Admittedly, using two-period mean consumption as the benchmark still under-states the total risk component. To completely address the problems in the intertemporal mean measurement, Elbers and Gunning (2003) provide a simulation-based stochastic measure for the household vulnerability. However, this is beyond the scope of our interest in this chapter.

[41] This is very similar to Jalan and Ravallion's (1998a) definition of chronic poverty, which compares the household's intertemporal mean consumption with poverty lines. LS also interpret the inequality component as relative poverty.

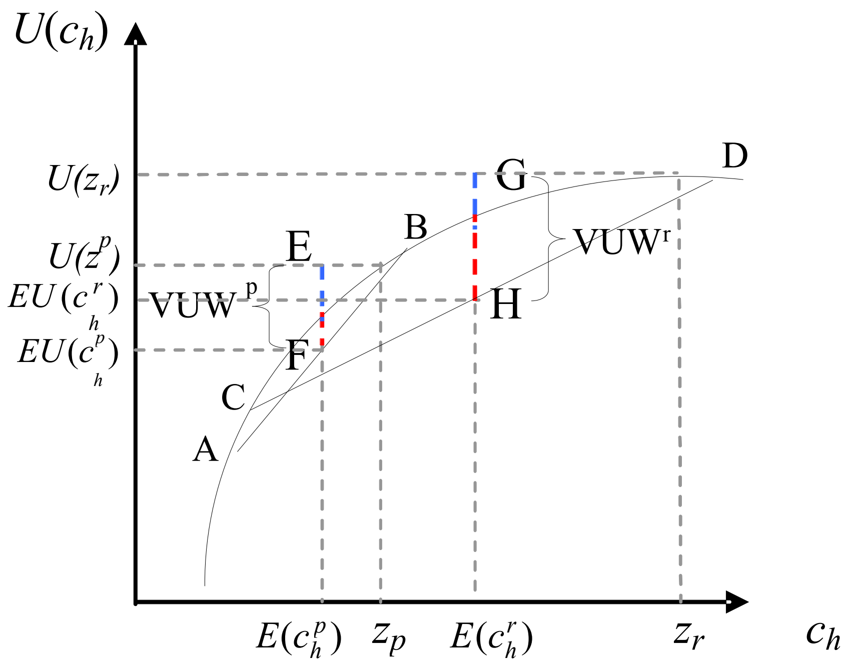
The above definition of vulnerability (Eq. 3.3) and its decomposition (Eq. 3.4) essentially make a household's welfare loss in a certain period of time a function of its expected consumption, the distance between its own expected consumption and the average consumption for all households, and the volatility in its consumption stream. That is,

$V_{ht} = f(Ec_h, Ec_h - z_t, \sigma_h)$.

It is useful to discuss how the movements of these three factors will affect household vulnerability. First, we assume there is an increase in Ec_h and hold the inequality and risk component constant respectively, as the cases introduced in Fig. 3.1 and 3.2 in Section 3.1. Fig. 3.3 illustrates how vulnerability changes in the two cases. For the household h, the horizontal and vertical axes of Fig. 3.3 track its consumption over time and the corresponding instantaneous utility respectively.

Fig. 3.3(a) illustrates the impact of the risk component. The household experiences consumption levels at A and B in the pre-reform period with lower mean and lower volatility and at C and D in the reform period with both higher mean and volatility, $E(c_h^p) < E(c_h^r)$ and $\sigma_h^p < \sigma_h^r$. The average consumption for the whole society also increases from z_p to z_r. In both periods, this household is assumed to be relatively poor. That is, its expected consumption is lower than the average, $E(c_h^p) < z_p$ and $E(c_h^r) < z_r$, indicating inequality. In order to discuss the risk component only, the welfare loss caused by this inequality is assumed to be same in both periods, i.e., distances represented by the blue lines are kept constant in two periods. It can be seen clearly that the welfare loss due to greater volatility, denoted by red lines, is larger in the reform period than in the pre-reform period, and this greater welfare loss makes this household more vulnerable in the reform period (GH>EF).

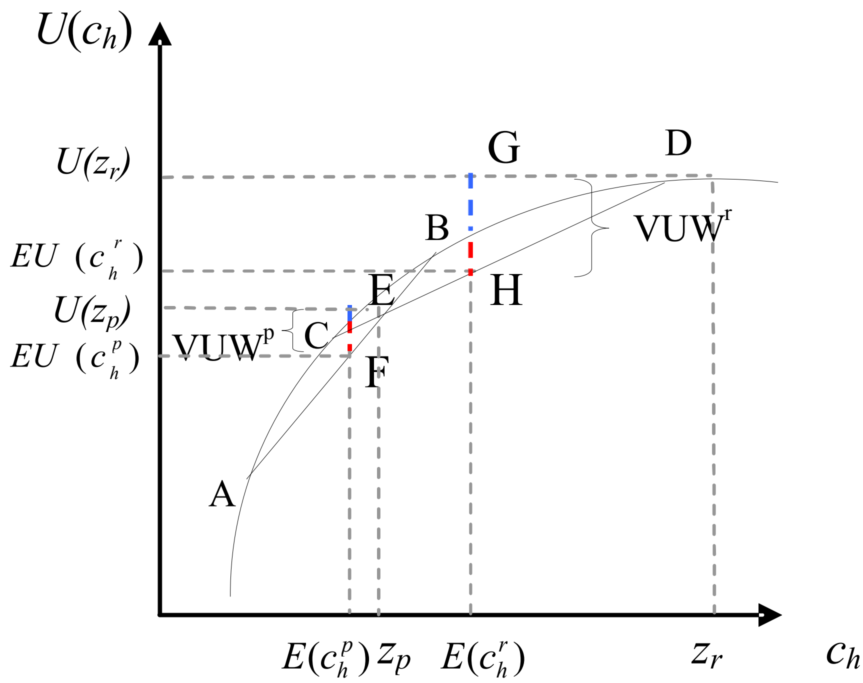
Figure 3. 3(a) Households' utility loss due to increasing volatility



Note: The blue and red lines represent inequality and risk components, respectively.

Fig. 3.3(b) examines the welfare loss due to inequality, while keeping the risk component identical. As the previous case, the household's expected consumption is assumed to increase from $E(c_h^p)$ in the pre-reform period to $E(c_h^r)$ in the reform period and the average consumption for all households also grows from z_p to z_r. It is relatively poor in both periods. The risk component, represented by the red lines, is unchanged. However, the inequality component represented by blue lines increases in the reform period, as seen at the horizontal axis, the distance between z_r and $E(c_h^r)$ is greater than z_p and $E(c_h^p)$. This results in greater VUW in the reform period, that is, GH>EF.

Figure 3. 3(b) Households' utility loss due to increasing inequality



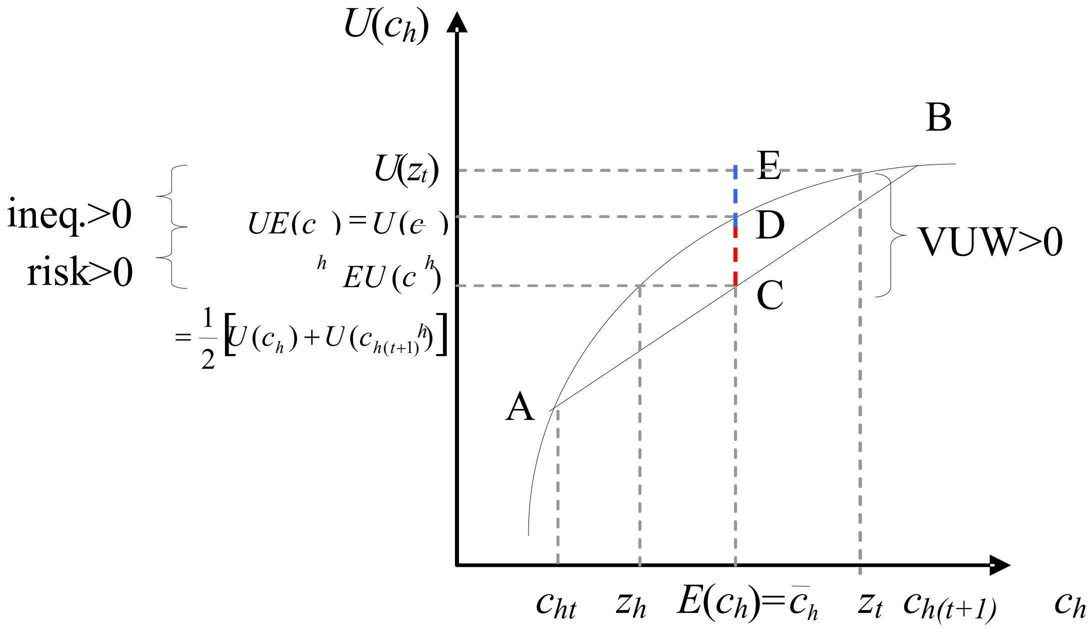
Note: The blue and red lines represent inequality and risk components, respectively.

Second, we hold the household's expected consumption constant and discuss the combined effect of inequality and risk components on vulnerability.[42] The above discussion is based on the case that the household is relatively poor as its expected consumption (measured as its intertemporal mean consumption) is held lower than the average intertemporal mean consumption across all households. Nevertheless, VUW is not restricted to the poor population measured by their consumption or income against some poverty lines, but rather would also take place among the non-poor. In Fig. 3.4, we illustrate how the household's relative position compared to z_t, combined with the risk component, affects the extent of vulnerability it may experience.

[42] According to Eq. (3.4), same household expected consumptions implicitly bring about same risk components, if the shape of the household's utility function is unchanged. Therefore, when we mean by the combined effect of inequality and risk components, we actually discuss the impacts of changing inequality components on vulnerability. We will generalise the situation after discussing all cases.

We begin with considering a relatively poor household h with $z_h < E(c_h) < z_t$, where, given z_t, z_h is defined as the consumption level that makes this household's VUW zero. That is, $U(z_h) = EU(c_h)$ and this household has positive V_{ht} in the domain of $(z_h, +\infty)$ and vice versa. In other words, if the average intertemporal consumption across all households, z_t, could have been at z_h, this household h would not have suffered utility losses. However, as shown in Fig. 3.4(a), we have assumed $z_h < E(c_h) < z_t$ and thus, h is vulnerable and the extent of its VUW is the distance between C and E, according to Eq. (3.3). The Eq. (3.4) decomposes VUW into the welfare loss caused by having lower intertemporal mean consumption than the average level (the inequality component represented by the distance between D and E) and by the household's risk aversion (the risk component represented by the distance between C and D). Both elements are positive and contribute to h's VUW.

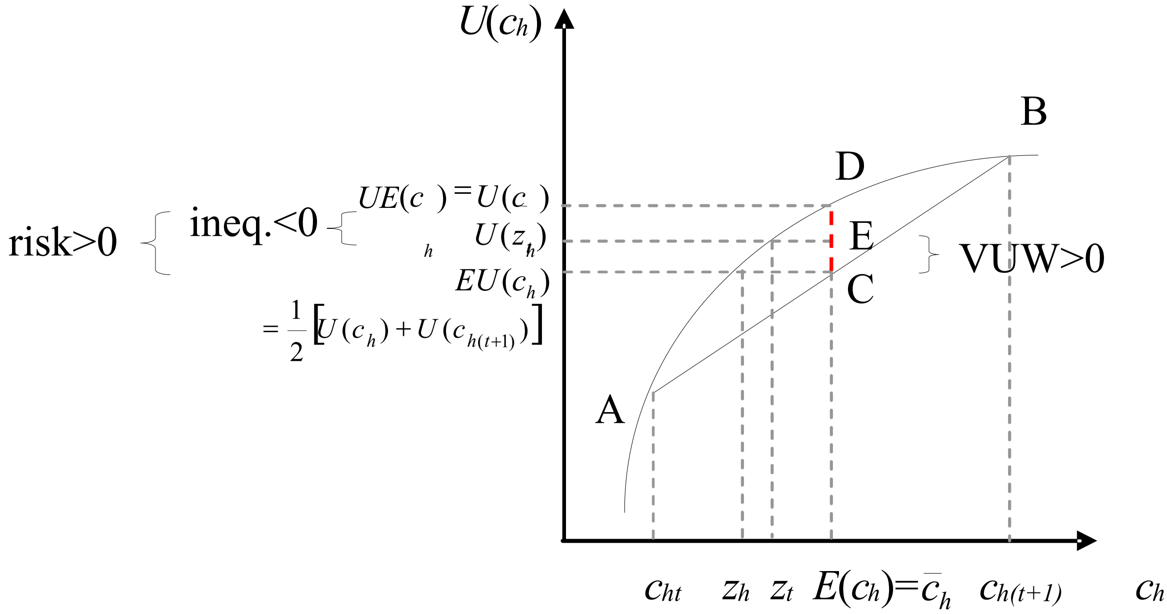
Figure 3.4 (a) Decomposition of VUW, $z_h < E(c_h) \leq z_t$



Note: The blue and red lines represent inequality and risk components, respectively.

Then, as illustrated in Fig. 3.4(b), it might also be the case that h is relatively rich with $E(c_h) > z_t$ and $z_t > z_h$, where z_h is defined as before. The household h's VUW is the distance between E and C. It is clear that the magnitude of VUW becomes smaller compared to the previous case but still positive. According to Eq. (3.4), the inequality component becomes negative, as h's intertemporal mean consumption $E(c_h)$ is higher than the average z_t across all households. This means that h is no longer subject to low welfare caused by its low consumption compared to the average household. The risk component is still positive due to h's risk aversion and contributes to VUW. However, the utility gained from a higher intertemporal mean consumption compared to others partly compensates the household for the utility loss due to risk and, therefore, VUW is smaller than in the previous case although still positive.

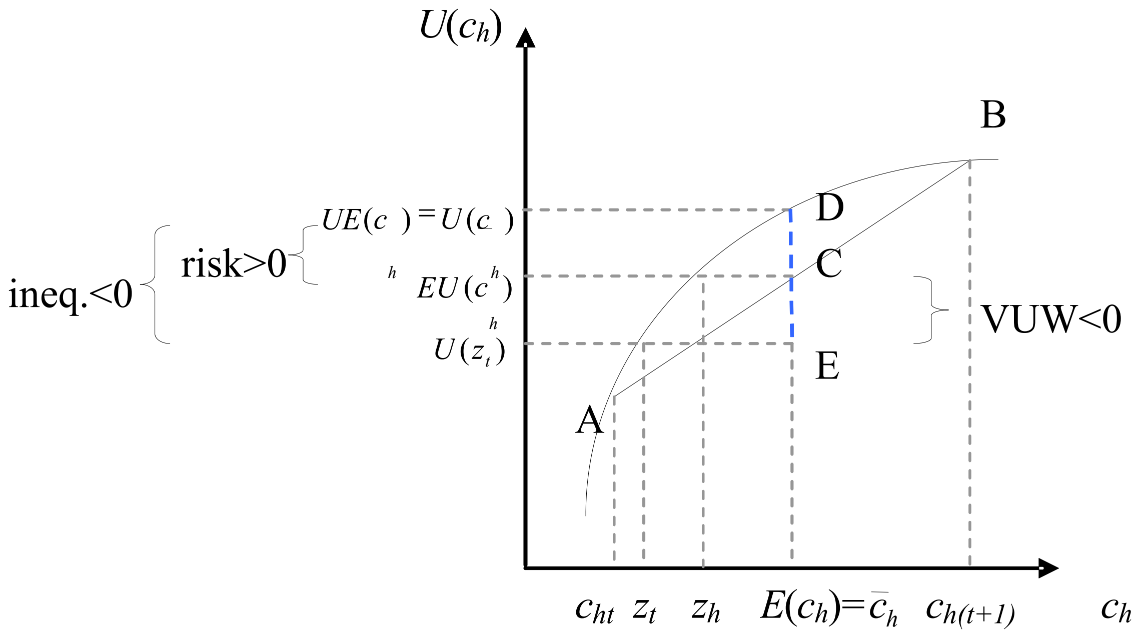
Figure 3.4 (b) Decomposition of VUW, $z_h<z_t<E(c_h)$



Note: The blue and red lines represent inequality and risk components, respectively.

Lastly, as seen in Fig. 3.4(c), a wealthier h's expected consumption $E(c_h)$ is assumed to be much higher than the average consumption z_t and $z_t < z_h$. The VUW, represented by the distance between E and C, becomes negative since h has higher expected utility than the utility derived from the average consumption for all households. The risk component is still positive due to risk aversion, but the inequality component becomes much larger due to h's much higher intertemporal mean consumption than the average. As a result, the utility gained from h's improved position in consumption distribution dominates completely the utility loss due to risk. The household is not vulnerable and its VUW becomes negative, indicating that, despite facing uncertainty and being risk averse, a wealthy household may prefer to remain as it is rather than switch to a situation in which its consumption is equivalent to the average across all households with certainty.

Figure 3.4 (c) Decomposition of VUW, z_t<z_h



Note: The blue and red lines represent inequality and risk components, respectively.

The above discussion suggests that the value of the inequality component could be positive, negative or zero, depending on the household's position in the consumption distribution. In contrast, the risk component is positive as long as the household is risk averse. In other words, although a household may be relatively rich compared to an average household within a certain period of time, it might still be subject to low utility due to fluctuations in its consumption stream. As a result, poor households may prefer a lower mean consumption with less variability (Ligon and Schecter, 2003). However, in contrast, much wealthier households may not experience vulnerability as the utility gained from a high mean consumption off-sets the utility loss caused by risk.

Nevertheless, it is still not clear, under Eq. (3.4), whether inter- or intra-regional inequality matters most in the total inequality component, which is important because China is a country with vast territories and significant regional disparities.[43] In fact, Knight *et al.* (2009b) find that it is the relative comparison within the village that affects Chinese rural households' perceptions of happiness.

To rectify this possible bias, we further decompose the inequality component by disentangling the welfare loss due to intra-village inequality from the inter-village influence.[44] Specifically, the time-dependent certainty-equivalent consumption is further adjusted to each village. The decomposition is expressed by:

[43] We find that z_t is closer to the average value in central provinces in our sample. Hence, the households' mean intertemporal consumptions in coast and inland provinces are relatively further from z_t than those of the central provinces by construction. As a result, both the coastal and western provinces see a higher vulnerability level by construction.

[44] Strictly speaking, the latter part also suffers the same problem, i.e. intra-village inequality may contribute a lot. Therefore, it cannot reflect the welfare loss due to poverty exclusively. This kind of decomposition can be carried out at different regional levels, for example, inter- and intra-province components.

$$
\begin{aligned}
Inequality = & \left[U(z_t) - U(z_{tv})\right] && inter-village\ inequality \\
& + \left[U(z_{tv}) - U(Ec_h)\right] && intra-village\ inequality
\end{aligned} \tag{3.5}
$$

where z_{tv} is the average of households' intertemporal mean consumption between t and $t+1$ within the village *v*, i.e., the village-specific average consumption. The first term in Eq. (3.5) measures the welfare difference caused by the differences in village-specific average consumption and the average consumption for the full sample. The second term compares household *h*'s utility from its expected consumption with the average utility within its own particular village. Using Eq. (3.5) should help to alleviate the problem of exaggerated vulnerability that would otherwise arise in some regions, where mean consumption is far from z_t, because of the inter-regional variation. It also complements the literature on subjective well-being by offering objective measurements of welfare loss due to some households' having a relatively low position in the village.

In the same way that the inequality component can be decomposed, so the risk component can also be further broke down. Based on the consumption regression in Section 3.2.1, Ligon and Schechter (2004) provide a more comprehensive breakdown, and this may also help with disentangling idiosyncratic risk from measurement errors.[45] The decomposition equation is as follows:

$$
\begin{aligned}
Risk = & \left[U(Ec_h) - EU\left(E(c_h \mid \bar{x}_t)\right)\right] && covariate\ risk \\
& + \left[EU\left(E(c_h \mid \bar{x}_t)\right) - EU\left(E(c_h \mid \bar{x}_t, x_{ht})\right)\right] && idiosyncratic\ risk \\
& + \left[EU\left(E(c_h \mid \bar{x}_t, x_{ht})\right) - EU(c_h)\right] && unexplained\ risk
\end{aligned} \tag{3.6}
$$

[45] As far as the possible measurement errors in consumption expenditures are concerned, Ligon and Schechter (2003) show that the calculation of per-period VUW, the anatomy of poverty and explained risk components would not be biased. However, the estimation of the part of unexplained risk would be biased as the measurement errors could change the expected utility.

where $\bar{x}_t$ is an aggregate vector including risk facing all households between t and $t+1$, which, in our case, includes the time fixed effects; and x_{ht} represents various household-specific characteristics, i.e., all explanatory variables in Eq. (3.1) except time fixed effects.

The expected consumption conditional on the aggregate vector at each time t is defined as:

$$E(c_h \mid \bar{x}_t) = \exp(\hat{\eta}_t)$$

where $\hat{\eta}_t$ are estimated time fixed effects in the consumption regression Eq. (3.1). Therefore, the first term in Eq. (3.6) measures how much utility loss is brought about by the covariate risk to all households.

By the same token, the conditional expected consumption controlling for both aggregate risk in terms of time fixed effects and household-specific risk is calculated as:

$$E(c_h \mid \bar{x}_t, x_{ht}) = \exp(x'_{ht}\hat{\beta} + \hat{\alpha}_h + \hat{\eta}_t)$$

where the vector $x'_{ht} = \left(x^P_{hmt}, x^{TS}_{hnt}\right)'$ includes factors influencing both permanent and transitory parts of consumption in Eq. (3.1). After controlling for household-specific characteristics in addition to covariate risk, the second term in Eq. (3.6) captures how much the combination of these idiosyncratic characteristics can generate expected low consumption, and hence, welfare loss for the household h.

Moreover, the 'explained' idiosyncratic risk component is also divisible. Schechter (2006) filters out *k* observed sources from the idiosyncratic risk component:

$$
\begin{aligned}
Idio.\ Risk = & \left[EU\left(E(c_h \mid \bar{x}_t)\right) - EU\left(E(c_h \mid \bar{x}_t, x_{h1t})\right)\right] \\
& + \left[EU\left(E(c_h \mid \bar{x}_t, x_{h1t})\right) - EU\left(E(c_h \mid \bar{x}_t, x_{h1t}, x_{h2t})\right)\right] \\
& + \left[EU\left(E(c_h \mid \bar{x}_t, x_{h1t}, x_{h2t})\right) - EU\left(E(c_h \mid \bar{x}_t, x_{h1t}, x_{h2t}, x_{h3t})\right)\right] \\
& \vdots \\
& + \left[EU\left(E(c_h \mid \bar{x}_t, x_{h1t}, \ldots, x_{h(k-1)t})\right) - EU\left(E(c_h \mid \bar{x}_t, x_{h1t}, \ldots, x_{hkt})\right)\right]
\end{aligned}
\tag{3.7}
$$

where k refers to the sum of m and n factors influencing households' consumption in Eq. (3.1). Specifically, the household's expected consumption conditional on the knowledge of aggregate risk and up to $k \in (1,2,\ldots,K)$ kinds of idiosyncratic risk is derived from:

$$
E\left(c_h \mid \bar{x}_{ht}, x_{h1t}, x_{h2t}, \ldots, x_{hkt}\right) = \exp\left(\sum_{k=1}^{K} \hat{\beta}_k x_{hkt} + \hat{\alpha}_h + \hat{\eta}_t\right)
$$

Each term in Eq. (3.7) measures the expected low utility brought by an additional idiosyncratic characteristic for the household h.

To sum up, based on the consumption regression Eq. (3.1), we can obtain the individual household's vulnerability level by the VUW calculation equations (3.2) and (3.3). Eq. (3.4)-(3.7) allow us to specify welfare losses associated with various sources.

3.3 Data

The construction of the panel and key variables has been described in Chapter 2.[46] Table 3.1 lists all independent variables used in the consumption regression.

[46] A concern over such a long panel covering 18 years is the aging problem of the samples. As samples get older, they would have less income and consumption due to retirement and ill health. As a result, they may appear to be poor simply because of aging rather than other reasons.

Table 3.1 Definitions of variables

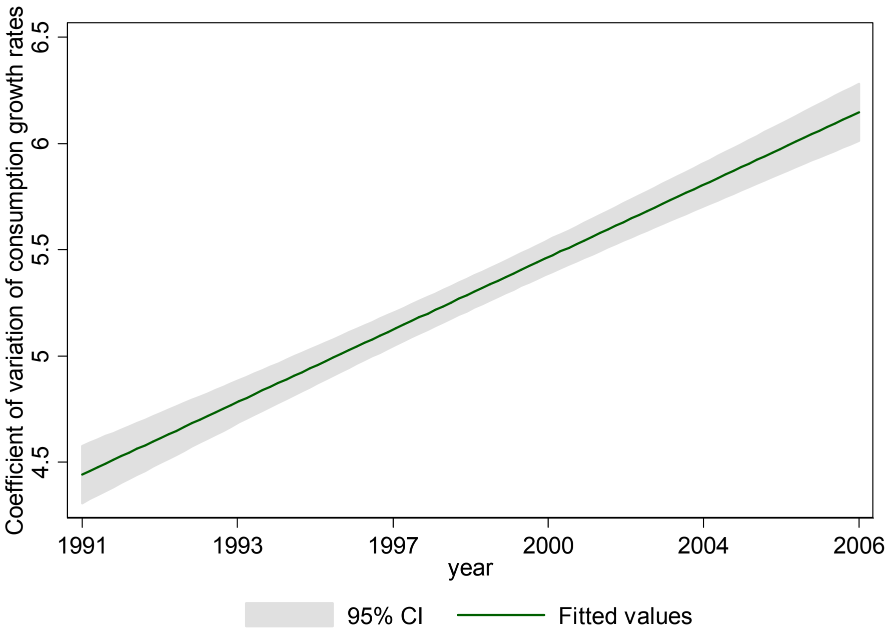
Variable	Definition
cons.	The household's total consumption expenditure
hhinc	The household's net income
asset_agri	The imputed value of agricultural equipment owned by the household
motor	Number of motorcycles owned by the household
land	Cultivated land owned by the household
hhage	Age of the household's head
hhedu	Number of years of formal education that the household's head has completed
hhsize	Household size
employ	Number of household members currently being employed
dt_agri	Deviation of working time devoted to agricultural production from the household's intertemporal mean
dt_busi	Deviation of working time devoted to households' business from the household's intertemporal mean
dt_work	Deviation of working time devoted to non-agricultural sectors from the household's intertemporal mean
dmedc	Deviation of the household's medical expenditure from the household's intertemporal mean

Note: The last four variables belong to the vector X^{TS} while the rest are elements in X^{P}.

Data support the hypothesis of increasing uncertainty in terms of both inequality and volatility. The exploratory analysis in Table 2.7 of Chapter 2 calculates Gini and Theil coefficients of household per capita income and consumption for each survey year. The spread of both income and consumption has widened with growing Gini and Theil coefficients. For example, the Gini coefficients of household per capita consumption rose up by 37.7 percent, from 0.257 in 1989 to 0.354 in 2006. The Gini coefficients of household per capita income increased proportionally less than consumption (14 percent), but the magnitude was much higher (0.513 in 2006).

In the meantime, rural households have also witnessed increasingly volatile consumption flows. Fig. 3.5 depicts the volatility of household per capita consumption over time.[47] It clearly has a positive linear trend. Food consumption, which on average accounts for about 66 percent of households' total consumption, shows the same pattern with a much greater slope and magnitude. Among all components of consumption, the greatest volatility lies in the expenditure on medical care and health insurance.

Figure 3.5 Volatility of households' total consumption expenditure



3.4 Estimation results and discussion

Section 3.4.1 tabulates the results of the VUW measure and decomposition outlined in Section 3.2. In the following sub-sections, we discuss two further aspects of these calculations. Section 3.4.2 compares households' chronic poverty and vulnerability status in each period. In the time domain, Section 3.4.3 demonstrates that vulnerability tends to be a persistent phenomenon facing households. Based on the

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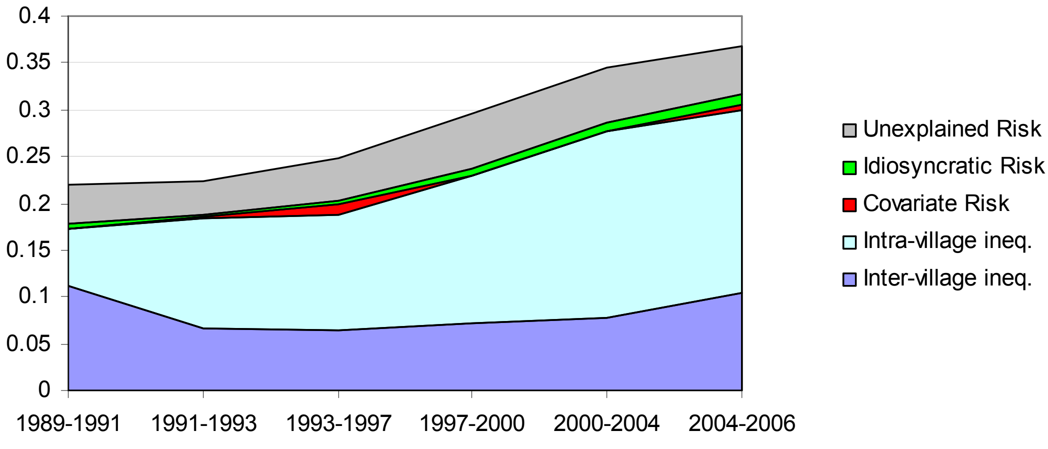
[47] The volatility is computed as the standard deviation of the growth rates of household per capita consumption. But the series of the growth rates is not detrended first, as the series only contains 6 rounds of the surveys. We have also experimented with the detrended series and the same general pattern holds.

estimates of VUW, Section 3.4.4 shows which, and by how much, socioeconomic factors may affect households' per-period VUW and its four components. The robustness of the estimates is discussed in Section 3.4.5.

3.4.1 Trajectories of per-period VUW and its components

We calculate the average per-period vulnerability and its components. The general finding is that, compared to improvements their absolute income and consumption, rural households appear not to have enjoyed commensurate improvements in their welfare. As can be seen in Fig. 3.6, the average rural household's utility in 1989-1991 was 21.9 percent less than it would have been if resources could have been costlessly redistributed so as to eliminate all inequality and risk in consumption. The average sub-period vulnerability consistently went up and reached 36.6 percent in 2004-2006.[48]

Figure 3.6 The average household per-period VUW and its breakdown



[48] It should be noted that one cannot interpret households' intertemporal vulnerability over the entire time span based on this per-period figures, since the aggregation over time should carefully take a set of desirable axioms into account. Refer to Calvo and Dercon (2009) for details.

The inequality component seems to have been the primary driving force of the overall increasing vulnerability. Nevertheless, the contribution of risk may have been over or understated by the LS methodology itself. Using the observed consumption data to calculate vulnerability, on the one hand, one would misattribute measurement errors to the risk component (Schechter, 2006), which can be seen from the last term of Eq. (3.6). This would lead to over-estimation of the contribution of risk to vulnerability. On the other hand, as argued by Elbers and Gunning (2003), risk component may have been under-estimated because vulnerability is calculated *ex post* households' coping with shocks. The risk component revealed by Fig. 3.6 therefore represents those remaining risks that a household is unable and/or unwilling to deal with.

In the inequality component, the contribution of the inter-village element first decreased and then increased after 2000, while the intra-village part was ever-increasing. The latter dominated the inequality component as well as VUW in all sub-periods following 1989-1991, when the inter-village was the main cause. Specifically, in 1989-1991, households' welfare would have been 6.19 percent higher if there had been no relative inequality within the villages. Since then, this welfare loss has increased quickly, becoming 3.15 times greater in the last study period 2004-2006 than in the late 1980s. In sum, the relatively large magnitude of the inequality component implies that policies aiming at eliminating inequality have the potential for playing a major role in fighting household vulnerability.

In the overall risk component, unexplained risk makes the largest contribution and is relatively stable over time. The reason for this may be that the covariates in the consumption regression do not capture entirely successfully the real sources of risk facing rural households. As warned by Elbers and Guning (2003), this drawback is hard to overcome in any regression-based measure of vulnerability. Comparing the impact of the idiosyncratic risk and the aggregate risk, the former becomes dominant over the latter. Among all sources of idiosyncratic risk, the number of household members currently employed in non-agricultural sectors plays a pivotal role, *ceteris paribus*, in bringing about the utility loss associated with idiosyncratic risk.

The discussion so far is for the full sample of households. In order to reveal which are more or less vulnerable, Table 3.2 calculates average VUW for different occupations of the household heads. Farmers are clearly the most vulnerable; their VUW was consistently higher than the average in all sub-periods except the first one. They are also the only group whose VUW increased over time, with an average sub-period proportionate growth rate of 16.14 percent. In 2004-2006, their potential welfare loss reached 0.45, which was 2.1 times higher than in the first sub-period. This is not surprising as farmers have long been excluded from the various social protection schemes which are enjoyed by their urban counterparts (Hebel, 2003; Dollar, 2007); hence their livelihoods are exposed to various shocks, such as weather (Yang, 2007) and price shocks (Ghatak and Seale Jr, 2001), and they lack access to either financial credit (Rui and Xi, 2010) or insurance (Giles, 2006) to protect themselves. Another reason may be the agricultural tax; using a definition of vulnerability to expected poverty, agricultural taxation has a detrimental impact on rural households' probabilities of falling into poverty (Imai *et al.*, 2010).

By contrast, three other occupation categories have seen decreased VUW to different extents. Comparing the first and last sub-periods, the VUW declined by 5 percent for non-skilled workers, and by 41.2 percent and 32.9 percent for skilled workers and professionals, respectively.

Table 3.2 Tabulation of households' VUW, by occupation

Sub-period	Farmer	Non-skilled Worker	Skilled Worker	Professionals	Average
1989-1991	0.214	0.224	0.216	0.164	0.219
1991-1993	0.247	0.174	0.137	0.139	0.222
1993-1997	0.276	0.202	0.168	0.158	0.248
1997-2000	0.353	0.206	0.094	0.136	0.294
2000-2004	0.415	0.140	0.160	0.073	0.345
2004-2006	0.449	0.214	0.127	0.110	0.366
Average	0.326	0.193	0.150	0.130	0.282

Note: a. Occupation is determined by the household head.

b. Non-skilled workers include labourer and homemakers.

c. Skilled workers include technical skilled workers (foremen, craftsmen, drivers, etc.) and service workers (housekeepers, cook, waiters/waitresses, doorkeepers, barbers/beauticians, counter sales, launderers, childcare, etc.).

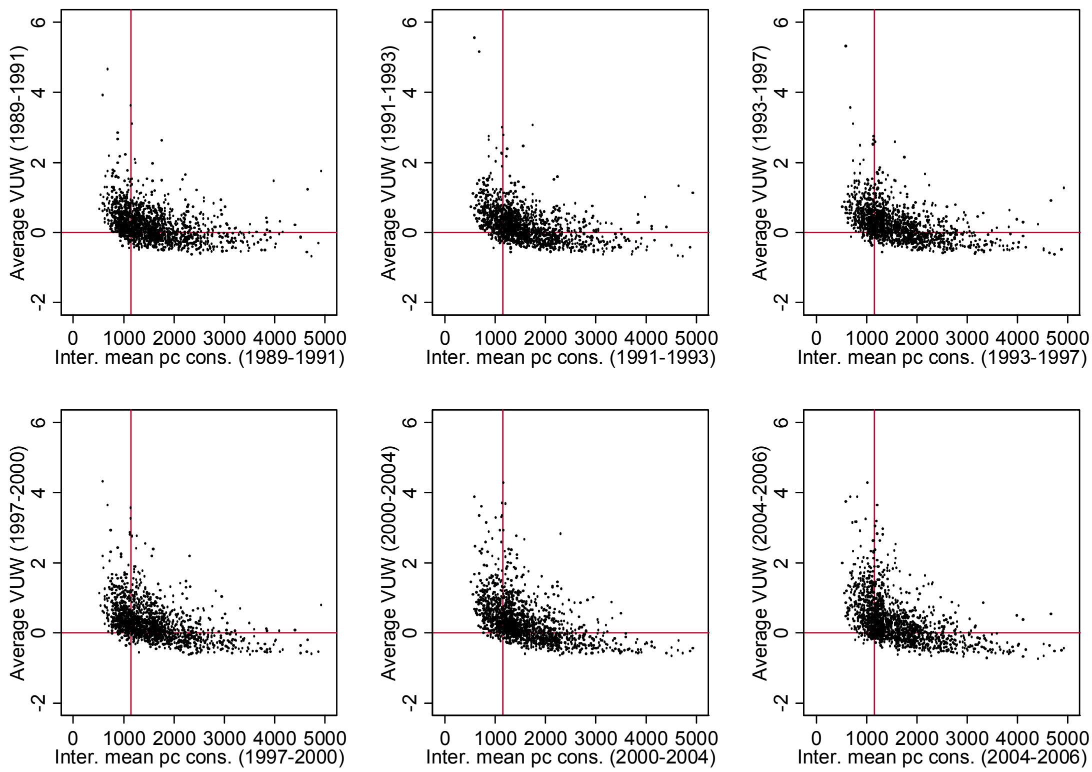
d. Professionals include doctors, nurses, lawyers, teachers, engineers, managers, government officials and office staff.

3.4.2 Comparison of per-period chronic poverty and VUW

This sub-section investigates households' VUW according to their poverty status in order to shed more light on who is subject to welfare losses. Rural households are classified as the chronically poor in a certain period of time if their intertemporal mean per capita consumption is lower than the poverty line[49]. Three implications can be drawn from Fig. 3.7.

[49] There are various definitions of chronic poverty. Here the concept is in line with Jalan and Ravallion (1998a).

Figure. 3.7 Comparison of household chronic poverty and VUW, by sub-period



Note: The poverty line represented by the vertical line is US$1.25/day in 2005 PPP adjusted to the rural-urban differences of cost-of-living.

First, there appears to be a positive correlation between consumption poverty and VUW. The chronically poor experience relatively greater utility loss than others. In addition to suffering a larger magnitude of VUW, the poor are also more likely to suffer vulnerability. About 89.7 percent of those who had been chronically poor until 2006 were also vulnerable (350 out of 390 households), while the overwhelming majority of the non-vulnerable were also non-chronically poor in every sub-period (Table 3.3). These findings are not surprising in the sense that our measure of vulnerability is inclusive of the poverty component, as suggested by Eq. (3.4) in Section 3.2.3. Moreover, given the definition of chronic poverty and the decomposition of vulnerability, it could be predicted that the chronically poor's vulnerability mainly comes from the inequality component, since their expected consumption is likely to be far below z_t. Actually, our calculations suggest that on average the inequality component accounted for 89 percent of the chronically poor's VUW. Nevertheless, as reported in section 3.2.2, Elbers and Gunning (2003) argue that at least some of this inequality component should in fact reflect households' behavioural responses to risk.

Table 3.3 Tabulation of the number of vulnerable and non-vulnerable households, by poverty status

Period	Non-vulnerable (VUW≤0)			Vulnerable (VUW>0)		
	Total	Non-Poor	Poor	Total	Non-Poor	Poor
1989-1991	528	386 (73.11)	142 (26.89)	918	166 (18.08)	752 (81.92)
1991-1993	515	419 (81.36)	96 (18.64)	931	209 (22.45)	722 (77.55)
1993-1997	477	447 (93.71)	30 (6.29)	969	458 (47.27)	511 (52.73)
1997-2000	447	441 (98.66)	6 (1.34)	999	663 (66.37)	336 (33.63)
2000-2004	445	435 (97.75)	10 (2.25)	1001	657 (65.64)	344 (34.37)
2004-2006	472	467 (98.94)	5 (1.06)	974	711 (73.00)	263 (27.00)

Note: a. Relative frequencies (%) within each row are in parentheses.

b. Poverty is defined by households' intertemporal mean per capita consumption in each sub-period being lower than the poverty line at US$1.25/day in 2005 PPP adjusted to the rural-urban differences of cost-of-living in China.

Second, what may alarm policy makers is that the non-chronically poor also experience low expected utility. As seen in Fig. 3.7, a number of households lying to the right of the poverty line are above the horizontal axis, indicating that many of the non-chronically poor, especially those who are 'near-poor', have positive VUW. More specifically, the right panel of Table 3.3 shows that 18 percent of vulnerable rural households were non-chronically poor in 1989-1991. This proportion rose sharply to 73 percent during 2004-2006, implying that vulnerability rises more over time in non-chronically poor households. Even though more households escape from chronic poverty over time, as reported by a number of empirical studies, many of them are still, or become, vulnerable in the presence of increasing uncertainty. Furthermore, as discussed in the previous paragraph, the non-chronically poor's vulnerability arises mainly from the risk component, since their expected consumption may be closer to z_t. We find that 36 percent of the non-chronically poor's vulnerability between 1989 and 2006 can be attributed to the impact of risk, while this proportion for the chronically poor is only 11 percent.

Third, household vulnerability seems not to decrease *pari passu* with increasing per capita consumption. According to Fig. 3.7, a non-linear and convex relationship may be postulated between households' VUW and consumption. This implies that, as households become richer in terms of per capita consumption, the marginal effect of one extra unit of consumption to vulnerability reduction is increasingly weakened, and occurs largely because the non-convexity of the utility function employed to construct vulnerability yields diminishing marginal utility.

It is also worth mentioning that, geographically, VUW is not restricted to less developed areas such as Guizhou and Guangxi, but is observed in all study regions, even though all of them have substantially reduced consumption poverty.[50]

In sum, household VUW seems to be a prominent, but empirically, under-researched phenomenon in rural China's development. It is common in both poor and non-poor

[50] The proportionate reduction rates of consumption poverty incidence in costal, central and western regions are approximate 80, 72 and 60 percent respectively.

households, whether they live in poor areas or not. This in turn implies that policies which have targeted consumption or income poverty alone may be insufficient for welfare improvement in rural China, but instead may have left those who have only just managed to escape poverty.

3.4.3 Prolonged welfare trauma

Low welfare caused by increasing uncertainty not only exists widely in rural China, but also reflects prolonged distress faced by rural households. As shown in Table 3.4, nearly 89 percent of rural households in our sample experienced at least one period of low expected utility during 1989-2006. Approximate 38 percent of households were persistently vulnerable in all periods, while only about 11 percent were never vulnerable. Geographically, roughly 42 percent of those who were vulnerable in every sub-period come from two western provinces. About 71 percent of sample households experienced vulnerability in at least three consecutive sub-periods (6-9 years).

Table 3.4 Cumulative distribution of households being vulnerable in consecutive sub-periods

Region	Number of consecutive sub-periods in vulnerability						
	0	1	2	3	4	5	6
Coastal	49 (30.44)	355 (27.63)	318 (29.04)	299 (29.29)	247 (30.01)	202 (30.10)	179 (32.31)
Central	84 (52.17)	502 (39.07)	384 (35.07)	351 (34.38)	262 (31.83)	201 (29.96)	145 (26.17)
Western	28 (17.39)	428 (33.31)	393 (35.89)	371 (36.34)	314 (38.15)	268 (39.94)	230 (41.52)
Total hh.	161 (11.13)	1285 (88.87)	1095 (75.73)	1021 (70.61)	823 (56.92)	671 (46.40)	554 (38.31)

Note: For each region, the proportions of households experiencing different lengths of vulnerability are calculated as the percentage in each column.

3.4.4 Correlates of per-period VUW and its components

This sub-section inspects the make-up of per-period household vulnerability and its correlates. Table 3.5 calculates the correlation coefficients across four components of per-period household vulnerability. Pearson correlation coefficients show that aggregate risk is significantly positively correlated with the inequality component. As discussed by Schechter (2006), this is because of diminishing marginal utility, which means the same shock brings about more welfare loss to the poor than those who are relatively affluent. Idiosyncratic risk is significantly positively correlated with the inequality component, indicating that wealthier households are more able to smooth their consumption (Schechter, 2006). The unexplained risk correlates positively with the idiosyncratic risk component. However, the extent and significance of this correlation is very limited. It is therefore hard to infer that these two kinds of risks share some common sources. Spearman rank correlation coefficients are all significantly positive, which means the orderings of vulnerability across households are consistent across different VUW components, although there is a large variation in the extent of the correlation.

Table 3.5 Correlations between elements of household per-period VUW, 1989-2006

	ineq.	cov. risk	idio. risk	unexp. risk
ineq.	1.000	0.894***	0.132***	0.532***
cov. risk	0.958***	1.000	0.131***	0.524***
idio. risk	0.554***	0.504***	1.000	0.010
unexp. risk	0.692***	0.631***	0.417***	1.000

Note: Spearman rank correlation coefficients and Pearson correlation coefficients are below and above the diagonal respectively.

Besides the correlation among VUW components, we examine a range of socioeconomic factors that may determine households' per-period vulnerability and its components for both the chronically and non-chronically poor.[51] Households' per-period VUW and each of its components are regressed on a number of variables. We employ a standard household fixed-effects model for each regression. Table 3.6 summarises the estimation for the chronically poor (Columns 1-5) and the non-chronically poor (Columns 6-10) in the period 1989-2006, respectively. The rest of this sub-section discusses results in greater detail.[52]

3.4.4.1 Income diversification

Rows 1-2 of Table 3.6 suggest that income from agricultural production and family-run businesses may reduce vulnerability for both groups of households when other variables are controlled. The magnitude of the impact of agricultural income is larger for the chronically poor compared to the non-chronically poor, while the effect of the household businesses reported by Row 2 is equally important for both. This is consistent with the fact that Chinese rural households, especially the poor, earn their livelihoods primarily from agriculture.

At the same time, our results are contrary to the prevailing discourse which claims that the income from non-agricultural employment, subsidies and other sources can generate tangible improvements in the poor's life. Indeed, our findings are partially in line with Zhang and Wan (2006b), who find that the diversification from

[51] There are various definitions for chronic poverty. Here we follow Jalan and Ravallion (1998a) and define the chronically poor in a sub-period as those whose intertemporal mean per capita consumption in that period is lower than the poverty line at the adjusted US$1.25/day.
[52] Note that many independent variables are also likely to be the income determinants which could affect relative inequality of individual households. As can be seen from Table 3.6, many of those variables appearing to have significant impact on vulnerability also significantly affect the relative inequality component.

agricultural production activities hardly reduces a household's probability of falling into poverty in the future. The difference from their results is that in our study, the role of diversification away from agriculture is contingent on which group of rural households one refers to and the kinds of non-agricultural activities rural households are involved in. More specifically, in view of the estimates in Row 1 and Columns 1 and 6, income from agriculture appears to be useful in alleviating the vulnerability of chronically poor households. In contrast, the non-chronically poor have significantly benefitted from diversification; ashown by Rows 2 and 4-6 in Column 6, incomes from household business, various subsidies, pensions and other sources suggest vulnerability-alleviating effects.

3.4.4.2 Households' demographic characteristics

Among various demographic characteristics, household size, the dependency ratio, and the household members' educational achievement are of paramount importance for both groups' welfare improvement (Rows 7-12).

Specifically, for the chronically poor, primary education in Row 10 and Columns 1 to 5 could help reduce the level of vulnerability and all its components when controlling for other variables. This impact still holds for the non-chronically poor, although the magnitude is smaller (Row 10 and Columns 6-10). By contrast, secondary education helps the non-chronically poor alleviate welfare loss better than for the chronically poor (Row 11 and Columns 1 and 6). However, higher education, shown in Row 12, is insignificant and turns out to have no impact for either group.

Table 3.6 Correlates of households' per-period VUW and its components, by chronic poverty status

Independent variables	Chronically poor during 1989-2006					Non-chronically poor during 1989-2006				
	Vuln. (1)	=Ineq. (2)	+Cov. Risk (3)	+Idio. Risk (4)	+Unexp. Risk (5)	Vuln. (6)	=Ineq. (7)	+Cov. Risk (8)	+Idio. Risk (9)	+Unexp. Risk (10)
Income diversification										
1. ln(income_ agriculture)	-0.029 (0.005)**	-0.029 (0.004)***	7.03×10^{-6} (0.000)	9.83×10^{-6} (0.000)	-0.0004 (0.000)	-0.003 (0.002)	-0.003 (0.002)	2.11×10^{-6} (7.45×10^{-6})	-0.0001 (0.000)*	-0.0002 (0.000)
2. ln(income_ business)	-0.004 (0.003)	-0.003 (0.003)	-3.09×10^{-6} (7.56×10^{-6})	-0.0001 (0.000)	-0.0004 (0.000)	-0.005 (0.001)***	-0.005 (0.001)***	-0.00001 (5.31×10^{-6})***	-0.0001 (0.000)	-0.0001 (0.000)
3. ln(income_ wages)	0.005 (0.003)*	0.004 (0.003)	6.36×10^{-6} (7.70×10^{-6})	-0.0001 (0.000)	0.0004 (0.000)	-0.001 (0.001)	-0.002 (0.001)	-8.30×10^{-6} (5.29×10^{-6})	-0.0001 (0.000)	0.0004 (0.000)**
4. ln(income_ subsidy)	-0.005 (0.005)	-0.005 (0.005)	-0.00002 (0.000)	-0.0001 (0.000)	0.0002 (0.001)	-0.009 (0.002)***	-0.009 (0.002)***	-3.51×10^{-6} (8.02×10^{-6})	-0.0002 (0.000)*	-0.0002 (0.000)
5. ln(income_ retire wage)	-0.008 (0.009)	-0.007 (0.009)	0.00001 (0.000)	0.00005 (0.000)	-0.001 (0.001)	-0.009 (0.003)***	-0.008 (0.003)***	-0.00003 (9.80×10^{-6})***	0.00005 (0.000)	-0.001 (0.000)***
6. ln(income_ other)	0.006 (0.003)**	0.005 (0.003)*	5.83×10^{-6} (7.69×10^{-6})	0.0002 (0.000)**	0.001 (0.000)**	-0.004 (0.001)***	-0.003 (0.001)**	-0.00001 (5.29×10^{-6})**	0.0001 (0.000)	-0.0004 (0.000)***
Household demographic characteristics										
7. household size	-0.242 (0.007)***	-0.236 (0.007)***	-0.0003 (0.000)***	4.22×10^{-6} (0.000)	-0.006 (0.001)***	-0.166 (0.004)***	-0.160 (0.004)***	-0.0003 (0.000)***	-0.0005 (0.000)***	-0.006 (0.000)***
8. % male adults	-0.052 (0.059)	-0.072 (0.057)	-0.0003 (0.000)**	0.0001 (0.002)	0.018 (0.006)***	-0.109 (0.032)***	-0.101 (0.031)***	-0.0004 (0.000)***	0.002 (0.001)	-0.010 (0.004)***
9. dependency ratio	0.185 (0.040)***	0.185 (0.038)***	-0.00002 (0.000)	0.002 (0.001)*	-0.003 (0.004)	0.132 (0.019)***	0.126 (0.018)***	0.0002 (0.000)***	-0.0003 (0.001)	0.006 (0.002)**
10. % primary edu.	-0.357 (0.041)**	-0.340 (0.039)***	-0.0003 (0.000)*	-0.002 (0.001)*	-0.015 (0.004)***	-0.262 (0.019)***	-0.248 (0.018)***	-0.0004 (0.000)***	-0.001 (0.001)	-0.012 (0.002)***
11. % secondary edu.	-0.195 (0.084)**	-0.191 (0.081)**	-0.00003 (0.000)	-0.001 (0.002)	0.003 (0.009)	-0.243 (0.035)***	-0.232 (0.034)***	-0.0004 (0.000)***	0.002 (0.001)	-0.013 (0.004)**

12. % tertiary edu.	-0.010 (0.448)	0.010 (0.432)	-0.001 (0.001)	0.002 (0.013)	-0.017 (0.048)	-0.045 (0.103)	-0.028 (0.100)	0.0001 (0.000)	-0.003 (0.004)	-0.014 (0.012)
13. farmland per adult	0.0002 (0.007)	-0.0005 (0.006)	-3.71×10^{-6} (0.000)	0.00001 (0.000)	0.0004 (0.001)	-0.001 (0.003)	-0.002 (0.003)	0.00001 (0.000)	0.0001 (0.000)	0.0004 (0.000)
Off- & within-farm diversification										
14. % skilled worker & prof. in public sec.	0.065 (0.045)	0.062 (0.044)	0.0002 (0.000)**	0.0005 (0.001)	0.003 (0.005)	0.035 (0.021)*	0.030 (0.020)	0.0001 (0.000)	0.00005 (0.001)	0.004 (0.003)*
15. % unskilled worker in public sec.	-0.108 (0.088)	-0.112 (0.085)	0.0002 (0.000)	0.001 (0.002)	0.005 (0.010)	-0.093 (0.036)***	-0.086 (0.034)**	0.0001 (0.000)	-0.001 (0.001)	-0.006 (0.004)
16. % skilled workers & prof. in private sec.	-0.273 (0.123)**	-0.253 (0.119)**	-0.0005 (0.000)*	-0.002 (0.004)	-0.015 (0.014)	-0.196 (0.062)***	-0.183 (0.059)***	-0.001 (0.000)***	0.001 (0.002)	-0.013 (0.007)*
17. % unskilled workers in private sectors	-0.246 (0.233)	-0.224 (0.225)	-0.0007 (0.001)	-0.002 (0.007)	-0.015 (0.025)	-0.291 (0.099)***	-0.268 (0.096)***	-0.001 (0.000)**	-0.004 (0.004)	-0.019 (0.012)
18. whether own livestock (own=1)	-0.060 (0.027)**	-0.060 (0.026)**	-0.0001 (0.000)	0.0001 (0.001)	-0.0001 (0.003)	0.0001 (0.012)	0.001 (0.012)	0.0001 (0.000)*	-0.00003 (0.000)	-0.002 (0.001)
Social protection										
19. % having health insurance	-0.149 (0.062)**	-0.140 (0.060)**	0.0001 (0.000)	-0.001 (0.002)	-0.009 (0.007)	-0.062 (0.018)***	-0.060 (0.018)***	-0.0001 (0.000)**	0.002 (0.001)**	-0.003 (0.002)
Rural infrastructure										
20. time to the nearest health	0.001 (0.000)**	0.001 (0.000)**	-1.06×10^{-6} (1.28×10^{-6})	3.96×10^{-6} (0.000)	-0.00002 (0.000)	0.0004 (0.000)	0.0003 (0.000)	2.84×10^{-6} (9.47×10^{-6})	5.57×10^{-6} (0.000)	0.0001 (0.000)**

facility (mins.)										
21. whether use clean fuel (use=1)	0.078 (0.042)*	0.071 (0.040)*	-3.72×10^{-6} (0.000)	-0.001 (0.001)	0.008 (0.005)*	0.163 (0.017)***	0.155 (0.016)***	0.0002 (0.000)***	0.0004 (0.001)	0.008 (0.002)***
22. improved drinking water (improve=1)	-0.008 (0.022)	-0.011 (0.021)	0.00004 (0.000)	-0.001 (0.001)*	0.003 (0.002)	-0.047 (0.011)***	-0.044 (0.010)***	-0.00005 (0.000)	0.0001 (0.000)	-0.003 (0.001)**
Other collective factors										
23. ln(provincial rural CPI)	0.742 (0.339)**	0.776 (0.327)**	0.0003 (0.001)	0.023 (0.010)**	0.001 (0.037)**	-0.024 (0.149)	-0.041 (0.144)	0.002 (0.001)***	0.009 (0.006)	0.008 (0.018)
24. year dummy × prov. cons. Gini coeff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
25. year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.460	0.463	0.949	0.056	0.084	0.371	0.367	0.891	0.039	0.080

Note: a. 390 out of 1446 households are chronically poor with an intertemporal mean per capita consumption during the entire time span being lower than the adjusted US$1.25/day poverty line.

b. Public sectors are government departments, state-owned enterprises and collective enterprises at different regional levels.

c. Private sectors include private enterprises and ‘three-capital’ enterprises which are owned by foreigners, overseas Chinese and joint venture.

d. ***, ** and * denote 1%, 5% and 10% significance levels. Standard errors are in parentheses.

It should be noted that a correlate between educational levels and VUW may not be a causal relationship. Some omitted variables associated with education may affect the extent of VUW. For example, those who have completed primary and secondary education are more likely to increase their consumption and/or more capable of coping with negative shocks. In this case, it is increased expected consumption and/or the capability of smoothing consumption that reduces vulnerability rather than education *per se*.

A larger household size (Row 7) appears to dramatically lower vulnerability and its components for both chronically and non-chronically poor households. Two possible reasons discussed in the existing literature may explain this. One can be drawn from Christiaensen and Subbarao (2005), who find that a larger rural household size in Kenya tend to induce a decreasing consumption variance. They attribute this positive effect to the higher supply of labour associated with large households in which children are sometimes forced to work as well. Our data appear to support this point of view. The mean intertemporal number of members currently employed is higher among chronically poor households (2.78) than the non-chronically poor (2.28), and the mean intertemporal number of children (under 18 years old) participating in income-earning activities is 0.34 in chronically poor households, compared with 0.14 in non-chronically poor households.

The other reason may be that 'the impact of family size may also capture effects of an omitted labour input variable' (Wan, 2004, p.358), when the regression includes household size and dependency ratio simultaneously. In this sense, household size might represent some elements of income from sideline products of rural households. Therefore, on the one hand, with more than one sources of income, there is a chance that variability of average income will fall. On the other hand, a larger family size may also be somewhat conterminous with higher income, which would in turn increase the consumption and reduce vulnerability.

Among households' other demographic characteristics, higher shares of male adult members within households (Row 8) are also good for both chronically and non-chronically poor households. However, it is statistically insignificant for the former (Row 8 and Column 1) and only works indirectly on vulnerability through reducing the welfare loss caused by aggregate and unexplained risk (Row 8 and Columns 3 and 5). The greater dependency ratio (Row 9) could intensify both groups' vulnerability.

3.4.4.3 Farmland

A larger quantity of land per adult would reduce the non-chronically poor's vulnerability (Row 13 and Column 1), but is unlikely to affect the chronically poor in the same way (Row 13 and Column 6). Geographic properties of land that the chronically poor households own may hold the key to understanding this seemingly divergent conclusion. In our panel, 229 out of 390 chronically poor households live in two western provinces that are dominated by hillsides and mountains. An increase in low quality or un-improvable land may not generate extra agricultural income for these households and may even incur increased exposure to risk, thereby driving labour into more risky but less lucrative agricultural production. Also, the marginal effect of farm land may well be highly dependent on its quality. It turns out that a more appropriate proxy for land quality than crude land holdings may be fertiliser use per adult equivalent, which is a proxy for agrarian quality or productivity as well as quantity, since more fertiliser input is usually expected when more farm land is owned by the household given the relatively stable technological environment.

3.4.4.4 Off-farm employment

Having more skilled workers or professionals in the private sector may help to reduce VUW for chronically poor households (Row 16 and Columns 1-3), while the effect of more unskilled labourers, although vulnerability-alleviating, is statistically insignificant (Rows 15 and 17 and Columns 1-5). For the non-chronically poor however, both skilled and unskilled jobs in the private sector (Rows 16-17 and Columns 6-10) and unskilled workers in the public sector (Row 15 and Columns 6-7) suggest vulnerability-reducing impacts. Looking at the components of VUW, these off-farm employment variables reduce vulnerability mainly through reducing the inequality within the village.

In addition to the above categorisations of off-farm jobs, we also investigate the role of local off-farm employment and out-migration, respectively.[53] For the non-chronically poor, 10 percent of extra local off-farm employment could reduce their VUW by an equivalent proportion, but this effect does not hold for the chronically poor. The population share of village out-migration indicates a vulnerability-reducing effect for both sub-groups but it is statistically insignificant. Overall, off-

[53] The regressions represented by each column are repeated with Rows 14-17 being replaced by the share of local off-farm employment with the household and the share of out-migration within the village. Full results are not reported here.

farm employment could alleviate households' welfare loss. However, this positive impact seems to be more likely to benefit the non-chronically poor.

Lastly, it is surprising that, for the non-chronically poor, the share of skilled workers and professionals in the public sector appear to drive up household VUW. It may worsen households' welfare through increasing the unexplained risk, a possible reason for which may be massive layoffs resulting in low welfare and more uncertain employment in public sector since the mid-1990s (Cai *et al.*, 2008).

3.4.4.5 Within-farm diversification: raising livestock

The possession of livestock would reduce vulnerability for the chronically poor more than for the non-chronically poor (Row 18 in Columns 1 and 6), which is not exactly consistent with Ligon and Schechter's (2002) finding that Bulgarian households owning animals are uniformly less vulnerable because of their higher consumption. We would argue that raising livestock could be a within-farm diversification strategy which allows households to pursue non-grain production. This may help poorer households to minimise agricultural risk and hence control income and consumption variations. However, as found by Démurger *et al.* (2010), wealthier households are more likely to choose off-farm diversification such as out-migration. Thus, the positive impact of raising livestock appears to be insignificant for them.

Caution is needed in ascribing a vulnerability-releasing role of within-farm diversification, given the weak proxy for this kind of diversification in our analysis. Compared with raising livestock, a more useful indicator might be the combination of different varieties of crops. Unfortunately, relevant data are not available in the CHNS.

3.4.4.6 Social protection

Health insurance significantly alleviates household vulnerability, especially for the chronically poor (Row 19 and Columns 1 and 6). However, Dercon (2005) mentions that households may change their behaviour when obtaining more insurance, i.e. they may pursue more remunerative as well as more risky activities. As a matter of fact, using the CHNS, Wagstaff *et al.* (2009a) find that both out-of-pocket payments per outpatient visit and in-patient stay did not decrease after introducing the New Cooperative Medical Scheme (NCMS) in 2003. There are evident problems of moral hazard and adverse selection among recipients of health insurance in rural China (Wagstaff and Lindelow, 2008; Sun *et al.*, 2009b). Given these findings, vulnerability cannot be deemed to decline with certainty in provision of more health insurance, but further research needs to take households' behavioural responses into consideration.

3.4.4.7 Rural infrastructure

We also proxy for rural infrastructure and living facilities by the time spent in reaching the nearest health facility (Row 20), the usage of clean fuel rather than traditional fire wood (Row 21) and improved drinking water (Row 22). It has been a long-established policy of China's government to fight poverty by focusing on the 'growth' of the infrastructure in extremely poor counties and villages. However, the effect of infrastructure on vulnerability seems to be mixed. Improved drinking water in terms of using tap water could help reducing vulnerability for the non-chronically poor (Row 22 and Columns 6, 7 and 10), but it appears to be a sluggish variable for the chronically poor (Row 22 and Columns 1-3). The time taken to reach the nearest health facility (Row 20) and the usage of clean fuel (Row 21) actually appear to drive up vulnerability, possibly due to the unequal spread of these facilities across households and thereby unequal costs needed to benefit from these facilities.

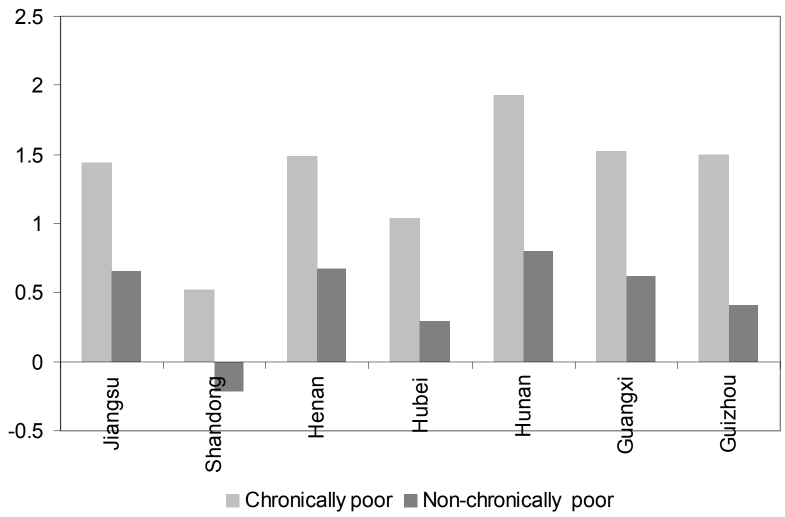
3.4.4.8 Prices

Row 23 and Column 1 clearly show that inflation tends to considerably aggravate the chronically poor's uncertain welfare, through adding to the inequality component and idiosyncratic and unexplained risk (Columns 2, 4 and 5). In sharp contrast, the non-chronically poor seem to be unaffected (Row 23 and Column 6). Also, inflation barely increases the welfare loss for these households caused by covariate risk (Row 23 and Column 8).

3.4.4.9 Inequality

Last but not least, inequality measured by consumption Gini coefficients at the province level is particularly detrimental to household vulnerability. As shown by Fig. 3.6, the chronically poor suffer much more from intra-province consumption inequalities in all sample provinces than their non-chronically poor counterparts. This is predictable as, in our decomposition, 89 percent of the chronically poor's VUW comes from the inequality component and much of it originates from intra-village disparities. It is also consistent with Zhang and Wan's (2006a) finding that intra-regional inequality is the driving force of the overall inequality in China, while the inter-regional inequality plays only a peripheral role. Moreover, the magnitude of marginal effects in Fig. 3.6 indicates that every unit of increase in the consumption Gini coefficients has imposed a larger impact on the chronically poor households' vulnerability.

Figure 3.6 Marginal impact of intra-province consumption inequality on household per-period vulnerability



3.4.5 Robustness checks

The estimates of VUW are built on the assumption that the coefficient of risk/inequality aversion (γ in Eq. 3.2) is two. This is potentially problematic as our estimates may be sensitive to household risk preferences. How would VUW estimates change if rural households were assumed to have different views of risk? Two ways of dealing with this problem are reported in the existing literature. One seeks to directly estimate the household parameter of risk aversion. For example, Ligon (2007) provides a GMM estimation based on various assumptions regarding the structure of financial markets and insurance mechanisms. However, this chapter, follows the alternative approach of Whalley and Yue (2009) and summarises the simulation of VUW and its components corresponding to different hypothesised values of household risk aversion, i.e. $\gamma = \gamma\ \{1, 1.5, 2, 2.5, 3\}$.[54] As γ becomes larger, households become more risk averse and less welfare weight is given to those having higher consumption expenditure. The same amount of shortfall in household consumption will bring more welfare loss to the rich when there is a higher γ. Also, the utility function takes the logarithmic form when γ is equal to one. As shown in Table 3.7, one would expect that VUW and its components rise with greater risk aversion. Moreover, the magnitude of the three risk components grows with an increasingly higher proportionate rate compared with the inequality component.

Table 3.7 Simulations of per-period VUW and its breakdown, 1989-2006

γ	Aver. Vuln.	Ineq.	Cov. Risk	Idio. Risk	Unexp. Risk
1	0.141	0.104	0.002	0.004	0.031
1.5	0.203	0.147	0.003	0.006	0.047
2	0.274	0.195	0.004	0.008	0.066
2.5	0.363	0.251	0.019	0.009	0.084
3	0.489	0.324	0.007	0.014	0.143

3.5 Concluding remarks

The analysis reveals an unneglectable welfare loss due to the increasing uncertainty facing rural households, despite the remarkable achievements in reducing poverty incidence in rural China. Most of the rural population are vulnerable in the sense that they are subject to uncertain low welfare in at least 6-9 years. The per-period average household vulnerability keeps increasing, from 21.9 percent in the late 1980s to 36.6 percent at the end of 2006. About 80 percent of this welfare loss is driven by the inequality component, of which 63 percent comes from intra-village inequality. Farmers appear to bear the brunt of increasing uncertainty. A more worrying finding is that, although consumption on average increases, those who are at the bottom of

[54] Note that γ should not be less than one since we assume all rural households are risk averse rather than risk loving.

consumption distribution seem not to have benefitted from the overall economic boom, but indeed have experienced decreasing welfare in terms of greater vulnerability in their consumption flows.

With respect to policy implications, the government should be vigilant to the undue because its reliance as a long-standing ‘growth’-oriented policy appears to have had little effect on improving the rural poor’s well-being. It is essential for China to adjust policy and adopt a multidimensional focus on rural development in order to stop the upward trend of vulnerability, particularly for farming and poor households as their welfare loss appears to be the highest.

Such a policy would preferably be designed to make rural households better-off not only in terms of raising their consumption level but also by insuring them against a more uncertain life during the process of radical economic reform and social changes. A viable prescription could involve providing rural households with sufficient and efficient social safety nets, preferably at the village level, which could cushion them against the negative effect of risk on their consumption flows. This would particularly benefit those who are just on or near the poverty line, because they tend to confront greater welfare costs arising from more volatile consumption while also being excluded from the benefits the government gives exclusively to the poor. With regard to specific policies, the empirical results indicate that providing more primary and secondary education and health insurance may improve rural households’ well-being, but one cannot assert a causal relationship. Diversification within the agricultural sector may also help to make the chronically poor better-off, while off-farm employment appears to be more effective for non-chronically poor households.

It is also worth noting some caveats to the present study, which might limit the utilisation and interpretation of VUW. First, VUW is essentially a static indicator of welfare (Guimaraes, 2007). Second, in the presence of the arbitrary coefficient of risk aversion, the LS measure of VUW assumes that households' behaviour on savings and investment does not respond to risk. In other words, risk does not affect mean consumption – a supposition that may obviously bias the VUW estimates (Elbers and Gunning, 2003). Moreover, Guimaraes (2007) and Elbers and Gunning (2003) emphasise that VUW fails to explain whether the welfare loss is due to receiving less risk or because the household is less capable in terms of managing risk. Third, the LS-type VUW is essentially *ex post* as it is calculated from observed consumption after coping with shocks. Fourth, Dercon (2005) points out that this way of constructing VUW actually takes all risk into account rather than 'downside risk' only. This hinders us from concentrating on those who are more likely to face reduced consumption and fall below the poverty line. In relating vulnerability measures to poverty, Calvo and Dercon (2005, 2009) have made some early attempts that deserve further investigation.

CHAPTER 4

RISK, AGRICULTURAL ASSETS AND THE PERSISTENCE OF POVERTY

4.1 Introduction

According to official governmental figures, over the last three decades, 230 million people have escaped poverty in rural areas of China. This has been reflected in a sharp reduction in the poverty headcount ratio from 30.7 percent in 1978 to 2.3 percent in 2006. However, it is also worth noting that 80 percent of this poverty reduction happened before 1996.[55] Ravallion and Chen (2007) find that since the late 1990s, poverty appears to have become more 'concentrated' and 'persistent' as the incomes of the rural poor have stagnated while others' incomes have risen, with actual increases in rural poverty in 1999, 2000 and 2001 relative to 1998.

But why has poverty persisted in rural China? Studies of rural China and from the rest of the world, sub-Saharan Africa in particular, might help answer this question. In particular, studies of rural China have identified three possible explanations for the persistence of rural poverty: inadequate endowments, such as those associated with living in remote or otherwise unfavourable geographical locations (Jalan and Ravallion, 2002), which reduced the productivity of farm households' investment

[55] The figures in this and the previous two sentences are the author's calculations based on data from Poverty Monitoring Report of Rural China 2008.

(Ravallion and Jalan, 1999), and poor education (Knight *et al.*, 2009a; 2010); social exclusion in an underclass associated with ethnicity and gender (Hebel, 2003; Cao *et al.*, 2009); and a range of institutional and market failures (Jacoby *et al.*, 2002; Cai, 2010).

In addition to these studies of China, there is a growing body of evidence from African economies which suggests that risk and shocks can be a further cause of persistent poverty (Rosenzweig and Binswanger, 1993; Dercon, 1996, 1998, 2004, 2006, 2009; Lybbert *et al.*, 2004; Carter *et al.*, 2007; Elbers *et al.*, 2007; Foster and Rosenzweig, 2010; Dercon and Christiaenaen, 2010). These studies find that exposure to uninsured risk and shocks tends to reduce farm households' incentives to engage in high-return but risky agriculture. This choice may lead them to low-equilibrium asset holdings and lower long-term incomes (Adato *et al.*, 2006; Barrett *et al.*, 2006; Carter *et al.*, 2007), which means they fall below the accepted poverty line. Through this mechanism, seemingly short-lived risk and shocks can generate persistent poverty in the long-term.

This chapter aims to examine whether this mechanism can explain the persistence of poverty in rural China. In particular, Huang *et al.* (2003) find that Chinese farm households do not use hybrid and high yielding varieties that might provide them with higher incomes. During field work, the CHNS directors also observed that many rural households did not invest at all for the three to four years after a relatively large-scale investment in agriculture failed.[56] These observations raise the issue of whether households' under-investment decisions in agriculture (and hence low

[56] This can be found in the CHNS document justifying income variable construction. Available at: http://www.cpc.unc.edu/projects/china/data/datasets/Household%20Income%20Variable%20Construction.pdf [accessed 24 January 2011]

income) can be attributed to their exposure to uninsured risk and shocks. In other words, the uninsured risk and shocks and limited means of countering the negative impact of risk may force households to move away from profitable investment in productive assets to low-return but less risky agricultural production. Such behavioural responses would bring them low income, which in turn, forces them to continue in low-return production. Research how this vicious circle might be broken is needed if policy makers are to help improve the condition of the poor and promote self-reinforcing growth via steady investment in profitable agricultural asset accumulation which has long helped rural China reduce poverty (Montalvo and Ravallion, 2010). However, there is a paucity of studies examining the impact of risk and shocks on Chinese rural households' long-term well-being in relation to their asset holdings.

This chapter therefore seeks to contribute to the literature in the following five ways. First, using a representative dataset over a long period of time, it provides the first econometric investigation of risk-induced persistent poverty in rural China. Second, following Dercon's (2009) suggestions, this investigation examines a wider range of shocks than the more 'easily' measured weather shocks that the existing literature has considered. Third, it draws upon counterfactual simulations to distinguish potential downside risks from realised shocks. Fourth, it uses a semi-parametric model to describe households' asset dynamics, which is less susceptible to the problems that bedevil fully parametric and non-parametric methods in the existing literature. Fifth, while previous studies only discuss the signs of estimates of household responses to risk, this chapter further gauges household-specific marginal effects of each explanatory variable after modelling responses to risk, which in turn permits household heterogeneity in both risk-enhancing and risk-mitigating factors to be addressed.

We find households' exposure to uninsured shocks and risk may cause deficiencies and inefficiencies of investment in agricultural asset accumulation. Such behavioural responses may lead some households into low-equilibrium asset traps, which will bring low income in the long-term, while other responses would enable them to converge to the high-equilibrium assets level and escape from poverty. The overall results resonate with Carter and Barrett's (2006) theory relating to asset-based poverty traps.

The remainder of this chapter is organized as follows. The next section spells out two mechanisms underpinning risk-induced persistent poverty. Their econometric specifications are presented in Section 4.3. Section 4.4 describes the dataset. Section 4.5 discusses the empirical results. Conclusions are summarised in Section 4.6.

4.2 The role of risk vis-à-vis household welfare status

Risk has two kinds of effect on household welfare and poverty status (Clarke and Dercon, 2009). Risk in the form of possible negative shocks may knock households into poverty, but households can, in principle, adjust and regain the pre-shock living standards as the shocks dissipate. However, the risk of some negative shocks (e.g., insecure asset and investment portfolios) may cause changes in household behaviour and/or preferences which make outcomes worse than they might otherwise be. Such behavioural responses to the risk of negative shocks might have a cumulative impact on a household's welfare trajectory.

Following Dercon (2006, 2009), this chapter hypothesises that the *ex post* and *ex ante* behavioural responses to uninsured shocks and risk jointly result in less investment in agricultural asset accumulation for some rural households, which could thwart their ability to escape from poverty.

4.2.1 *Ex post* responses to shocks: self-insurance behaviour

People confront various shocks. Negative shocks include falls in assets and income, rainfall, drought and events such as illness and death (Carter *et al.*, 2007; Dercon, 2004; Dercon *et al.*, 2005; Quisumbing and Baulch, 2009). These shocks can bring significant consumption shortfalls to households, and there are no effective risk sharing for households within the village to minimise these consumption shortfalls (Morduch, 1995; Dercon and Christiaesen, 2010; Jalan and Ravallion, 1999). In such circumstances, poorer households may protect themselves against adverse shocks by liquidating or trading productive assets (Rosenzweig and Wolpin, 1993; Dercon *et al.*, 2005) and/or holding substantial precautionary savings in non-productive forms such as grain stocks and cash, neither of which are not allocatively efficient (Jalan and Ravallion, 2001; Park, 2006; Giles and Yoo, 2007).

They tend to reduce households' productive investment. Specifically, liquidation of productive assets implies that households may choose to subsist on a lower but more stable income if offered a trade-off against higher but riskier predicted income. At the same time, under credit constraints, substantial precautionary savings discourage households from making profitable agricultural investment because of their irreversibility and non-divisibility (Fafchamps, 2003).

4.2.2 *Ex ante responses* to risk: income-skewing behaviour

Households are not affected only by the shocks themselves, but also adjust their behaviour towards risk and uncertainty. Poor rural economies are rife with risk and often characterised by ill-functioning financial markets. Under credit/liquidity constraints and limited insurance, poorer farm households are forced to choose low-risk low-return agricultural production in order to reduce their exposure to potential risk (Foster and Rosenzweig, 2010).

Two reasons for this choice have been identified in the existing literature. First, high-value production usually requires lumpy initial inputs and higher educational levels (Dercon, 1998), but poorer households often cannot afford these (e.g., McKenzie and Woodruff, 2006). Second, households' productive investment decisions can be shackled by their 'loss aversion', i.e., the fear of bad consumption outcomes if the high-value production were to be unsuccessful (Dercon, 2006; Dercon and Christiaesen, 2010).[57] This may be due to the non-separability in household behaviour: household consumption characteristics are both consequences and correlates of their production choices (Bowlus and Sicular, 2003; de Janvry and Sadoulet, 2006). Households' differentiated capabilities of smoothing consumption *ex post* of shocks may also influence their uptake of risk (Hoogeveen, 2001). In this sense, the *ex post* and *ex ante* mechanisms are not independent of each other but,

[57] Dercon (2006) and Fafchamps (2009) argue that this fear should be viewed as a joint result of rational motives under risk aversion and behavioural motives observed from field experiments (e.g., loss aversion, quasi-hyperbolic preferences, impulse purchases and peer effects). Even normally risk neutral households may not be willing to invest because of extensive market failures and may well behave as if they are risk averse (Dercon, 2006).

jointly, they lead households to low-equilibrium agricultural production which is less risky but less profitable.[58]

4.3 Econometric approaches

This section presents the econometric models used to investigate the *ex post* and *ex ante* mechanisms linking risk and poverty discussed in Section 4.2.1 and 4.2.2.

4.3.1 Coping with negative shocks

We begin by studying the impact of various shocks on households' consumption. Following Dercon and Christiaensen's (2010), for the household h at time t, per capita consumption, $c_{ht,}$, is regressed using a fixed-effects model:

$$\begin{aligned}\ln c_{ht} = \gamma_1 A_{h(t-1)} + \sum_{j=1}^{J} \gamma_{2j} s_{htj} + \gamma_3 s_{ht}^{iinc.} \cdot G_{ht} + \sum_{k=1}^{K} \gamma_{4k} B_{h(t-1)k} s_{ht}^{inc.} + \sum_{k=1}^{K} \gamma_{5k} B_{htk} s_{ht}^{inc.} I_{ht} \\ + x'_{ht} \gamma_6 + \alpha_h + \varepsilon_{ht}\end{aligned} \tag{4.1}$$

where $A_{h(t-1)}$ denotes agricultural assets;[59] s_{htj} represents $j \in \{1,2,\ldots,J\}$ kinds of shocks; $s_{ht}^{inc.}$ includes idiosyncratic and covariate income shocks, while $s_{ht}^{iinc.}$ denotes idiosyncratic income shocks only; the indicator variable G_{ht} equals one if the negative idiosyncratic income shock is below the median of all the negative idiosyncratic income shocks; B_{htk} encompasses $k \in \{1,2,\ldots,K\}$ kinds of assets (including agricultural assets); I_{ht} is another indicator variable equalling one if the household's assets B_{htk} are fewer than the median; household characteristics are

[58] Morduch (1995) and Rosenzweig and Binswanger (1993) provide early empirical support. Dercon and Christiaensen (2010) present a theoretical model leading to this result.

[59] Note that the time intervals between every two surveys in our data range from 2 to 4 years. Thus, $A_{h(t-1)}$ is actually the agricultural assets owned by the household in the previous survey. Nevertheless, the current data are the best we can obtain.

included in x'_{ht} controlling for the life-cycle effect, and household-specific time-invariant effects α_h.

In this model, rural households' consumption is assumed to be influenced by their agricultural asset holdings. In order to avoid endogeneity, we use lagged asset data $A_{h(t-1)}$ at $t-1$, as suggested by Dercon and Christiaensen (2010).

When identifying various shocks, the existing literature either distinguishes between asset and income losses (Carter *et al.*, 2007) or gauges the impact of other negative events such as rainfall and drought shocks (Dercon, 2004), and illness and death (Quisumbing and Baulch, 2009). Our analysis instead focuses on a wider range of shocks to better describe households' uncertain livelihoods, as suggested by Dercon (2006, 2009). Specifically, s_{htj} encompasses idiosyncratic and covariate income shocks, institutional failures in terms of agricultural price shocks, weather shocks and other random events experienced by individual households including illness, death, and the burden of weddings, dowries and funerals. A more detailed discussion of data will be presented by Section 4.4. The estimated coefficient γ_{2j} is expected to be negative for unfavourable shocks as they may bring consumption shortfalls.

Among these various shocks, income shocks are of particular interest. Greater negative income shocks for household h compared with its peers may be more difficult to deal with (Dercon and Christiaensen, 2010). This is captured by multiplying $s_{ht}^{iinc.}$ by the indicator variable G_{ht}. Households' wealth-differentiated coping capability when faced with income shocks is reflected by the interaction terms $\sum_{k=1}^{K} B_{h(t-1)k} s_{ht}^{inc.}$. Furthermore, $\sum_{k=1}^{K} B_{htk} s_{ht}^{inc.} I_{ht}$ helps indicate if the asset-poor would be less capable of smoothing consumption.

Besides describing consumption responses to shocks, Eq. (4.1) also allows us to simulate households' precautionary behaviour as well as the counterfactual consumption levels under varied magnitudes of shock. That is, assuming different degrees of income shocks, we use the estimates of Eq. (4.1) to calculate predicted household per capita consumption. As we can also obtain observed savings by subtracting observed income by observed consumption, this counterfactual consumption can in turn be used to calculate the savings that households would hold in hand under the presumed income shocks. The difference between the observed and this counterfactual savings is the household precautionary savings when they face a certain level of income shocks. Both precautionary savings and counterfactual consumption are proxies for potential downside risks and will be used in investigating households' risk mitigation behaviour in the next sub-section.

4.3.2 Mitigating downside risks

The *ex ante* responses to risk can be described by incorporating model specifications from Carter *et al.* (2007), Dercon and Christiaesen (2010) and Quisumbing and Baulch (2009). The annual growth rate of household agricultural assets (from t to $t+1$) is represented by a latent variable g_{ht}^{*}, and is determined by a number of factors as follows:

$$
\begin{aligned}
g_{ht}^{*} &= \beta_1 A_{h(t-1)} + \beta_2 c_{ht} + \beta_{12} c_{ht} \cdot A_{ht-1} + \beta_{23} c_{ht} \cdot m_{v(t-1)} + \beta_{123} c_{ht} \cdot A_{ht} \cdot I_{ht} \\
&\quad + \beta_4 p_{ht}^{iinc.} + \beta_{14} p_{ht}^{iinc.} \cdot A_{h(t-1)} + \beta_5 p_{ht}^{cinc.} + \beta_{15} p_{ht}^{cinc.} \cdot A_{h(t-1)} \\
&\quad + \sum_{j=1}^{J} \beta_{6j} s_{htj} + x'_{ht}\beta_7 + \alpha_h + \varepsilon_{ht}
\end{aligned}
\tag{4.2}
$$

where $A_{h(t-1)}$ denotes households' agriculture asset holdings at $t-1$ as in Eq. (4.1), but here is considered as a proxy for the *ex ante* cost of agricultural production facing households at the time of making production decisions;[60] c_{ht} is the counterfactual consumption depending on the degrees of income shocks; $m_{v(t-1)}$ measures a village's out-migration network; $p_{ht}^{iinc.}$ and $p_{ht}^{cinc.}$ are simulated unproductive precautionary savings as the responses to idiosyncratic and covariate income shocks respectively; s_{htj} includes all other shocks specified in Eq. (4.1) except income shocks; x'_{ht} and α_h have same the definitions as in Eq. (4.1).[61]

A negative estimate for β_1 means that working capital constraints are binding in households' decision-making. Considering the fact that rural households could use their available agricultural assets for loans or liquidate assets in hard times, a negative coefficient also implies that more productive but riskier investments in agriculture are less likely to be disbursed if credit and liquidity constraints are tighter.

The present study distinguishes two kinds of potential risk from shocks drawing upon counterfactual simulations. On the one hand, following Dercon and

[60] The regression should ideally include households' received financial credits as in Liverpool *et al.* (2010) or multiply $A_{h(t-1)}$ by the access to credits to reflect real constraints as in Dercon and Christiaesen (2010). These studies have found a positive impact of financial credits on asset growth and the use of improved technology. Unfortunately, CHNS did not collect data on household credits.

[61] Due to the lack of data in CHNS, we cannot include property security (an important institutional risk pointed out by Dercon, 2009) in terms of the re-allocation of cultivated land and the party memberships that may also influence household *ex ante* asset portfolios and access to financial credits.

Christiaesen (2010), the counterfactual consumption c_{ht}, based on various income shocks, indicates the potentially low welfare consequences if production were to fail. A positive coefficient $\hat{\beta}_2$ indicates households' reduced investment under 'loss aversion'.[62] On the other hand, we simulate precautionary savings $p_{ht}^{iinc.}$ and $p_{ht}^{cinc.}$ in response to idiosyncratic and covariate income shocks respectively. As discussed in Section 4.2.1, the household precautionary motive may also discourage productive investment, pointing to negative coefficients $\hat{\beta}_4$ and $\hat{\beta}_5$.

Households may well resort to other means to mitigate risk, typically invoking social networks (Baulch and Hoddinott, 2000; Fafchamps, 2009). For rural China, given the rapidly expanding number of migrants, migrant networks through kinship and friendship can largely reduce the informational and psychological costs of out-migration and the probability of unemployment by providing direct job search assistance and, therefore, facilitate migration (Zhao, 2003). As rural labour gets more involved with out-migration, there are more remittances; these not only improve the remaining residents' livelihoods by adding to their consumption (de Brauw and Giles, 2008), but also reduce their precautionary savings (Giles and Yoo, 2007). Both functions of out-migration might alleviate households' fear of the risk of negative shocks in agricultural production and, therefore, encourage them to pursue more profitable but riskier investment plans. To capture this effect, we interact c_{ht} with village out-migration networks $m_{v(t-1)}$ and expect a positive estimate.

62 Although we control for out-migration as an interaction term with agricultural assets, the agricultural investment growth model may overlook households' decisions of pursuing non-agricultural production activities. Given this, $\hat{\beta}_2$ may be downwardly biased.

In order to model wealth-differentiated risk-taking abilities (Foster and Rosenzweig, 2010), we multiply c_{ht}, $p_{ht}^{iinc.}$ and $p_{ht}^{cinc.}$ by agricultural assets at the time of decision-making. It might also be the case that asset growth for those with less asset than the median is more sensitive to exposure to risk. This is indicated by a negative coefficient $\hat{\beta}_{123}$ on the term $c_{ht} \cdot A_{ht} \cdot I_{ht}$.

We implement the following three methods to estimate Eq. (4.2). First, we follow Carter *et al.* (2007) and use a random-effects tobit model. Carter *et al.* (2007) argue that the poorest households may be so poor that there is no room for further reduction of their asset holdings. In addition, Chinese farm households' limited range of crop varieties may be dictated by the grain procurement quota system (Yang, 2009) rather than by behavioural adjustments to risk. Both of these effects will bias the OLS estimates in Eq. (4.2) as they tend to capture 'the inability of households in the lowest strata to liquidate assets' (Carter *et al.*, 2007), rather than genuine risk-mitigating behaviour. To make our estimates resistant to these potential biases, we adjust Eq. (4.2) to a tobit specification with random effects:

$$\begin{cases} g_{ht} = g_{ht}^{*} & if \;\; g_{ht}^{*} > 0 \\ g_{ht} = 0 & if \;\; g_{ht}^{*} \leq 0 \end{cases} \tag{4.3}$$

By left-censoring the growth rates at zero, the estimates will be free of distortion.

Second, we employ a fixed-effects tobit model. The possible correlation between household-specific effects α_h and other explanatory variables in Eq. (4.2) will give rise to spurious risk management behaviour. Households sharing certain unobserved characteristics may suggest positive/negative asset growth rates, which can overshadow the genuine response to risk. In fact, Foster and Rosenzweig (2010) note that the problem of unobservables is likely to exist. For example, poorer households' risk aversion may change their asset holdings; total wealth, including both liquid and illiquid components, may alter households' responses given the commonly observed negative relationship between wealth and household absolute risk aversion, while land quality perhaps also plays a role in determining households' choices of crop varieties. To control for the unobservables, we follow Dercon and Christiaesen (2010) and adopt Honoré's (1992) semi-parametric approach to re-estimate the tobit model (Eq. 4.2 and 4.3) but with fixed effects.

Third, although the tobit specifications can be used to examine the determinants of the magnitude of asset accumulation, they are powerless to find correlates of accumulation decisions. Thus, a conditional fixed-effects logit model, following Dercon and Christiaesen (2010) and Liverpool *et al.* (2010), is used to assess whether the explanatory variables in Eq. (4.2) alter households' production decisions. Controlling for fixed effects, Eq. (4.2) is re-written as,

$$g_{ht} = \mathbf{1}\left(z'_{ht}\beta + \alpha_h + \varepsilon_{ht} \geq 0\right) \tag{4.4}$$

where $z'_{ht} = \begin{pmatrix} A_{h(t-1)}, c_{ht}, c_{ht} m_{v(t-1)}, c_{ht} A_{h(t-1)}, c_{ht} A_{ht} I_{ht}, \\ p^{iinc.}_{ht}, p^{cinc.}_{ht}, p^{iinc.}_{ht} A_{h(t-1)}, p^{cinc.}_{ht} A_{h(t-1)}, \sum_{j=1}^{J} s_{htj}, x'_{ht} \end{pmatrix}'$. According to Arellano and Honoré (2001), for $T > 2$, the conditional distribution for the household h having a sequence of asset growth $(g_{h1}, \ldots, g_{ht})$ given $\sum_{t=1}^{T}$ is expressed by

$$\Pr\left(g_{h1}, \ldots, g_{ht} \mid \sum_{t=1}^{T} g_{ht}, z'_{ht}, \alpha_h\right) = \frac{\exp\left(\sum_{t=1}^{T} g_{ht} \beta z'_{ht}\right)}{\sum_{(d_1, \ldots, d_t) \in \mathrm{B}} \exp\left(\sum_{t=1}^{T} d_t \beta z'_{ht}\right)} \tag{4.5}$$

where B is the set of all sequences of zero and ones that have $\sum_{t=1}^{T} d_{ht} = \sum_{t=1}^{T} g_{ht}$ and $\sum_{t=1}^{T} g_{ht}$ is a *sufficient statistic* for α_h.[63] Eq. (4.5) can be estimated by Chamberlain's (1980) conditional maximum likelihood method[64]. However, one cannot directly interpret the magnitude of estimates in latent variable models (Wooldridge, 2005). Therefore, we further define and calculate the household-specific marginal effects of each explanatory variable in Appendix B in order to enrich the discussion and address household heterogeneity. Section 4.5 will discuss the calculation results.

4.4 Data

The panel data set has already been described in Chapter 2. Therefore, as this chapter focuses on households' asset holdings, we only present the construction of asset indices in Section 4.4.1. Section 4.4.2 describes assets and shocks. Section 4.4.3 examines asset dynamics underpinning households' long-term well-being trajectories. Identifying multiple equilibria in asset dynamics gives rise to possible low-equilibrium traps for some households.

4.4.1 Constructing asset indices

Following Moser and Felton (2009), household assets are categorised into three elements – physical, productive and human capital – as shown in Table 4.1.

[63] See Arellano and Honoré (2001) for details.
[64] As can be seen in Eq. (4.5), the conditional logit model actually nets out fixed effects in the estimation process. Given this shortcoming, we also apply OLS to a fixed-effects linear probability model as a robustness check. It makes the accumulation decisions directly dependent on household fixed effects, although still suffering some drawbacks (e.g., there are constant marginal effects and some households' predicted probabilities of asset accumulation may go beyond [0,1]).

We use Moser and Felton's (2009) regression method to construct human capital. The wage regression is estimated to obtain different weights for primary, secondary and tertiary education.[65] Weighted years of schooling for individuals add to household human capital.

Table 4.1 Components of household assets

Capital type	Category	Components
Physical capital	Housing	Age of house; roof/floor/wall material; size of dwelling; drinking water source; lighting source; toilet type; main cooking fuel
	Consumer durables	Types of transport; living/entertainment durables[66]
Productive capital	Agricultural assets	Fixed assets including the quantity of different types of farming machinery & irrigation;[67] financial assets including money spent on seed, fertilisers, labour, etc.
	Business assets	Fixed assets including the quantity of different types of commercial business equipment;[68] financial assets including money spent on raw materials, labour, etc.
Human capital	Education	Weighted years of schooling

The indices for the other four asset categories (housing, consumer durables, agricultural assets and business assets) are constructed by using Kolenikov and

[65] The wage earned in labour market is regressed on three levels of education and other common controlling variables and household fixed effects. Weights are the estimated coefficients for each educational level.

[66] Transport includes bicycles, tricycles, motorcycles and automobiles. The living and entertainment durable goods include radios, VCRs, televisions, washing machines, refrigerators, air conditioning, sewing machines, electric fans, big wall clocks and cameras.

[67] Farm machines include large or medium sized tractors, walking tractors, animal carts, irrigation equipment, power threshers and household water pumps. Land owned by households is not included, since in rural China, land is not transferable as it is allocated by local/village officials according to the number of household members. Land is not, therefore, a tangible asset that households can freely accumulate or divest.

[68] Commercial equipment that households use in their small business activities includes cooking equipment, carpentry equipment, haircutting equipment, sewing machines (excluding those treated as consumer durables that are used for daily life), welding machinery, small machine-shop tools or equipment and other unspecified equipment.

Angeles's (2009) polychoric Principal Component Analysis (PCA). We use the index B_{htk} to denote the asset category k owned by the household h at time *t*. It is a linear combination of different asset components a_{hjt} which are orthogonal to each other and maximise the variance of $a = (a_{h1t}, a_{h2t}, \ldots, a_{hjt}, \ldots, a_{hJt})$. The rest of this sub-section presents the construction of asset indices.

We first assume an *iid* distribution for each asset component *j* across all households in each time period. This is a common assumption of standard PCA (Filmer and Pritchett, 2001). For the household *h* at time *t*, its asset category k, B_{htk}, which contains $j = (1,2,\ldots,J)$ kinds of assets can be explained by a set of latent components C_{hjt}:

$$\begin{aligned} a_{h1t} &= v_{11t}C_{h1t} + v_{12t}C_{h2t} + \ldots + v_{1Jt}C_{hJt} + u_{h1t} \\ &\vdots \\ a_{hJt} &= v_{h1t}C_{h1t} + v_{h2t}C_{h2t} + \ldots + v_{hJt}C_{hJt} + u_{hJt} \end{aligned} \tag{4.6}$$

where $v_J = (v_{h1t}, \ldots v_{hJt})$ are factor loadings which portray the correlation between the asset a_{hjt} and factor component C_{hjt}; the factor components are uncorrelated with the disturbances, $E(u_{hjt} \mid C_{hjt}) = 0$; the disturbances do not necessarily satisfy the *iid* distribution. At time *t*, the variance-covariance matrix of disturbances is defined as

$$E(u_{ht}u'_{ht}) = Diag\{\sigma_{1t}^2, \ldots \sigma_{Jt}^2\} = \Psi_t \tag{4.7}$$

Note that we allow the variance-covariance matrices to vary over time, considering the possibility that even the same kind of assets could provide different information on households' wealth in different time periods. For example, in the late 1980s, the ownership of a bicycle was indicative of wealthier households, while in the late

1990s, owning a car might signal wealthier households and owning a bicycle be indicative of relative poverty.

Technically, in each time period, obtaining a linear combination of at set of a_{hjt} with maximum variance is equivalent to solving the characteristic equations of Eq. (4.6), $\det[\Sigma - \lambda_J I_J] = 0$, for the eigenvalues λ_J and eigenvector v_J, where Σ denotes the matrix of correlations between a set of a_{hjt}. Note that, unlike standard PCA, Σ is composed of the polychonic correlations as Kolenikov and Angeles's (2009) maximum likelihood estimates of the correlation between the unobserved continuous asset data underlying their observed but discretised values. Then, reverting the characteristic equations yields latent components equalling linear combinations of assets:

$$\begin{aligned} C_{h1t} &= w_{11t}a_{h1t} + w_{12t}a_{h2t} + \ldots + w_{1Jt}a_{hJt} \\ &\vdots \\ C_{hJt} &= w_{J1t}a_{h1t} + w_{J2t}a_{h2t} + \ldots + w_{JJt}a_{hJt} \end{aligned} \tag{4.8}$$

The PCA approach restricts our view to the first component C_{h1t} which is usually thought to best reflect the correlations among a set of a_{hjt}. Normalising C_{h1t} in Eq. (4.8) gives the index of B_{htk}:

$$B_{htk} = \sum_{j=1}^{J} w_{1jt} \frac{a_{hjt} - \overline{a}_{jt}}{\sigma_{jt}} \tag{4.9}$$

where $\overline{a}_{jt}$ and σ_{jt} respectively denote the mean and standard deviation of the asset *j* at *t* across all households.

The above procedures are applied in every survey year to obtain time-varying weights ($\hat{w}_{1jt}$) for each asset component *j* to accommodate the possible changing indicative meanings of the same asset on households' wealth over time. A positive weight for the asset j indicates that its ownership is indicative of possession of more other kinds of assets, and vice versa. Thus, B_{htk} can be either negative or positive. It is important to note that for different asset categories owned by the same household, the values of the indices cannot be compared with each other, since we construct B_{htk} for each k separately.

The polychoric PCA not only retains the strengths of standard PCA initially used by Filmer and Pritchett (2001), but also takes advantage of ordinal asset data.[69] It also should outperform the regression-based method pioneered by Adato *et al.* (2006) for two reasons. Firstly, the regression-based method imposes a pre-determined relationship between consumption and assets, which raises the concern of reversed causality in the subsequent consumption regression. Secondly, the estimates would be biased if assets were correlated with measurement errors in income (Antman and McKenzie, 2007). Sahn and Stifel (2003) demonstrate that using the asset index to study households' poverty and long-term wealth generates fewer errors compared with expenditure data.

4.4.2 Data description

This sub-section scrutinises households' asset holdings and various shocks in greater detail, in order to describe basic features of household livelihood.

[69] The weights alter according to different utilities brought by various assets. For example, it can be reasonably assumed that a car brings more utility than a horse for a typical rural Chinese household and this can be reflected by their weights in the polychoric PCA. However, the weights are equal if using the standard PCA as both indicate the household owns a certain means of transport. See Moser and Felton (2009) for detailed comparisons between the two methods.

4.4.2.1 Asset portfolio

Table 4.2 displays how five asset categories differ in size and shape across income groups. The poorest quintile appears to invest mainly in agricultural production and consumer durables, while the richest quintile engages in both agricultural production and business. Although both the poorest and richest quintiles tend to pursue more agricultural production than others, the rich enjoy on average 14.3 percent more predicted marginal returns to their agricultural asset holdings than the poor.[70] In general, the wealthier the household, the more education, housing and consumer durables it can afford.

Table 4.2 Household asset portfolios, by quintile of permanent income (1989-2006)

Quintile	Agricultural assets	Business assets	Investment in consumer durables	Investment in housing	Human capital
1 (poor)	0.050	-0.124	0.031	-0.038	5.871
2	-0.060	-0.062	-0.107	0.016	7.377
3	-0.031	-0.018	0.066	-0.046	8.242
4	0.005	0.072	0.002	0.042	8.729
5 (rich)	0.034	0.134	-0.010	0.020	10.068

Note: a. Human capital is re-scaled by dividing the magnitude by 100 in order to compare it with the other four categories of assets.

b. Figures are only comparable across income quintiles. The values of different asset indices within the same income quintile cannot be compared with each other by construction.

Over time, our calculations based on the constructed agricultural asset index suggest that the proportion of those whose agricultural assets increased was as high as 64 percent in 1989-1991, but declined to 23 percent in 2004-2006. Furthermore, where it existed, growth was unevenly spread.[71] As a result, the mean agricultural asset across the full sample grew less than 1 percent per annum. This in turn led to a slow

[70] We use the semi-parametric regression presented in Appendix D to estimate returns to agricultural assets. Based on the estimates, we calculate predicted returns to agricultural assets for each quintile.
[71] Fig. A2 in Appendix A draws the distribution of annual growth rates in each period.

increase in rural households' real per capita aggregate income from agriculture, with an average annual growth rate of 3 percent over the period 1985-2006.[72]

A typical concern with rotating panels is that potential bias in estimation may arise if the households that drop out of the panel follow systematically different paths of asset accumulation over time compared with those remaining in the panel (Giesbert and Schindler, 2010). This may be particularly problematic in studying household coping strategies in response to shocks if a household's drop-out is a result of suffering a catastrophic negative shock (Jalan and Ravallion, 2005). In other words, the attrition may be endogenous to the shocks. We carry out various diagnostic tests to investigate whether our panel is subject to this attrition problem.[73] From these tests, it can be reasonably inferred that attrition is not informative on households' livelihoods and asset accumulation paths.

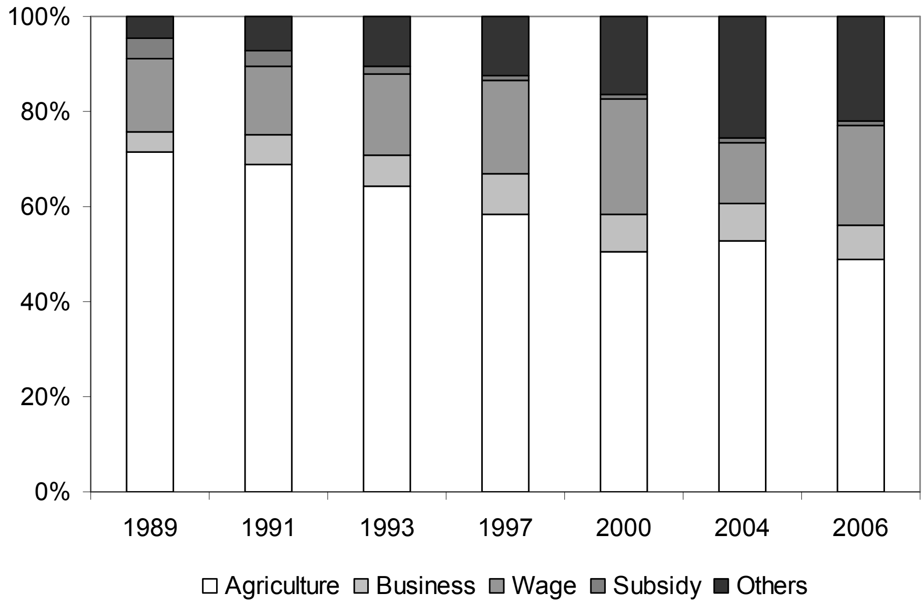
[72] This figures in the previous and this sentences are author's calculation based on the constructed agricultural asset index in this chapter and China Agricultural Development Report (2007), respectively.

[73] Attrition can be based on both the observed and unobserved characteristics. We use Giesbert and Schindler's (2010) added regressor test to investigate the former case. Specifically, we first construct a binary selection indicator taking unity if the household was excluded from the original surveys. This indicator is multiplied with households' various observed characteristics and agricultural asset holdings. In each survey year, the household welfare indicator, per capita log of consumption, is regressed on these interaction terms, the selection indicator and provincial dummies. The estimated coefficients of both the selection indicator and its interaction with agricultural assets are insignificant, indicating attrition might not cause systematic differences in marginal returns to agricultural assets between the attriters and remaining households. Then, a probit model for whether households being in the second survey and thereafter is estimated, with households' observed characteristics and provincial dummies as explanatory variables. The estimated coefficients of agricultural assets are insignificant in the periods except 1991, 2000 and 2006, indicating that in these three rounds, agricultural asset holdings might play a role in determining whether a household was interviewed. To investigate the non-random attrition based on households' unobserved characteristics, we use Heckman-type selection methods proposed by Wooldridge (2002). We estimate a pooled sample selection probit model (to save degrees of freedom) with a Mundlak (1978) specification and calculate the inverse Mills ratio. This ratio is substituted into the household livelihood regression as described in the added regressor test. We estimate this regression by household-specific fixed effects. The estimated inverse Mills ratio is insignificant, indicating that attrition is irrelevant to households' unobservables.

4.4.2.2 Income structure

As can be seen in Fig. 4.2, the proportion of agricultural income in household income decreased over time, but agriculture still dominated rural household income compared with other sources. We also calculate proportions of different income components for the poor and the non-poor respectively. The proportion of income of the poor coming from agriculture was consistently more than fifty percent of their total income. This figure was on average 7 percent higher than that for the non-poor. Agricultural gains matter most in reducing rural poverty compared to the growth of secondary and tertiary industries (Ravallion and Chen, 2007; Huang *et al.*, 2008; Montalvo and Ravallion, 2010). As with non-agricultural wage income, its proportion for the full sample increased from 15 to 21 percent between 1989 and 2006. However, this trend was not significant for the poor: in the same period, their wage income accounted for roughly 15 percent and was relatively stable.

Figure 4.2 Sources of household per capita income, full sample



Source: Author's calculations based on the constructed panel from CHNS.

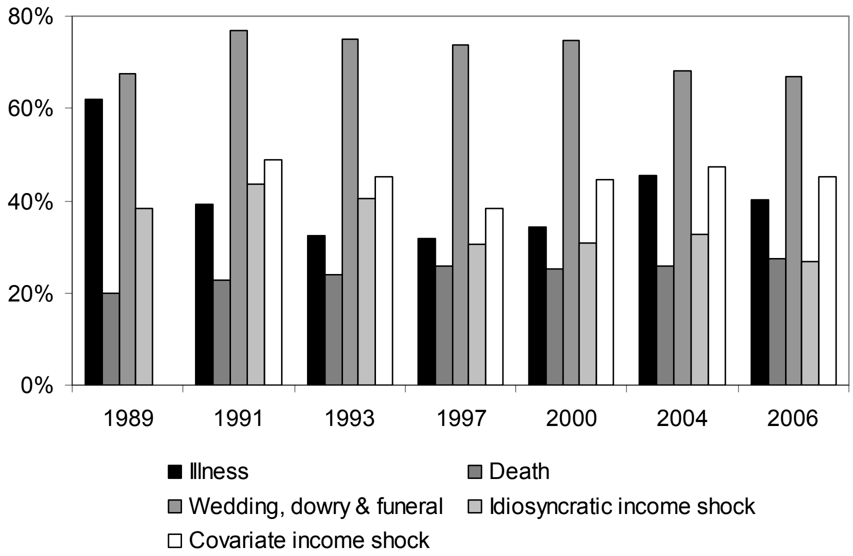
4.4.2.3 Measuring shocks

The frequency with which households are hit by various shocks is illustrated in Fig. 4.3, and several patterns can be identified. First, two aspects of income shocks are distinguished. Using Carter *et al.*'s (2007) definition, the covariate income shock in a certain period is the proportion of those who are subject to income shortfall within the county. It describes the magnitude of shocks which can be observed by all households within the county. In addition, we extend Jalan and Ravallion's (2001) method to estimate the severity of household-specific income shocks and distinguish between positive and negative ones.[74] Over the sample period, 35 and 45 percent of the study population suffered idiosyncratic and covariate income shocks respectively. Moreover, households appear to be unable to protect themselves fully by informal risk-sharing arrangements within the village. Using Jalan and Ravallion's (1999) approach to test the hypothesis of perfect risk-sharing,[75] it is found that, for an average household, 18 percent of idiosyncratic income shocks and 43 percent of covariate income shocks are passed on to its consumption.

[74] See Appendix C for the estimation and calculations.

[75] We employ one-step System-GMM (Blundell and Bond, 1998) to address endogenous income and household size, instead of using the less efficient Difference-GMM method as in Jalan and Ravallion (1999). Table A1 in Appendix A summarises the estimates.

Figure 4.3 Incidence of shocks, from CHNS



Source: Author's calculations based on the constructed panel from CHNS.

Second, we also distinguish between other positive events and negative shocks: the number of household members who were ill in the previous four weeks, the number of deaths and whether the household had expenditure on a wedding, dowry or funeral in the previous year.[76] Overwhelmingly, expenditure on weddings, dowries or funerals happened most frequently. This may be because expenditure on a wedding, dowry or funeral is not restricted to households themselves, but also includes contributions to relatives and friends' weddings, dowries or funerals, since the CHNS questionnaires did not separate these two kinds of expenditure. The next most frequently occurring 'event' was illness, with an average 41 percent incidence over time.

Third, other collective shocks due to bad and unforeseeable weather and institutional failures could substantially affect households' livelihood over a longer period (Dercon, 2006). The former are proxied by the share of sown land affected by

[76] We use dummy variables as the indicators for these events. They take the value one if the event happens.

various natural disasters in the province. Overall, 16 percent of sown areas were affected per year, as seen in Fig. 4.4. The latter is measured by price shocks of agricultural input and output, since they reflect households' difficulty in obtaining input and inability to sell output which are indicative of distortions in the process of market reform (Dercon, 2006).[77] In our analysis, the price shocks are calculated as percentage variations of real price indices of agricultural input and output relative to the preceding year.[78] As can be seen from Fig. 4.5, both agricultural input and output prices have been very volatile over the past three decades. Of the various products, the prices of grain and cash crops appear to have been more variable since the late 1990s, which may be expected to have exerted a significant influence on rural households' livelihood. Grain accounted for roughly 80 percent of agricultural production and 60 percent of sold farm products in the study provinces during the period 1985-2008.[79]

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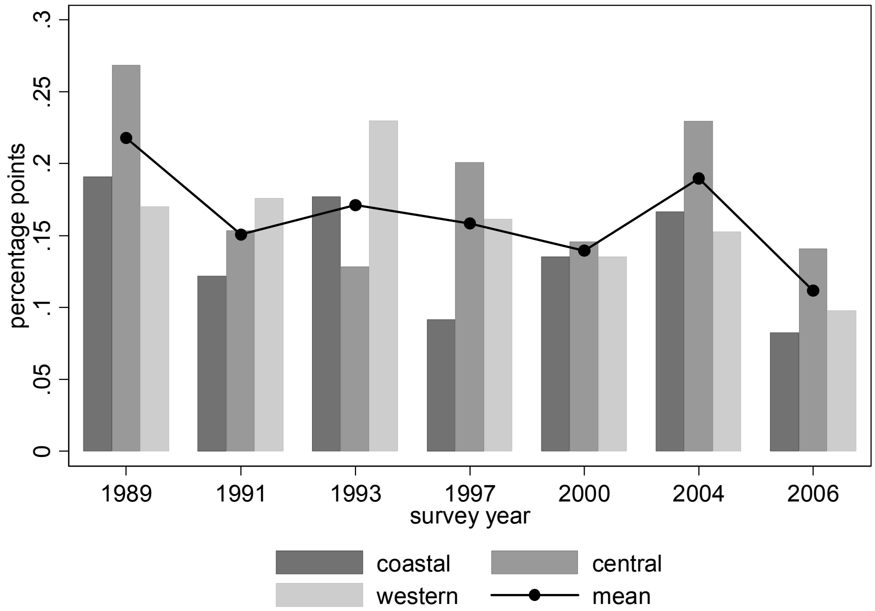
[77] Unfortunately, data in CHNS do not allow us to include other important institutional issues such as land expropriation, the rule of law and property rights (Dercon, 2009).

[78] The definition is in line with Yang (2007) using the absolute percentage variation. However, our analysis does not take absolute values, considering different effects of positive and negative price shocks on rural households' behaviour.

[79] Author's calculations based on data from various issues of the China Statistical Yearbook.

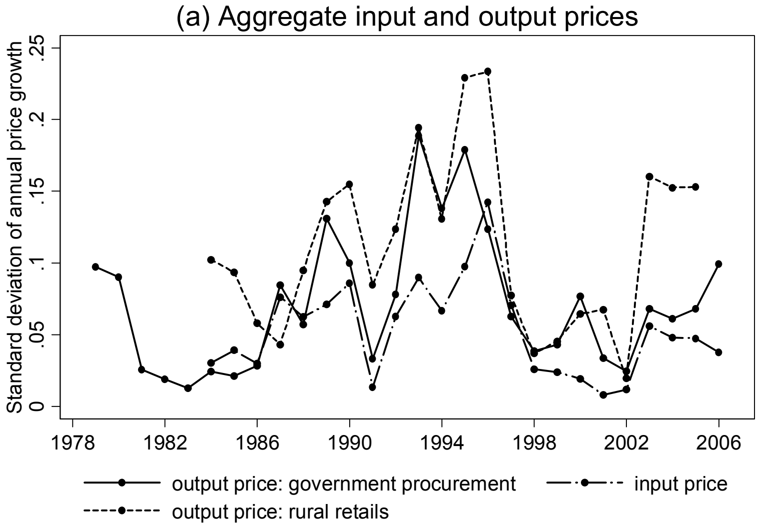
Figure 4.4 Sown land affected by natural disasters in study provinces

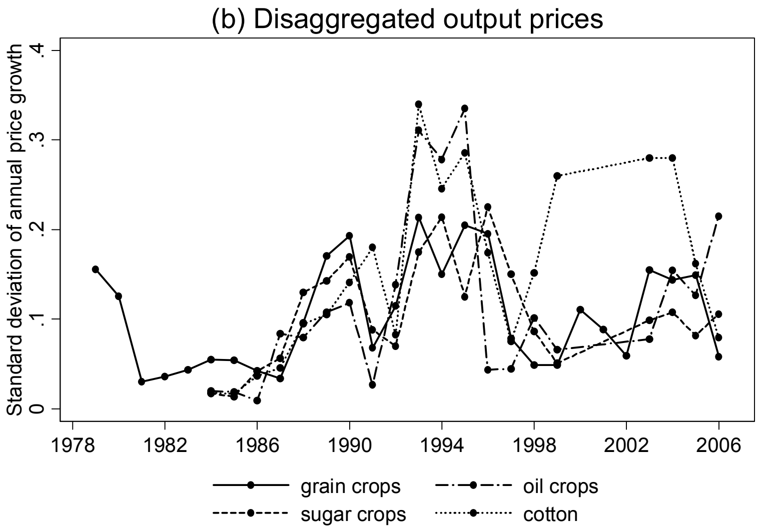


Source: Author's calculations based on data from various issues of China Statistical Yearbook and Statistics on the Sixty-Year Agricultural Development of New China.

Note: Natural disasters include drought, flood and typhoon.

Figure 4.5 Volatility of agricultural prices, 1978-2007[a, b]





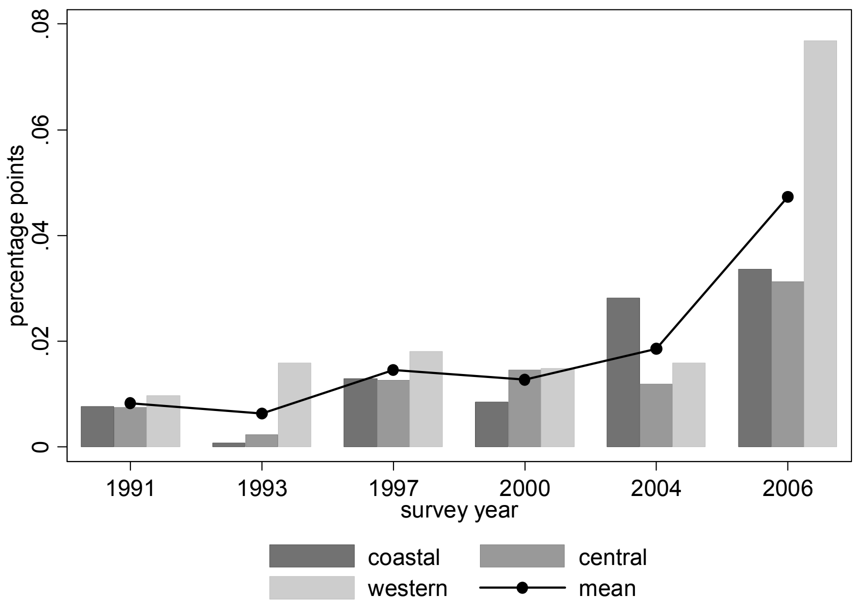
Source: Author's calculations based on data from various issues of China Statistical Yearbook.

Note: Both diagrams are robust for 2-year and 5-year moving coefficients of variation.

4.4.2.4 Ameliorating factors

Access to the local labour market is defined as the share of household members having off-farm employment within the county. The proxy for out-migration networks is the proportion of temporary out-migrants relative to the village total population (Giles and Yoo, 2007). Evidently, more and more of the rural population pursue non-agricultural employment somewhere other than their original residences, especially in the western provinces, which are poorer than others (Fig. 4.6). For example, the proportion of temporary emigration in villages reached 12 percent for Guizhou in 2006 (while it was only 3 percent in Jiangsu).

Figure 4.6 Village out-migration networks (stratified by region)



Source: Author's calculations based on the constructed panel from CHNS.

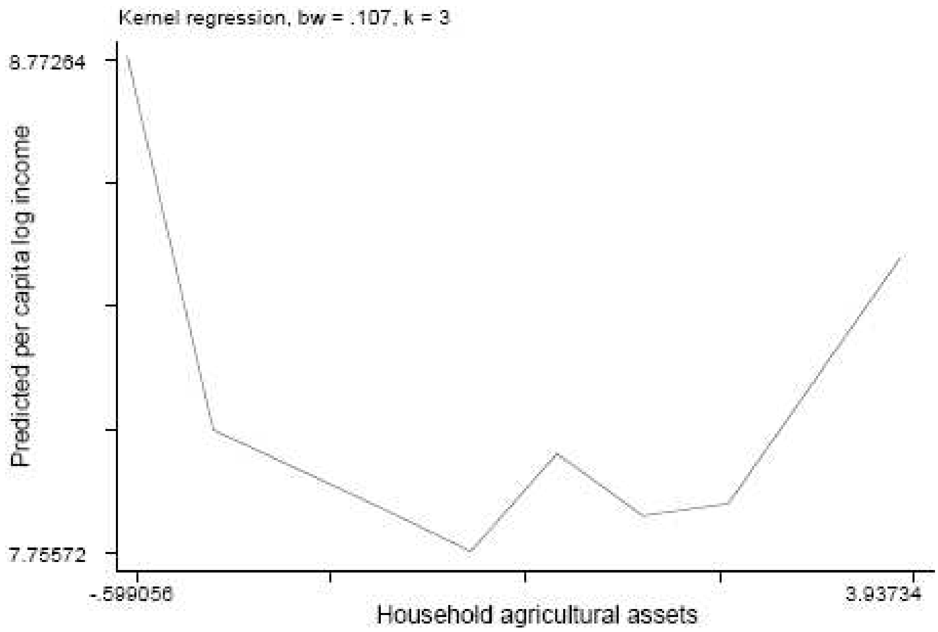
4.4.3 Asset dynamics and bifurcated livelihoods

To depict the evolution of assets, two problems must be addressed: higher order non-linearity and underlying household livelihood strategies. Fully non-parametric and parametric methods in the existing literature can only address one of the problems (Carter and Barrett, 2006; 2007). Therefore, this chapter employs Mesnard and Ravallion's (2001) semi-parametric method to deal simultaneously with both of challenges.[80]

[80] See Appendix D for regressions and robustness checks.

We first use Mesnard and Ravallion's (2001) framework to investigate the expected returns to agricultural assets, because multiple equilibria in asset dynamics implicitly require locally decreasing returns in the vicinity of the lower equilibrium and locally increasing returns to scale at higher asset levels (Carter and Barrett, 2006). Fig. 4.7 depicts the predicted returns to scale for agricultural assets. It clearly shows decreasing returns to scale, represented by the predicted income, at lower asset levels and increasing returns to scale as assets keep growing. Such a profile of profitability of agricultural assets gives rise to the possibility that some households with relatively more assets may optimally choose to accumulate and therefore converge to the high equilibrium due to locally increasing returns, while those with limited assets may sub-optimally prefer to stay at the low equilibrium level.[81]

Figure 4.7 Predicted returns to scale for agricultural assets



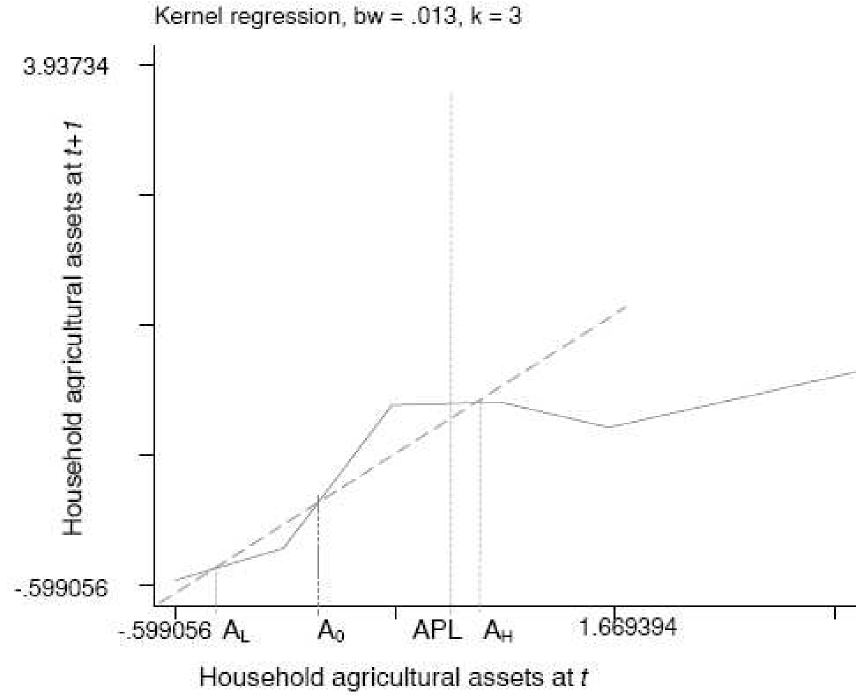
[81] Although our agricultural asset index excludes land, Wan and Cheng (2001) do find locally increasing returns to farm land. It can be plausibly argued that our estimates for returns to agricultural assets are quite robust.

As indicated by the expected returns to agricultural assets, we explore multiple equilibria in agricultural asset dynamics. The equilibrium would be achieved when household asset holdings are the same at t and $t+1$, where, in Fig. 4.8, the agricultural asset dynamics cross the 45-degree line. More specifically, we can find two stable equilibria (A_L and A_H) and one unstable equilibrium (A_0).[82] In the presence of locally increasing returns to assets, those owning more agricultural assets than A_0 would optimally converge to A_H , which is also above the static asset poverty line,[83] implying that they would be able to escape from poverty given sufficient time. By contrast, those facing credit constraints and lying below A_0 would sub-optimally slide towards A_L which is lower than the static asset poverty line, and end up in persistent poverty. The latter may be subject to 'needless chronic poverty' (Adato *et al.*, 2006; Barrett *et al.*, 2008) as they could have accumulated assets (i.e. on the growth route from A_0 to A_H) and ultimately risen above the asset poverty line if there were effective productive safety nets, which could prevent them from falling below A_0, and/or sufficient credits.

[82] By contrast, there is only one stable equilibrium for each of the other asset categories (see Fig. A3 in Appendix A).

[83] The static asset poverty line is the asset level that could bring household income up to the monetary poverty line at US$1.25/day adjusted to the urban-rural price gap (as suggested by Ravallion and Chen, 2007). Following Barrett *et al.* (2006), we use a fixed-effects panel model to regress household assets on household net income and time-varying village effects. The asset poverty line is predicted by substituting the income poverty line in the regression.

Figure 4.8 Dynamics of agricultural assets, 1989-2006



Note: APL denotes the static asset poverty line which is equivalent to the income poverty line of US$1.25/day.

The above analysis provides evidence of bifurcation in agricultural asset holdings. Furthermore, the lack of asset accumulation leading to the high equilibrium for households underpins a medium or longer term inability to escape from poverty.[84] This leads us to a discussion on why some households are more likely than others to be trapped in low equilibrium asset holdings in the next section, which examines the underlying *ex post* and *ex ante* mechanisms outlined in Section 4.2.

[84]To see this, we also draw the dynamics of per capita household income and consumption, using both semi- and non-parametric means. A single equilibrium (higher than US$1.25/day) with slight concavity is found in both cases, indicating a long time for recovery from transitory income losses for the poor. This is consistent with Jalan and Ravallion (2005).

4.5 Estimation results and discussion

4.5.1 Household wealth-differentiated risk-coping capability

The *ex post* mechanism in Section 4.2.1 indicates that households not only experience decreased consumption under shocks, but also were inclined to hold precautionary savings in unproductive forms. This sub-section discusses empirical results for both of these situations.

4.5.1.1 Consumption responses to shocks

Table 4.3 summarises household consumption responses to various shocks. Columns (1)-(5) gradually add explanatory variables which are specified in Eq. (4.1).[85] Agricultural asset holdings are insignificant in all columns. Notwithstanding this, one cannot conclude that agriculture assets are not an important means to improve households' well-being. Since the CHNS was not conducted annually, the asset variable $A_{h(t-1)}$ used in regressions is actually households' asset holdings 1-3 years ago depending on the real time interval between surveys. Hence, the impact of agricultural assets on consumption in the subsequent period may have disappeared.

Idiosyncratic income shocks (Row 2) are insignificant in all regressions compared with significant covariate income shocks (Row 20). This may be because wealthier households can more readily protect themselves against idiosyncratic income shocks. Table A1 in Appendix A reports our tests for this. Specifically, the hypothesis of full

[85] The Hausman test prefers fixed effects to random effects in all columns at 1% significance level.

Table 4.3 Household per capita consumption response to shocks

Independent variables	(1)	(2)	(3)	(4)	(5)
1. initial agricultural assets at *t-1*	-0.030 (0.025)	-0.030 (0.025)	-0.030 (0.025)	-0.033 (0.025)	-0.030 (0.025)
Idiosyncratic shocks					
2. hh income shocks	0.015 (0.032)	0.007 (0.048)	0.025 (0.062)	0.003 (0.048)	0.003 (0.048)
3. hh income shock×initial agricultural assets at *t-1*	-0.007 (0.027)	-0.017 (0.028)	-0.017 (0.028)	-0.019 (0.028)	-0.020 (0.028)
4. hh income shock×initial business assets at *t-1*	-0.006 (0.023)	-0.013 (0.023)	-0.012 (0.023)	-0.012 (0.023)	-0.015 (0.023)
5. hh income shock×initial invt in housing at *t-1*	-0.001 (0.010)	0.001 (0.010)	0.001 (0.010)	0.002 (0.010)	0.003 (0.010)
6. hh income shock×initial invt in consumer durables at *t-1*	-0.026 (0.014)*	-0.029 (0.016)*	-0.029 (0.016)*	-0.028 (0.016)*	-0.025 (0.016)
7. hh income shock×initial human capital at *t-1*	0.003 (0.004)	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)
8. no. of ill members in last 4 weeks	0.064 (0.010)***	0.064 (0.010)***	0.064 (0.010)***	0.064 (0.010)***	0.074 (0.011)***
9. no. of ill members in last 4 weeks×initial agricultural assets at *t-1*	0.022 (0.015)	0.022 (0.015)	0.022 (0.015)	0.021 (0.015)	0.019 (0.016)
10. no. of dead members	0.007 (0.023)	0.007 (0.023)	0.006 (0.023)	0.007 (0.023)	0.004 (0.023)
11. no. of dead members×initial agricultural assets at *t-1*	-0.022 (0.033)	-0.020 (0.033)	-0.019 (0.033)	-0.019 (0.033)	-0.016 (0.033)
12. whether have wedding, dowry or funeral expenditure	0.020 (0.014)	0.020 (0.014)	0.020 (0.014)	0.018 (0.014)	0.024 (0.015)
13. whether have wedding, dowry or funeral expenditure×initial agricultural assets at *t-1*	0.013	0.014	0.014	0.013	0.019

	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
14. hh income shock×agricultural assets×agricultural assets below median		0.343 (0.110)***	0.342 (0.110)***	0.342 (0.110)***	0.334 (0.110)***
15. hh income shock×business assets×business assets below median		-0.083 (0.076)	-0.085 (0.076)	-0.083 (0.076)	-0.079 (0.077)
16. hh income shock×invt in housing×invt in housing below median		-0.027 (0.022)	-0.027 (0.022)	-0.026 (0.022)	-0.030 (0.022)
17. hh income shock×invt in consumer durables×invt in consumer durables below median		0.013 (0.024)	0.013 (0.024)	0.012 (0.025)	0.014 (0.025)
18. hh income shock×human capital×human capital below median		0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.003 (0.005)
19. hh income shock×hh income shock below median			-0.035 (0.075)		
Covariate shocks					
20. covariate income shock within the county	-0.102 (0.057)*	-0.104 (0.056)*	-0.102 (0.057)*	-0.088 (0.057)	-0.042 (0.058)
21. covariate income shock×initial agricultural assets at *t-1*	0.031 (0.040)	0.031 (0.040)	0.031 (0.040)	0.037 (0.040)	0.021 (0.041)
22. covariate income shock×initial business assets at *t-1*	-0.032 (0.019)*	-0.031 (0.019)*	-0.031 (0.019)*	-0.030 (0.019)	-0.038 (0.019)**
23. covariate income shock×initial invt in housing at *t-1*	0.010 (0.008)	0.011 (0.008)	0.011 (0.008)	0.009 (0.008)	0.006 (0.008)
24. covariate income shock×initial invt in consumer durables at *t-1*	-0.010 (0.014)	-0.012 (0.014)	-0.012 (0.014)	-0.013 (0.014)	-0.013 (0.014)
25. covariate income shock×initial human capital at *t-1*	-0.009 (0.005)*	-0.009 (0.005)*	-0.009 (0.005)*	-0.009 (0.005)*	-0.009 (0.005)*
26. price shock of agricultural input at *t-1* within the province					-0.994 (0.214)***

27. price shock of agricultural output at *t-1* within the province					0.399 (0.151)***
28. % sown land affected by natural disasters within the province					-0.598 (0.126)***
Demographic characteristics					
29. hh size	-0.088 (0.005)***	-0.089 (0.005)***	-0.089 (0.005)***	-0.088 (0.006)***	-0.088 (0.006)***
30. age of hh head	0.023 (0.001)***	0.023 (0.001)***	0.023 (0.001)***	0.023 (0.001)***	0.019 (0.001)***
31. years of education of hh head	0.024 (0.004)***	0.025 (0.004)***	0.024 (0.004)***	0.025 (0.004)***	0.019 (0.004)***
32. % male adults	0.205 (0.025)***	0.204 (0.025)***	0.204 (0.025)***	0.201 (0.025)***	0.203 (0.025)***
33. dependency ratio	-0.021 (0.026)	-0.019 (0.026)	-0.019 (0.026)	-0.015 (0.026)	-0.018 (0.027)
Labour market access					
34. % local off-farm employment	0.063 (0.022)***	0.065 (0.022)***	0.065 (0.022)***	0.066 (0.022)***	0.062 (0.022)***
35. village out-migration networks				0.304 (0.173)*	0.256 (0.175)
No. of observations	6931	6931	6931	6889	6714
F-test for all $\alpha_h=0$ (*p*-value)	0.000	0.000	0.000	0.000	0.000
R^2	0.174	0.176	0.176	0.177	0.177

Note: ***, ** and * denote 1%, 5% and 10% significance levels. Standard errors are in parentheses.

risk-sharing against idiosyncratic income shocks is significantly rejected for the asset-poor whose agricultural asset holdings are in the lower half of the asset distribution. By comparison, wealthier households' consumption seems to be less affected, but tends to suffer relatively more from covariate income shocks.

The consumption for those possessing more durable goods is less sensitive to idiosyncratic income shocks (Row 6). Given the positive relation between consumer durables and household total wealth found by Park and Ren (2001), this lends support to the above argument that wealthier households are better able to smooth consumption when experiencing the same size of negative income shocks. Agricultural assets appear to be particularly crucial for households in coping with negative idiosyncratic income shocks (Row 14). The asset-poor whose agricultural asset holdings are less than the median would suffer further consumption shortfalls under the same degrees of negative idiosyncratic income shocks. Among other household-specific events, only illness significantly increases expenditure (Row 8-13), which is predictable given long absence of health and medical insurance for rural households.

Covariate income shocks bring substantial consumption shortfalls (Row 20). The estimates are significant and negative in the first 3 columns. Negative coefficients for interaction terms between covariate income shocks and business assets (Row 22) and human capital (Row 25) suggest that those with more business assets and human capital tend to undergo a greater decrease in consumption. This may be partly due to the fact that households with more human capital are engaged in more businesses that may suffer during an economic recession. Another reason may be that these households can afford to cut more consumption in the short term in order to maintain their longer term production.[86]

Consistent with previous studies (e.g., Dercon, 2006; Minten and Barrett, 2008), poorly functioning markets represented by agricultural input and output price shocks (Rows 26-27) have a substantial impact on household consumption with predicted signs. They even dominate the effect of covariate income shocks, as the coefficient of the latter becomes insignificant in Column (5). Weather shocks (Row 28) also substantially reduce consumption; more importantly, their negative effects could continue over at least 3 to 4 years. To see this, following Dercon (2004), we replaced the variable of natural disasters at *t* with those which occurred several years previously. The coefficient declines marginally to -0.27, indicating that a short-lived shock is likely to influence households' welfare in at least the medium term.

The above discussion of the estimates confirms one implication of the *ex-post* mechanism, namely that negative shocks cut back consumption. Households' capability for consumption smoothing appears to be wealth-differentiated.

4.5.1.2 Precautionary motives

As stated in Section 4.2.1, the other implication of the *ex post* mechanism points to holding precautionary savings as a coping means for negative shocks. This is examined by using the second estimated consumption regression presented in

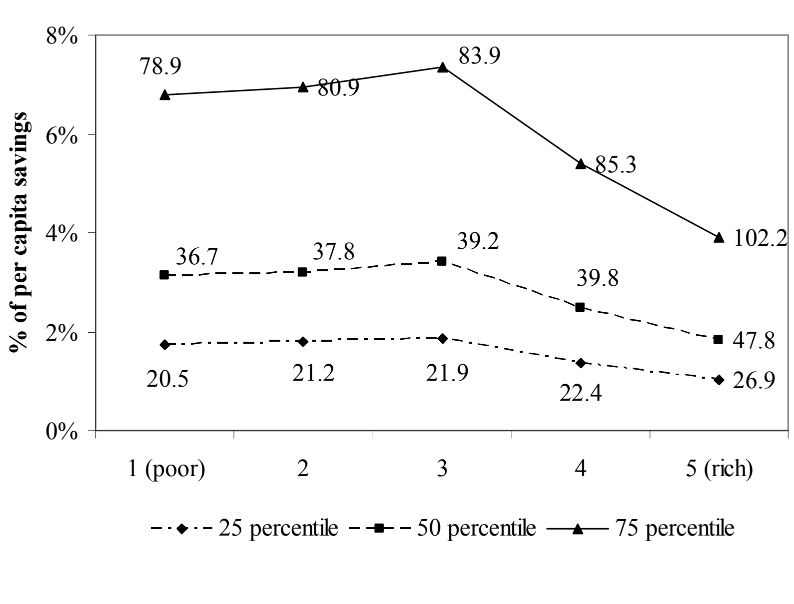
[86] We compare households' real consumption between those with more and less human capital (business assets) than the median in each year. The former group's consumption is on average 46 (12) percent higher relative to the latter. Thus, it seems safe to argue here that households with more human capital and business assets are more capable of sacrificing some of their consumption to sustain production. As a result, real per capita permanent income for those possessing more human capital (business assets) than the median is 27 (6) percent higher than that of those below the median.

Column 2 of Table 4.3 to simulate per capita unproductive precautionary savings under various idiosyncratic and covariate income shocks. Columns (1), (3) and (5) are not used because either not all explanatory variables are in the regression or some key variables are not statistically significant (e.g., (household-specific income shocks×below the median) in Column (3) and covariate income shocks in Column (5)). Following Giles and Yoo (2007), we use estimates in Column 2 to calculate per capita precautionary savings as (Coef.)×different levels of income shocks. Households' per capita savings are derived by subtracting per capita income by per capita consumption. The ratio of per capita precautionary savings over per capita total savings measures the degrees of households' precautionary motives (as shown in Fig. 4.9).

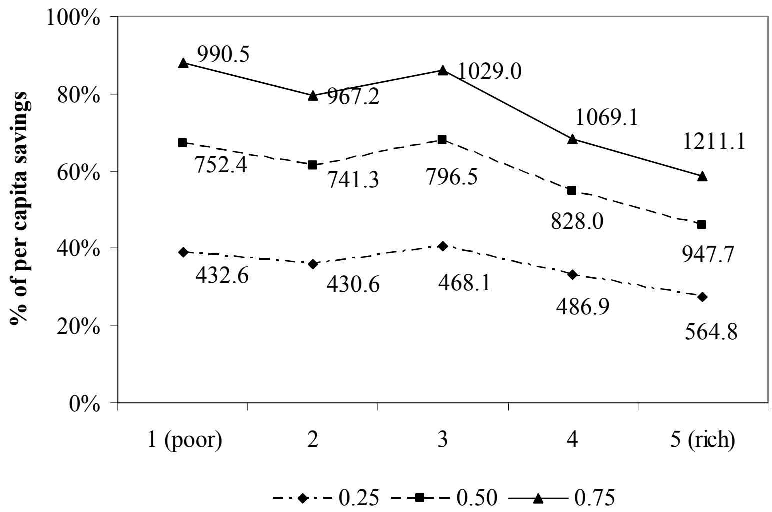
In general, results reaffirm Jalan and Ravallion's (2001) finding of an inverted-*U* relationship between households' wealth, which is represented by their per capita permanent income, and per capita unproductive precautionary savings (Fig. 4.9).

Figure 4.9 Simulated households' per capita unproductive precautionary savings in response to income shocks (by quintile)

(a) Behavioural responses to negative individual income shocks



(b) Behavioural responses to negative covariate income shocks



Note: a. The dots denote proportions of per capita precautionary savings in total per capita savings for each income quintile. The figures along the lines are absolute values of precautionary savings in 2006 prices.

b. Quintiles are based on households' per capita permanent income and sorted in ascending sequence.

Under all three levels of idiosyncratic income shocks, the share of precautionary savings in households' total savings increases from the 1st to the 3rd quintile but decreases as households become much richer. Poorer households tend to have relatively more savings in unproductive forms to protect themselves from negative shocks, but wealthier households may not need to do so. Similar behaviour can also be found when covariate income shocks occur. In both idiosyncratic and covariate cases, the greater the income shocks, the more precautionary savings households hold, in terms of percentages of total savings as well as real monetary values.[87]

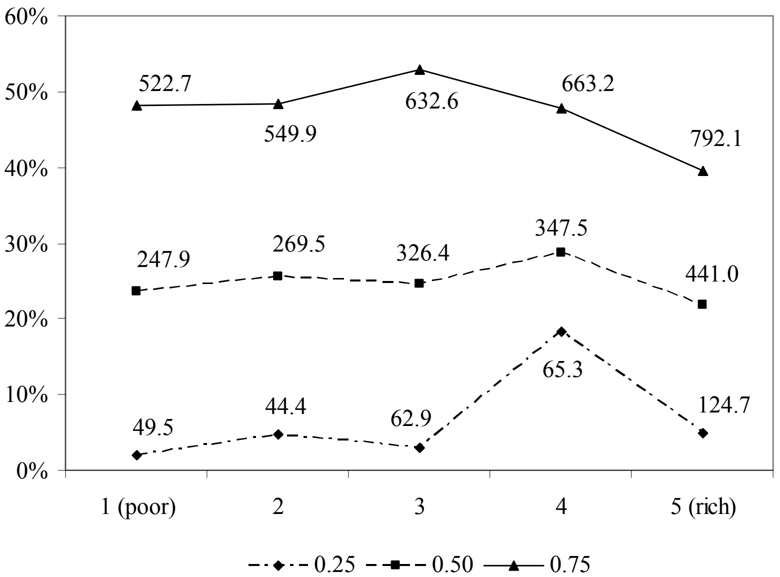
[87] Our simulation of precautionary savings should be treated as a lower bound of the real value as it does not consider the impact of households' concern over limited access to credits. In fact, Lee and Swada (2010) find that, in the case of rural Pakistan, the strong motive for precautionary savings is also tied with household liquidity constraints. Taking this into account, households' real precautionary motives might be stronger than our simulation results.

When comparing the impact of covariate and idiosyncratic income shocks, covariate uncertainties pushes households to save more than do the idiosyncratic ones. Furthermore, as mentioned by Giles and Yoo (2007), the monetary values of precautionary savings are also quantitatively meaningful. For example, the net profit in 2005 for grain crops per *mu* was 124.4 *yuan*.[88] This means that if 25 percent of population within the county experienced income shortfalls, i.e., 0.25 covariate income shocks, average households would preserve 432.6 *yuan* as precautionary savings, which is equivalent to the net profits from 4 out of the 14 *mu* of cultivated land owned by an average household. Clearly, strong precautionary motives cause inefficient resource allocation.

However, out-migration networks could provide safety to households so that they may reduce precautionary savings (Giles and Yoo, 2007). Supposing there were 20 percent of the village who had migrated outwards (i.e., 0.2 value for the out-migration networks), we simulated precautionary savings again based on Column 4. Comparing these new results in Fig. 4.10 with Fig. 4.9 shows that households' per capita precautionary savings dramatically falling by around a half under 0.75 covariate income shocks (from 990.5 to 522.7 *yuan*) and 89 percent under 0.25 covariate income shocks (from 432.6 to 49.5 *yuan*).[89]

[88] Mu is the Chinese measurement unit for land, 1 mu≈666.67 m^2. The figure is the national average value in 2006 prices. Author's calculations based on data from China Agricultural Yearbook (2006) and China Statistical Yearbook (2009).
[89] The simulations based on idiosyncratic income shocks are not shown, as most of households no longer tend to hold precautionary savings under the 25th and 50th percentile of shocks.

Figure 4.10 Predicted effects of out-migration networks on unproductive precautionary savings



Note: a. The dots denote proportions of per capita precautionary savings in total per capita savings for each income quintile. The figures along the lines are absolute values of precautionary savings in 2006 prices.

b. Quintiles are based on households' per capita permanent income and sorted in ascending sequence.

The simulation exercise confirms the *ex post* behavioural responses of holding unproductive liquid wealth under shocks. Such substantial precautionary savings may well hamper households' future productive investment, which will be tested directly in the following *ex ante* mechanism.

4.5.2 Household wealth-differentiated risk-mitigating capability

This sub-section concentrates on households' risk management were there to be negative income shocks. In the spirit of Dercon and Christiaesen (2010), we calibrate three cases. Case (a) assumes that every household receives the 25th percentile of a negative idiosyncratic income shock and 0.25 covariate income shock in each year. Case (b) simply employs the empirical distribution of idiosyncratic and covariate income shocks. Case (c) also makes use of the empirical distribution of income shocks but in order to emphasise greater downside risk, the observed idiosyncratic income shocks are right-truncated at the median of all negative ones. That is, all idiosyncratic income shocks above this median take the value of zero. Similarly, the covariate income shocks are also right-truncated at their median.

Based on these three cases, we draw upon counterfactual simulations to obtain two kinds of downside risk: low consumption outcomes and substantially unproductive precautionary savings. The risk of low welfare consequences is measured by predicted counterfactual log per capita consumption in Case (a) and predicted probability weighted mean log per capita consumption in Cases (b) and (c). The risk of inefficient resource allocation is indicated by predicted log per capita unproductive precautionary savings as responses to relevant idiosyncratic and covariate income shocks in the three cases. Using predicted values in the above simulations helps to obviate measurement errors in consumption (Dercon and Christiaesen, 2010).

Table 4.4 summarises households' *ex ante* risk-taking in agricultural production.[90] The discussion focuses on Case (a), while the levels of income shocks in Cases (b) and (c) are referred for comparison and/or robustness checks.

[90] Estimates of linear probability models are not reported. They are similar to conditional fixed-effects logit models. Models including price shocks, natural disasters, illness, death and weddings are not reported, because, strictly speaking, they are *shocks* rather than potential *risk*. However, including them does not fundamentally change our conclusions.

4.5.2.1 Working capital-related credit and liquidity constraints

The coefficient of initial agricultural assets is significantly negative in all cases (Row 1). This indicates that facing more *ex ante* costs of agricultural production, households would be less willing to invest in the subsequent period.[91] However, our calculations of marginal effects reported in Appendix B suggest an unequal spread of this probability-reducing influence across households.[92] The average marginal probability-reducing effect across all households is 23 percent in Case (a). Since we cannot multiply this by available credits to the household, the estimate should be treated as an upper bound of working capital-related credit and liquidity constraints.

The binding credit and liquidity constraints are also supported by the existing literature. From the supply side, rural households have access to limited amounts and types of both formal financial credit (Dong and Featherstone, 2006) and formal and informal consumption insurance (Giles, 2006). In ten representative provinces, 71 percent of rural households face credit constraints (Rui and Xi, 2010). Even when limited formal financial credits (mainly Rural Credit Cooperatives) are available, they lack efficiencies and incur risk (Dong and Featherstone, 2006). Although some households may obtain informal loans, they are mainly used to cope with unexpected shocks rather than productive investment (de Brauw and Rozelle, 2008a). From the demand side, in the period of 1985-2006, on average 78 percent of household expenditure on production takes the form of cash (Fig. A1 in Appendix A), but agricultural assets are neither as easy nor as efficient to liquidate as might be

[91] If not censoring the model at zero growth rates, negative coefficients of lagged assets indicate the catch-up effects of those initially lagging behind in terms of asset stocks. We also estimate the fixed-effects models without left-censoring. The coefficients are insignificant in all three cases. This finding rejects the conditional convergence of agricultural assets and is consistent with multiple-equilibrium dynamics illustrated by Fig. 4.8.

[92] See Fig. A4 in Appendix A for the distribution of marginal effects.

Table 4.4 The correlates of agricultural asset growth

Independent variables	Case (a) The 25th percentile negative hh idiosyncratic income shock			Case (b) Probability weighted (without truncation)			Case (c) Probability weighted (with truncation)		
	Cond. FE Logit (1)	Honoré FE Tobit (2)	Std. RE Tobit (3)	Cond. FE Logit (4)	Honoré FE Tobit (5)	Std. RE Tobit (6)	Cond. FE Logit (7)	Honoré FE Tobit (8)	Std. RE Tobit (9)
1. hh agricultural assets at *t-1*	-2.054 (0.561)***	-0.146 (0.046)***	-0.340 (0.164)**	-50.921 (6.910)***	-1.239 (0.684)*	-15.232 (2.403)***	-1.838 (0.292)***	-0.146 (0.039)***	-0.466 (0.098)***
2. ln(per capita counterfactual cons.)	1.754 (0.809)**	0.143 (0.048)***	-0.023 (0.054)	-24.675 (4.066)***	-1.460 (0.277)***	-0.175 (0.064)***	-0.152 (0.061)**	-0.011 (0.004)***	-0.032 (0.021)
3. ln(per capita counterfactual cons.)×% village out-migration at *t-1*	2.120 (1.044)**	0.065 (0.069)	0.615 (0.330)*	0.781 (1.182)	0.060 (0.061)	-0.017 (0.376)	-3.787 (3.323)	-0.110 (0.261)	-1.911 (1.192)
4. ln(per capita counterfactual cons.)×agri. assets at *t-1*	0.226 (0.223)	-0.016 (0.022)	-0.017 (0.064)	20.312 (2.850)***	0.462 (0.293)	6.121 (0.990)***	0.045 (0.072)	0.004 (0.007)	0.011 (0.026)
5. ln(per capita counterfactual cons.)×agri. assets×agri. assets below median	-1.293 (0.165)***	-0.072 (0.008)***	-0.271 (0.045)***	-1.273 (0.172)***	-0.071 (0.010)***	-0.292 (0.049)***	-1.061 (0.326)***	-0.069 (0.013)***	-0.311 (0.109)***
6. ln(per capita precautionary savings responding to hh income shocks)	-0.174 (0.044)***	-0.007 (0.003)	-0.042 (0.012)***	-0.039 (0.042)	0.003 (0.002)	0.020 (0.014)	-0.126 (0.033)***	-0.0004 (0.002)	-0.011 (0.012)
7. ln(per capita precautionary savings responding to hh income shocks)×agri. assets at *t-1*	0.439 (0.054)***	0.012 (0.006)**	0.121 (0.018)***	0.238 (0.054)***	0.013 (0.006)**	0.064 (0.020)***	0.186 (0.044)***	0.017 (0.005)***	0.060 (0.018)***
8. ln(per capita precautionary savings responding to	-0.179	-0.006	-0.086	-0.189	-0.008	-0.126	-0.359	-0.018	-0.165

covariate income shocks)	(0.101)*	(0.006)	(0.025)***	(0.112)	(0.007)	(0.028)***	(0.097)***	(0.009)**	(0.023)***
9. ln(per capita precautionary savings responding to covariate income shocks)×agri. assets at *t-1*	0.157 (0.099)	0.032 (0.011)***	0.042 (0.032)	0.288 (0.110)***	0.037 (0.014)**	0.052 (0.036)	0.547 (0.087)***	0.045 (0.012)***	0.140 (0.030)***
10. hh size	0.229 (0.083)***	0.017 (0.005)***	0.004 (0.010)	0.090 (0.052)*	0.004 (0.003)	0.028 (0.011)***	0.153 (0.046)***	0.009 (0.003)***	0.020 (0.010)**
11. age of hh head	-0.085 (0.021)***	-0.007 (0.001)***	-0.004 (0.001)***	-0.013 (0.014)	-0.001 (0.001)	-0.004 (0.002)**	-0.058 (0.010)***	-0.005 (0.001)***	-0.005 (0.001)***
12. years of education of hh head	-0.126 (0.039)***	-0.012 (0.003)***	-0.005 (0.005)	-0.008 (0.044)	-0.001 (0.003)	-0.005 (0.005)	-0.087 (0.036)**	-0.008 (0.003)***	-0.003 (0.005)
13. % male adults	-0.004 (0.249)	-0.011 (0.014)	0.110 (0.046)**	0.348 (0.223)	0.015 (0.016)	0.142 (0.053)***	0.388 (0.198)**	0.019 (0.013)	0.057 (0.048)
14. dependency ratio	-0.143 (0.209)	-0.010 (0.012)	-0.024 (0.056)	-0.419 (0.258)	-0.026 (0.015)*	-0.033 (0.066)	-0.312 (0.219)	-0.019 (0.015)	0.032 (0.063)
15. % local off-farm employment	0.387 (0.173)**	-0.005 (0.009)	0.248 (0.050)***	-0.114 (0.213)	-0.025 (0.013)*	0.312 (0.058)***	0.304 (0.169)*	0.010 (0.009)	0.241 (0.052)***
16. whether a specialized farm hh (yes=1)	0.458 (0.103)***	0.034 (0.006)***	0.168 (0.032)***	-0.053 (0.128)	0.002 (0.008)	0.155 (0.035)***	0.200 (0.097)**	0.020 (0.006)***	0.080 (0.032)**
17. land-on farm labour ratio	-0.064 (0.033)*	-0.002 (0.002)	-0.028 (0.010)***	-0.013 (0.034)	0.0002 (0.001)	-0.019 (0.012)	-0.004 (0.030)	0.001 (0.003)	-0.015 (0.012)
Pseudo R^2	0.208			0.209			0.132		
Prob.>ChiSq.		0.00	0.00		0.00	0.00		0.00	0.00

Note: a. In the fixed-effects tobit model, the objective function is minimised by estimators taking the form of the absolute error loss in Honoré (1992).
b. Standard errors are in parentheses and those for Honoré's (1992) fixed-effects probit models are estimated by 300 bootstraps.
c. ***, ** and * denote 1%, 5% and 10% significance levels.

thought.[93] In sum, the greater working capital-related credit and liquidity constraints, the less investment in agricultural asset accumulation would a household undertake.

Before continuing, it is noticeable that the magnitude of the coefficients varies to a large extent across the three cases. When more weight is given to downside risk (Case (b)), households are particularly reluctant to increase accumulation. Nevertheless, so far as greater negative income shocks are concerned (Case (c)), households' accumulation decisions are less likely to be influenced than in Case (b). The reason might be that households have to protect the fewer assets on which their minimum livelihood depends, although extremely hard times are expected.

4.5.2.2 The risk of a low consumption outcome

As predicted, the coefficient of counterfactual consumption (Row 2) is significantly positive in Case (a). This implies that when negative income shocks are anticipated, the lower the counterfactual consumption level, the less would households invest in agricultural asset accumulation. Households' reduced capacity for accumulation may be due to their lower permanent income, fewer total wealth or poorer quality land. Such less favourable endowments make households less able to resist income losses and therefore see relatively lower counterfactual consumption (Dercon and Christiaesen, 2010).

However, when more weights are assigned to downside risk in Case (b) and (c), the coefficients of counterfactual consumption become significantly negative, indicating

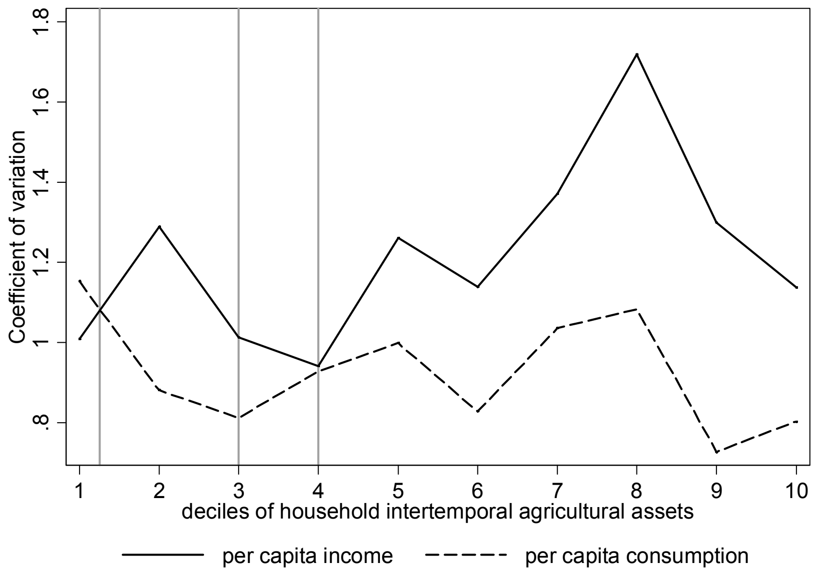
[93] One reason lies in limited channels of liquidation. A more important reason could be that if many households sell productive assets under shocks, the prices would decrease so that the returns would be insufficient to cope with shocks (Dercon, 1998).

that households are more inclined to accumulate when facing greater risk of low welfare.

The existing literature offers two possible reasons for the above seemingly contradictory estimates of the coefficient of counterfactual consumption. One reason that has been identified (in rural Zimbabwe in Hoddinott, 2006; northern Kenya in Barrett *et al.*, 2006; and Ethiopia and Honduras in Carter *et al.*, 2007) is that the poorest households have to safeguard fewer productive assets on which their subsistence depends (Carter *et al.*, 2007; Zimmerman and Carter, 2003). The other explanation offered refers to a two-way effect between wealth dynamics and risk-taking behaviour. Lybbert and Barrett's (2010) model shows that there is a reverse effect of a dynamic asset threshold on household risk-taking behaviour. They find that those at, or slightly above, the asset bifurcation level may face a greater probability of getting trapped into the low equilibrium under risk should income losses occur. Therefore, perceiving this impending danger of backsliding, these not-so-poor households may prefer a conservative investment strategy.

Our data lend support to both explanations. To see this, following Barrett *et al.* (2006), we compute coefficients of variation in income and consumption (Fig. 4.11). The overall pattern of risk management is that wealthier households smooth consumption more effectively and undertake more risky production than poorer households. On the one hand, the poorest 12.5 percent have larger consumption variability compared with income, implying asset smoothing at the cost of variable consumption particularly in consumer durables, medical and insurance expenditures, but rarely food.[94] They are unwilling to stake survival as it is at least better than starvation (Fafchamps, 2003). On the other hand, income volatility for those lying between the 30th and 40th percentile of asset distribution decreases as households become wealthier, while consumption volatility increases. This movement suggests that the not-so-poor who are perhaps near the bifurcation point might be asset smoothers rather than consumption smoothers.[95]

Figure 4.11 Wealth-differentiated risk management, 1989-2006



The above analysis reveals that a household's position in the wealth distribution could influence its risk-taking behaviour. In addition to this, the magnitude of risk also matters. It can be seen from Columns (4)-(9) that the absolute magnitudes of the estimated coefficients are much smaller in all the model specifications in Case (c) than in (b). The accumulation decisions for those who are equivalently poor/rich seem to be less influenced when the greatest downside risk is expected. Both poor

[94] For the lowest decile, the coefficients of variation of per capita expenditure on medical and health insurance and consumer durables are 8 and 3 times as high as that of per capita total consumption expenditure. By comparison, the coefficient of variation of food consumption is basically the same as that of per capita total consumption expenditure.

[95] In Fig. 4.11, the richest 10 percent of households also appear to be asset smoothers as their income volatility decreases and consumption volatility increases. However, they are less of our concern, considering that their consumption is not easy to fall below the poverty line.

and rich households would have to protect the, perhaps minimal, agricultural assets which allow them to survive if something catastrophic were to take place.

It should be noted that the asset-defending behaviour for some households by no means assures them of a leap to a high equilibrium because of the structure of household expenditure. Apart from spending on production, money is largely used for living and over half of the living expenditure goes on food (Fig. A3 in Appendix A). This implies rigidity in further reducing consumption to support production. Therefore, facing possible low-equilibrium traps, the foregone consumption is more of a short-term palliative in favour of preserving crucial assets than a long-term feasible means for escaping from poverty.

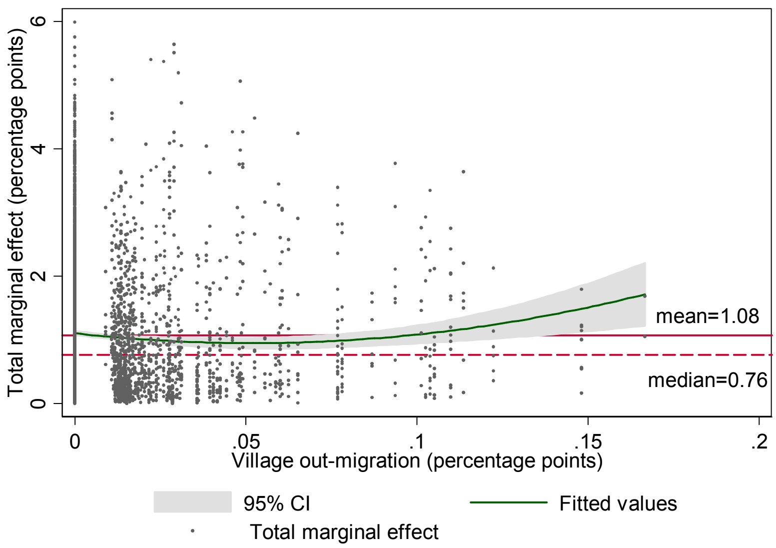
As with ameliorating factors, both out-migration and agricultural asset holdings are likely to alleviate the negative impact of low consumption outcomes on productive investment, which is indicated by positive signs on the interaction terms $c_{ht} \cdot m_{v(t-1)}$ and $c_{ht} \cdot A_{h(t-1)}$ (Rows 3-4).[96] We further calculate household-specific marginal effects of out-migration and agricultural asset holdings in Appendix B.

Specifically, Fig. 4.12 calculates the total marginal effect of out-migration, including both direct and indirect effects through the interaction term $c_{ht} \cdot m_{v(t-1)}$. In Case (a), the more village out-migration, the more likely households would undertake accumulation (Fig. 4.12). On average, an additional 10 percent of village-level out-

[96] We also discover whether out-migration networks help with mitigating weather and price risks by including interactions between the village share out-migration at *t-1* and the sown areas affected by natural disasters and the price shocks of agricultural input and output. Out-migration can counter the impact of price risk in the case of the 25th percentile and mitigate weather risk in two cases of probability weighted mean.

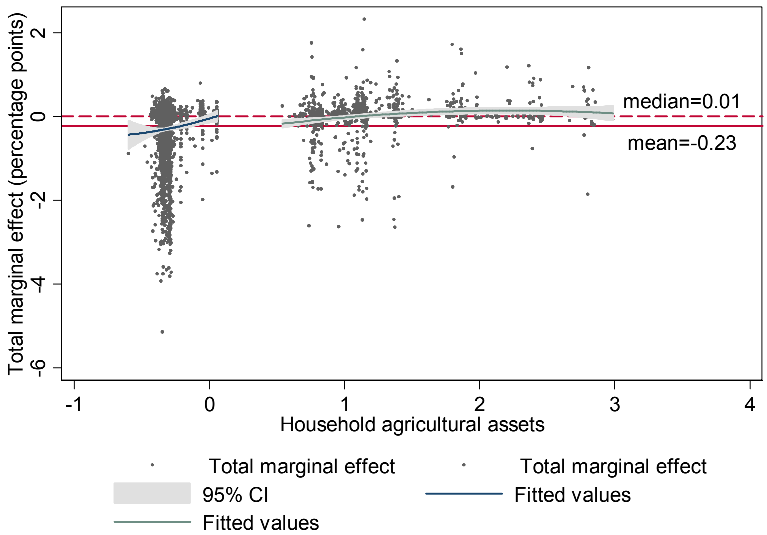
migration could double the probability of asset accumulation. Moreover, out-migration helps households dampen their loss-aversion under the risk of low consumption. To see this, we further calculate the full partial derivatives of $c_{ht} \cdot m_{v(t-1)}$ for each household which indicate how village out-migration affects the effect of low consumption on accumulation decisions. The calculations show that many of the interaction effects are positive and increase as more out-migration occurs in the village. This suggests that although the risk of low consumption would result in low probability of asset accumulation as revealed by the positive coefficient in Row 2 of Table 4.4, a greater share of village out-migration population appears to raise households' probability of undertaking asset accumulation in the presence of fear for the risk of failures in production in the future. Across all households, an additional 10 percent of more village population in out-migration increases the estimated impact of low consumption on probability of accumulation by 68 percent.

Figure 4.12 Total marginal effect of village out-migration on the probability of asset accumulation, Case (a)



With respect to the impact of agricultural asset holdings, Fig. 4.13 draws the total marginal effect of households' agricultural asset holdings at the time of making accumulation decisions. The general pattern, represented by the fitted line, is that the more the asset holdings, the higher the probability of undertaking accumulation. However, again, the total marginal effects are unequally distributed across households. For example, on average, a 10 percent increase in agricultural asset holdings decreases 25 percent more to the probability of accumulation. In comparison, the median total marginal effect remains positive, but the magnitude is only 1 percent.

Figure 4.13 Total marginal effect of agricultural assets on the probability of asset accumulation, Case (a)



These unequal total marginal effects of assets play a role through both direct and indirect channels. As discussed in Section 4.5.2.1, assets in hand at the time of decision-making could be a proxy for the *ex ante* working-capital constraints and, therefore, directly restrict households from accumulation in the subsequent production period, especially those with limited loans and credits. It can be seen from

Fig. 4.13 that many households at the bottom of asset distribution, who are more likely to face credit constraints and find difficulties in obtaining loans, experience much greater negative total marginal effects of agricultural asset holdings than those wealthier households. However, at the same time, asset holdings at the time of decision-making also positively influence subsequent accumulation by an indirect manner, which is captured by the interaction term $c_{ht} \cdot A_{h(t-1)}$. According to the formulas in Appendix B, we calculate this interaction effect for each household, which is indicative of how the level of agricultural asset holdings affects the impact of possibly low consumption on the incidence of accumulation. In general, we find that more agricultural assets can help households resist from the fear of possible low consumption. A 10 percent of increase in agricultural assets raises the impact of possibly low consumption on the probability of accumulation by 3.4 percent.

Nonetheless, under the anticipation of catastrophic income losses, asset holdings take over the role of out-migration (Rows 3-4 in Cases (b) and (c)): perceiving the same levels of counterfactual consumption, those with more assets tend to maintain their investment.

Although the significance of the impact of agricultural assets depends on the magnitude of the risk, owning fewer assets than the median ($I_{ht} = 1$) does, in all cases, significantly reduce the probability that households will decide to accumulate (Row 5). We also calculate the impact of $I_{ht} = 1$ on the accumulation-increasing effect of household asset holdings. All these trivariate interaction effects are negative, indicating that under the same level of downside consumption risk, having less agricultural asset than the median weakens households' investment incentives. The less the asset, the greater this negative influence would be. On average, the positive influence of asset holdings at the time of decision-making on undertaking subsequent accumulation (i.e., the interaction effect $c_{ht} \cdot A_{h(t-1)}$) could be reduced by 50 percent if the household falls in the bottom half of asset distribution.

4.5.2.3 Risk of substantially unproductive precautionary savings

Our analysis reveals an 'implied risk premium for self-insurance strategies' in risk mitigation (Barnett *et al.*, 2008). Holding precautionary savings as a self-insurance strategy should idiosyncratic and/or covariate income shocks occur is at the cost of higher expected income, namely reduced investment in agricultural asset accumulation (Rows 6 and 8).[97] Fig. 4.14 depicts the total marginal effects of having precautionary savings on the probability of asset accumulation. As can be seen in Fig. 4.14(a), for those with relative limited assets, holding precautionary savings as a response to household idiosyncratic income shocks reduces the probability of undertaking asset accumulation, while wealthier households seem to be less influenced as the many become to experience positive total marginal effects. This phenomenon is also revealed by the positive estimate of $p_{ht}^{iinc.} \cdot A_{h(t-1)}$ (Rows 7 of Table 4.4). The calculation of this interaction effect suggests that, in the presence of idiosyncratic income shocks, having 10 percent more assets alleviates the probability-reducing impact of precautionary savings on accumulation by 8.5 percent.

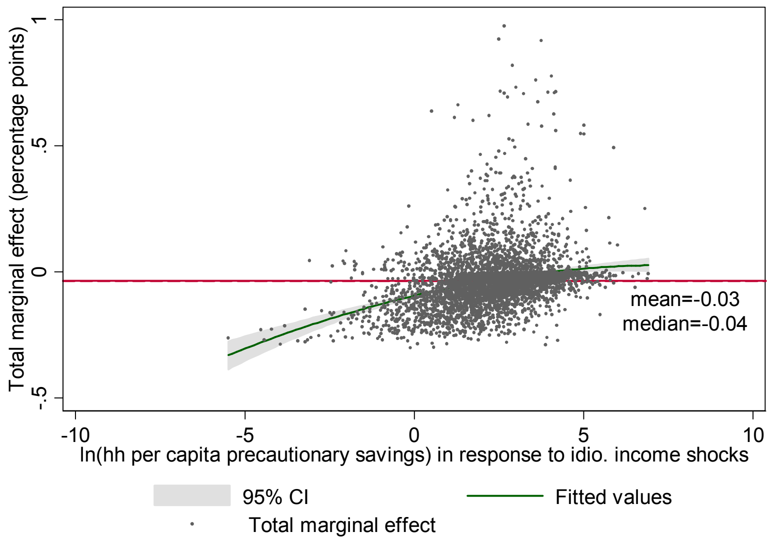
However, under covariate income shocks, all households tend to suffer from reduced probability of asset accumulation (Fig. 4.14b). More agricultural assets seem to be

[97] It can be plausibly argued that the real negative impact of strong precautionary motives is more than that revealed by our estimates because rural households would have greater prudence when faced with liquidity constraints (Lee and Swada, 2010).

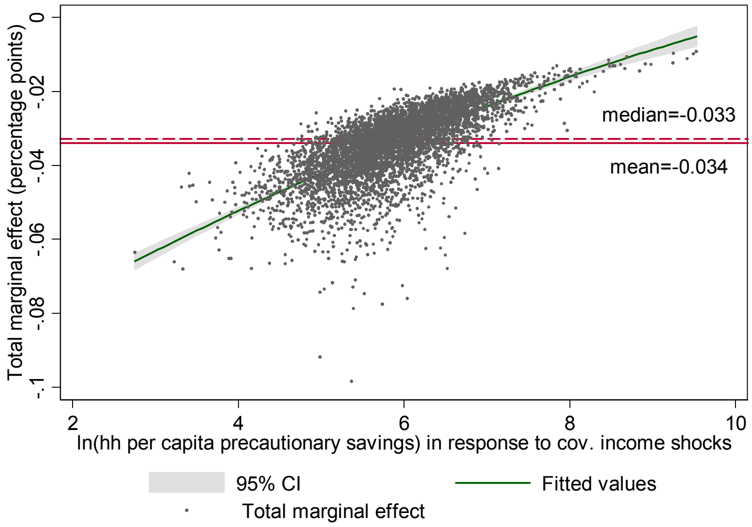
able to push households to undertake accumulation even under covariate income shocks and substantial precautionary savings (Row 9 of Table 4.4). However, the interaction effect ($p_{ht}^{cinc.} \cdot A_{h(t-1)}$) is negative for those at the bottom of asset distribution, but turns to be positive for those who are wealthier. This implies that the asset-poor will suffer a further reduction in the probability of accumulation in addition to the negative impact of precautionary savings on investment, since they are more likely to be constrained by the lack of credit. On average across all households, having 10 percent more assets only alleviates the probability-reducing impact of precautionary savings on accumulation by 1.4 percent.

Figure 4.14 Total marginal effects of precautionary savings on the probability of asset accumulation, Case (a)

(a) Precautionary savings under household idiosyncratic income shocks



(b) Precautionary savings under covariate income shocks



4.5.2.4 Factors facilitating accumulation

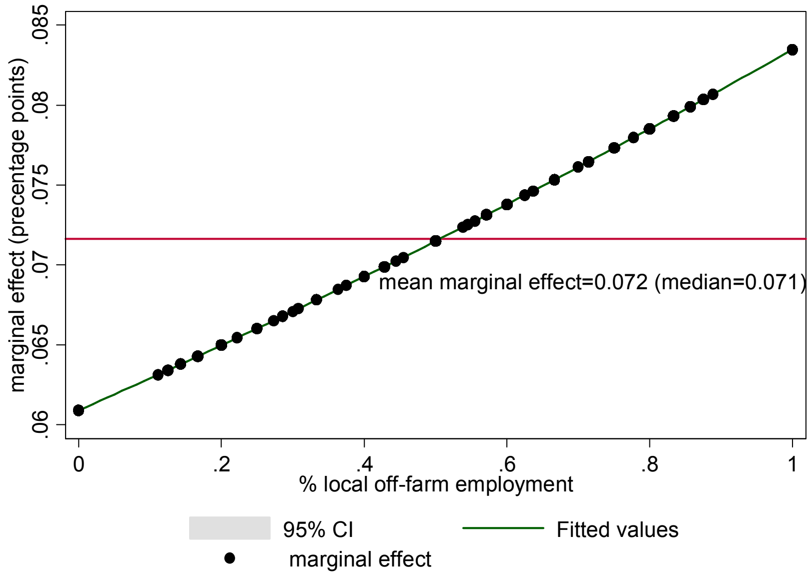
Local off-farm employment is positively related to asset growth in most of the regressions (Row 15).[98] Considering Case (a), we calculate the household-specific marginal effects of local off-farm employment, as shown in Fig. 4.15, and average them across all households to obtain the mean impact. Clearly, the marginal effect increases as more household members have off-farm jobs. On average, an extra 10 percent of off-farm employment raises the probability of accumulation by 7.1 percent.

Specialised farm households (those whose farm sizes are more than 20 *mu*[99]) are more likely to invest in agricultural assets (Row 16). The reason is quite straightforward: a larger farm size may allow households to diversify into different crops, which could help them to resist the potential production risk. However, this

[98] The only exception is Column (5) where local off-farm employment has a negative sign.
[99] Although farm land is distributed according to family size in rural China, some households 'chose to rent their land, negotiate share-cropping arrangements or lend their land to kinsmen or neighbours who agreed to assume responsibility for the contract grain quota' (de Janvry *et al.*, 2005). This allows some households to participate in more non-farm activities, while others specialise in farming.

mechanism seems not to work well if more downside risk is anticipated, as the estimated coefficients become insignificant in Cases (b) and (c).

Figure 4.15 The estimated marginal effect of local off-farm employment, Case (a)



The land-(on farm) labour ratio is significantly negative in Case (a) (Row 17), meaning that a higher land-labour ratio may reduce a household's incentives to accumulate. As a higher land-labour ratio implies relatively less labour has been used in farming under decreasing marginal returns, this negative estimated coefficient of land-labour ratio indicates that households would prefer to use agricultural labour to substitute for assets, as far as comparative advantage of agricultural labour is concerned (Dercon and Christiaesen, 2010). Nevertheless, this choice is unequally distributed[100] and disappears in Cases (b) and (c) where more downside risk is introduced.

Before concluding, it is helpful to know that in addition to identified marginal effects of various growth correlates on the *probability* of accumulation, our analysis

[100] See Fig. A4 for the distribution of marginal effects.

nevertheless does not exclude the possibility that these variables may change the *magnitude* of asset growth. In fact, the probability and magnitude effects co-exist, although the former appears to dominate the latter.[101] If the 25th percentile of negative idiosyncratic incomes were to be realised, our results of McDonald and Moffitt (1980) decomposition show that 78 percent of the investment-response would be due to changes in the probability of asset creation, while only 22 percent could be ascribable to the changes in the magnitude of growth rates among those having already accumulated.

In sum, the analysis in Section 4.5.2 suggests that households' limited means to mitigate risk dampen their willingness to invest in agricultural asset accumulation and therefore lead to a low income equilibrium. More alarmingly, as warned by Dercon (2006, 2009), micro-level income losses due to deficient and inefficient investment might be transferred to lower growth at the macro-level if there are many rural households confronting such situations. In fact, China's agricultural sector saw an average growth rate of 7.5 percent in 1980-1985 (Ravallion, 2009), of which 48.64 percent stemmed from the shift from the collective production-team system to the Household Responsibility System (RHS) and 45.79 percent resulted from increases in inputs, such as fertiliser (Lin, 1992). However, since the RHS reform was completed in 1983-1984, agricultural output growth has dropped to under 4 percent (Ravallion, 2009), which could be largely due to the sharp decline in the growth rate of fertiliser usage (Lin, 1992). This may significantly handicap poverty

[101] To see this, we apply McDonald and Moffitt's (1980) decomposition to random-effects tobit models (Eq. 4.2 and 4.3). The average marginal effect of the *j*th independent variable on asset growth is calculated as the aggregate effect of the probability of deciding to accumulate and the magnitude of accumulation for those having undertaken accumulation. The proportion of probability and magnitude effects in total marginal effects are $1 - z\left[\frac{\phi(z)}{\Phi(z)}\right] - \left[\frac{\phi(z)}{\Phi(z)}\right]^2$ and $\Phi(z)$, respectively, where z is a vector including all independent variables.

reduction in rural China given the appreciable poverty-alleviating effect of productivity growth in smallholder agriculture (Ravallion and Chen, 2007; Huang *et al.*, 2008; Montalvo and Ravallion, 2010; Christiaensen *et al.*, 2010).

4.6 Concluding remarks

This chapter presents an examination of risk-induced persistent poverty in rural China, stressing the impact of households' behavioural responses to uninsured shocks and risk on their agricultural asset accumulation. We make three points below indicating some possible policy implications of our findings.

First, in the presence of negative income shocks, households' consumption declines and they tend to hold substantial precautionary savings which could be as high as 85 percent of their total savings. Both risks of low consumption and holding precautionary savings reduce the growth rates of agricultural assets. There is evidence that under credit and liquidity constraints and low insurance, the asset-poor's limited ability to cope with and mitigate shocks and risk could reduce their investment in profitable agricultural asset accumulation. This could force them to sink into a low equilibrium of asset holdings, which generates lower income. Consequently, they are more likely to suffer prolonged hardship. As warned by Dercon (2009), these micro-level income losses might add up and contribute to macro-level reduced growth, which could slow down overall poverty reduction.

Second, results emphasise the importance of establishing productive safety nets to promote households' self-reinforcing growth by asset accumulation via steady investment.

Third, the safety net policy should not only consider the magnitude of adverse shocks, but also pay attention to households' asset position after a shock, and their risk management, in order to protect households from downward mobility (Elbers *et al.*, 2007). In terms of specific policies, it would therefore seem to be desirable to provide formal financial credit and insurance for the poor. More importantly, given the usual difficulties in providing safety nets for the poor in difficult times (Clarke and Dercon, 2009), the government could better facilitate rural-urban labour mobility and develop local enterprises in order to increase the scope of out-migration networks and the possibilities of local off-farm employment. These two factors could make the poor more capable of self-protecting and self-financing and, at the same time, improve allocative efficiencies by weakening households' precautionary incentives.

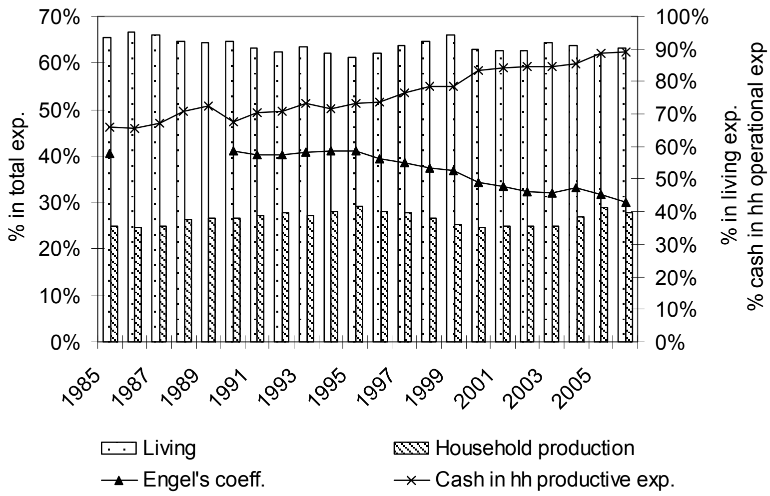
Although it has been shown that risk could trap households in a low equilibrium via their behavioural responses, it is still unclear from the work in this chapter if this is actually an important cause. The next chapter will look at how much risk-induced persistent poverty actually accounts for total chronic poverty, by measuring *genuine* state-dependence in poverty.

Appendices

Four appendices provide some supporting evidence for various parts of the arguments in this chapter. Appendix A documents households' consumption structure. It also describes asset indices in more detail and examines to what extent households are exposed to income shocks. Appendix B lists calculations of marginal effects for the conditional logit model. Appendix C gives the construction of household-specific income shocks which have been used in estimations for both *ex-post* and *ex-ante* mechanisms. The regression and robustness checks for agricultural asset dynamics are presented in Appendix D.

A: Supplementary figures and tables

Fig. A1 The structure of rural household expenditure, 1985-2006



Source: Author's calculations based on China Statistical Yearbook (2009) and China Agricultural Development Report (2007).

Fig. A2 Distribution of annual growth rates of households' agricultural assets

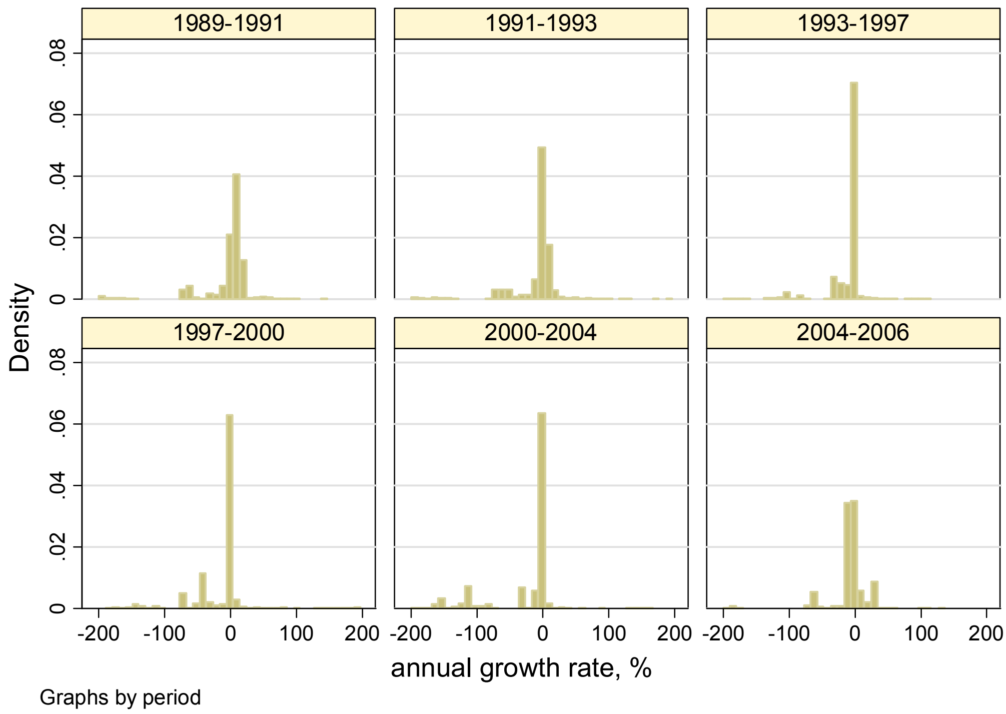


Fig. A3 Dynamics of household assets, 1989-2006

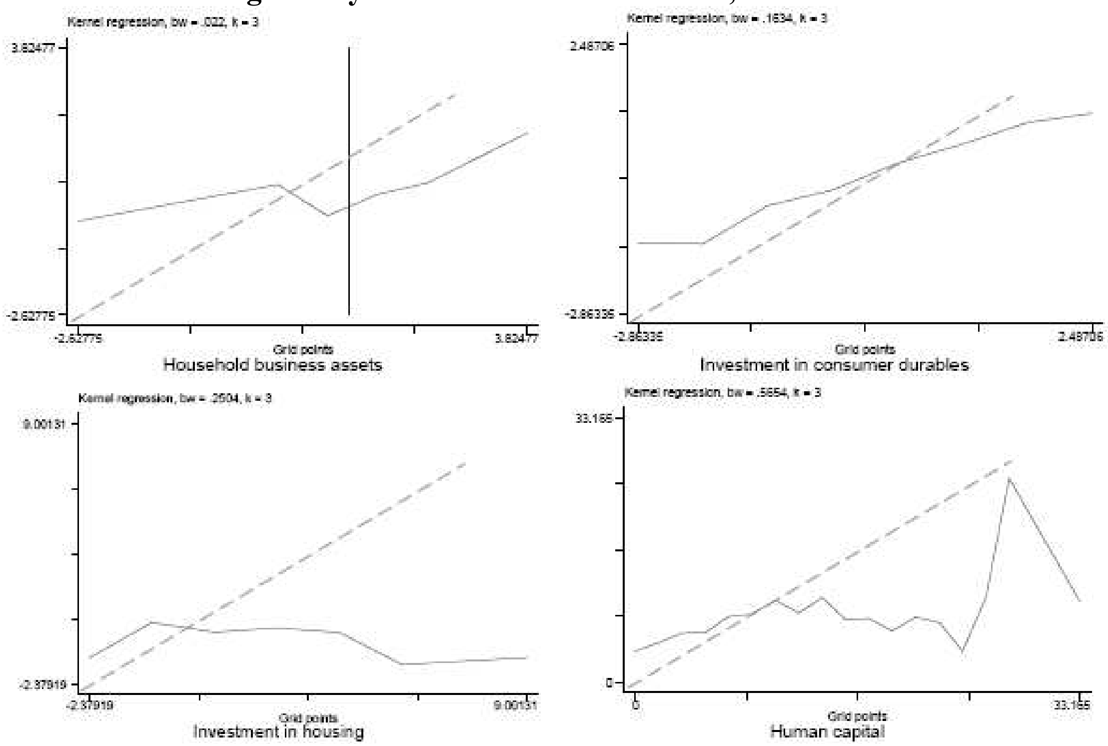


Fig. A4 Distribution of marginal effects, Case (a)

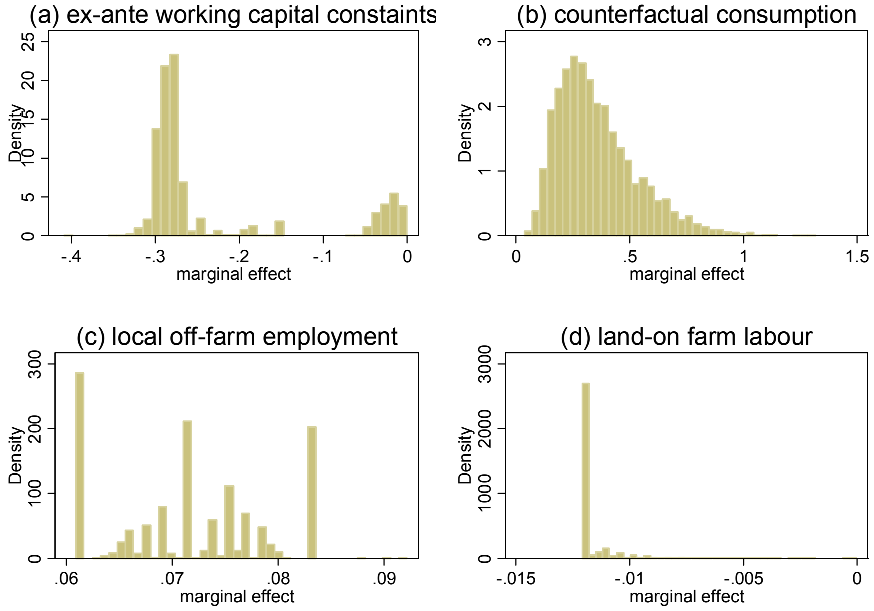


Fig. A5 Distribution of interaction effects, Case (a)

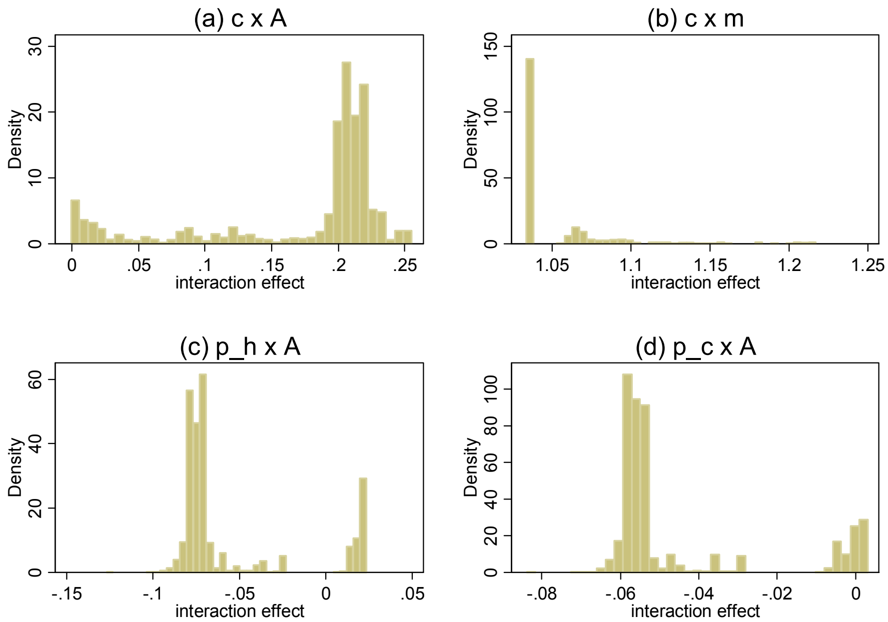


Table A1 Test of perfect risk-sharing within the village[b]

	Idiosyncratic shocks (with village-time dummies)		Idiosyncratic & covariate shocks (without village-time dummies)		Covariate shocks[c]
	$\Delta \ln income_{ht}$	$\Delta \ln hhsize_{ht}$	$\Delta \ln income_{ht}$	$\Delta \ln hhsize_{ht}$	
Stratified by intertemporal agricultural assets					
poorest 25%	0.103*	-0.445***	0.496***	-0.338**	0.393
25-50th	0.107**	-0.252***	0.409***	-0.194*	0.392
50-75th	0.070	-0.264***	0.405***	-0.288**	0.405
richest 25%	0.017	-0.541***	0.417***	-0.120	0.417
Stratified by region					
costal	0.140***	-0.251***	0.323***	-0.309***	0.183
central	0.079*	-0.278***	0.372***	-0.238**	0.293
western	0.089*	-0.272***	0.452***	-0.115	0.363
Stratified by poverty status[d]					
churning poor	0.211***	-0.244***	0.511***	-0.109	0.300
occasionally poor	0.100***	-0.291***	0.498***	-0.206**	0.398
Average	0.186***	-0.247***	0.615***	-0.074	0.429

Note: a. Only the second lags of endogenous income and household size are used as instruments. The Hansen test for over-identification is rejected. No $AR(2)$ process exists in error terms. Difference test supports endogeneity in both income and household size.

b. In line with Jalan and Ravallion (1999), our analysis is restricted to villages with no fewer than 6 households.

c. The impact of covariate income shocks on consumption is derived by subtracting Column 3 by Column 1, as suggested by Skoufias and Quisumbing (2005).

d. The churning poor are those whose per capita real consumption was lower than the US\$1.25/day in most of the survey years ($4 \leq poverty\ spells$). In comparison, those seldom falling below the poverty line ($0 < poverty\ spells < 4$) are defined as the occasionally poor. Neither the always poor nor the always non-poor in all survey years are considered as the sample sizes are too small to use instruments in System-GMM.

B: Computing marginal effects in fixed-effects logit models with interaction terms

Computing marginal effects in censored regressions require independence between regressors and the error terms (i.e., random effects). Honoré (2008) shows that, in the case of fixed-effects censored regressions, one can still calculate and interpret the marginal effect of an explanatory variable as in the case of random-effects models, as long as one holds the unobservables fixed. Therefore, we present the following equations for calculating marginal effects based on the random-effects specification, but the interpretations are essentially the same as those for the fixed-effects conditional logit model, assuming constant household-specific unobservables.

The probability of accumulation via investment is expressed as:

$$\Pr\left(g=1 \mid c_{ht}, A_{h(t-1)}, m_{v(t-1)}, p_{ht}^{iinc.}, p_{ht}^{cinc.}, \tilde{x}\right) = F\begin{pmatrix} \beta_1 A_{h(t-1)} + \beta_2 c_{ht} + \beta_{12} c_{ht} A_{h(t-1)} \\ + \beta_{23} c_{ht} m_{v(t-1)} + \beta_{123} c_{ht} A_{ht} I_{ht} \\ + \beta_4 p_{ht}^{iinc.} + \beta_{14} A_{h(t-1)} p_{ht}^{iinc.} \\ + \beta_5 p_{ht}^{cinc.} + \beta_{15} A_{h(t-1)} p_{ht}^{cinc.} + \tilde{x}\tilde{\beta} \end{pmatrix} \quad \text{(B.1)}$$
$$= F(u)$$

where $F(u) = \dfrac{1}{1+\exp(-X\beta)}$ denotes the c.d.f of the logistic distribution; other explanatory variables are included in $\tilde{x}$, except those specified in Eq. (B.1). The marginal effect of a single continuous variable x_i in $\tilde{x}$ is

$$\frac{\partial \Pr(g=1)}{\partial x_i} = F'(u)\beta_i \quad \text{(B.2)}$$

If x_i is a dummy variable, for example, whether being a specialised farm household, the marginal effect is

$$\frac{\Delta \Pr(g=1)}{\Delta x_i} = F(\beta_i + x\beta) - F(x\beta) \quad \text{(B.3)}$$

For single continuous variables that also appear in interaction terms, the total marginal effects are as follows:

$$\frac{\partial \Pr(g=1)}{\partial A} = \left(\beta_1 + \beta_{12} c_{ht} + \beta_{123} c_{ht} I_{ht} + \beta_{14} p_{ht}^{iinc.} + \beta_{15} p_{ht}^{cinc.}\right) F'(u) \quad \text{(B.4a)}^{102}$$

$$\frac{\partial \Pr(g=1)}{\partial c} = \left(\beta_2 + \beta_{12} A_{ht-1} + \beta_{23} m_{v(t-1)} + \beta_{123} A_{ht} I_{ht}\right) F'(u) \quad \text{(B.4b)}$$

$$\frac{\partial \Pr(g=1)}{\partial p^{iinc.}} = \left(\beta_4 + \beta_{14} A_{h(t-1)}\right) F'(u) \quad \text{(B.4c)}$$

$$\frac{\partial \Pr(g=1)}{\partial p^{cinc.}} = \left(\beta_5 + \beta_{15} A_{h(t-1)}\right) F'(u) \quad \text{(B.4d)}$$

The *full* partial effects of the interaction terms with two continuous variables are the second partial derivatives (Norton *et al.*, 2004). Using this definition, we calculate the effects of two-way interaction terms as

$$\begin{aligned} \frac{\partial^2 \Pr(g=1)}{\partial c \partial A} = {} & F''(u)\left(\beta_1 + \beta_{12} c_{ht} + \beta_{123} c_{ht} I_{ht} + \beta_{14} p_{ht}^{iinc.} + \beta_{15} p_{ht}^{cinc.}\right) \\ & \cdot \left(\beta_2 + \beta_{12} A_{h(t-1)} + \beta_{23} m_{v(t-1)} + \beta_{123} A_{ht} I_{ht}\right) + F'(u)\left(\beta_{12} + \beta_{123} I_{ht}\right) \end{aligned} \quad \text{(B.5a)}$$

$$\frac{\partial^2 \Pr(g=1)}{\partial c \partial m} = \beta_{23}\left[F'(u) + F''(u) c_{ht}\left(\beta_2 + \beta_{12} A_{h(t-1)} + \beta_{23} m_{h(t-1)} + \beta_{123} A_{ht} I_{ht}\right)\right] \quad \text{(B.5b)}$$

$$\frac{\partial^2 \Pr(g=1)}{\partial p^{iinc.} \partial A} = \beta_{14} F'(u) + F''(u)\left(\beta_4 + \beta_{14} A_{h(t-1)}\right) \quad \text{(B.5c)}$$

$$\frac{\partial^2 \Pr(g=1)}{\partial p^{cinc.} \partial A} = \beta_{15} F'(u) + F''(u)\left(\beta_5 + \beta_{15} A_{h(t-1)}\right) \quad \text{(B.5d)}$$

---

[102] Here A_{ht-1} and A_{ht} are treated equally for simplicity.

By the same token, the *full* partial difference of the triple variable interaction term with two continuous variables and one dummy variable is computed by

$$\frac{\Delta\left(\frac{\partial^2 \Pr(g=1)}{\partial c \partial A}\right)}{\Delta I} = \beta_{123}\left\{\begin{array}{l} F'(u) + \\ F''(u)\left[\begin{array}{l} A_{h(t-1)}\left(\beta_1 + \beta_{12}c_{ht} + \beta_{14}p_{ht}^{iinc.} + \beta_{15}p_{ht}^{cinc.}\right) \\ + c_{ht}\left(\beta_2 + \beta_{12}A_{h(t-1)} + \beta_{23}m_{v(t-1)}\right) + \beta_{123}c_{ht}A_{h(t-1)} \end{array}\right] \end{array}\right\} \quad \text{(B.6)}$$

The marginal effects (Eq. B.1-B.6) can be evaluated for an average household with all independent variables at their own mean. We alternatively calculate household-specific marginal effects and then take the mean and the median across all households, since Greene (2003) advises this. Our calculations, in a finding similar to Norton *et al.* (2004), suggest that the mean partial effects calculated in this way differ from the marginal effects for an average household.

C: Estimating household-specific income shocks

Following Jalan and Ravallion (2001), the panel income generation model is

$$\ln y_{ht} = \beta X + v_h + \varepsilon_{ht} \quad \text{(C.1)}$$

where X controls for household characteristics. We implement Wooldridge's (2002) test for autocorrelation in idiosyncratic errors in the context of linear panel regression and find $AR(1)$ process in ε_{ht} at 1% significance level. Thus, we further adjust the random individual effect to an $AR(1)$ process within each panel, allowing for the transfer of the effect of shocks on household income from one period to at least the next period:

$$\varepsilon_{ht} = \rho_h \varepsilon_{h(t-1)} + u_{ht}$$

where $u_{ht} \rightarrow i.i.d$. Jalan and Ravallion (2001) note that ignoring this mechanism will underestimate households' income uncertainty. The time invariant household-specific serial correlation coefficient ρ_h is bounded within $[-1,1]$ and varies across households, while Jalan and Ravallion (2001) restrict it to be identical for all households. Then, we derive unbiased and consistent estimates of 'household-specific income uncertainty'

$$\hat{\sigma}_{h,y}^2 = \frac{1}{T}\sum_{t=1}^{T}\left(u_{ht} - \bar{u}\right)^2 \quad \text{(C.2)}$$

and the household permanent income

$$\hat{y}_h^P = \frac{1}{T}\sum_{t=1}^{T}\ln \hat{y}_{ht} \quad \text{(C.3)}$$

The severity of a particular income shock experienced by individual household is therefore defined by the ratio, $\frac{\hat{\sigma}_{h,y}^2}{\hat{y}_h^P}$. Different from Jalan and Ravallion (2001), we further multiply -1 to that ratio if $u_{ht} < \bar{u}$, considering differentiated impact of positive and negative income shocks on households' behaviour.

D: Semi-parametric regression of asset dynamics

Adopting Mesnard and Ravallion's (2001) specification, household asset stocks at t are defined by

$$A_{ht} = f\left(A_{h(t-1)}\right) + X\beta + \varepsilon_{ht} \qquad \text{(D.1)}$$

where $X = \{x_1, \ldots, x_n\}$ contains n covariates. The initial asset holding is included in an unknown function f, indicating non-linearity. We use i) kernel regressions to obtain Nadaraya-Watson estimators of f taking the form of Epanechnikov kernel function with Silverman's (1986) optimal bandwidth, and ii) LOWESS as a robustness check. Applying Lokshin's (2006) first-differencing estimation approach to Eq. (D.1) gives a consistent and efficient $\hat{\beta}$. We find similar asset dynamics when we estimate using both i) and ii).

In addition, we also implement Lokshin's (2006) test for the specification of the non-parametric part f against parametric forms. That is, f is replaced by initial asset stocks and their quadratic and cubic forms[103]. The statistic is constructed as

$$V = \frac{\sqrt{mT}\left(s_p^2 - s_{sp}^2\right)}{s_{sp}^2}$$

where s_p^2 and s_{sp}^2 are mean square residuals of parametric and semi-parametric regressions respectively; $V \to N(0,1)$. Tests support the semi-parametric specification in all asset categories, with significance levels varying from 1 to 5 percent.

Eq. (D.1) also facilitates the estimation of returns to assets. In doing so, A_{ht} is replaced by income per capita as the new dependent variable. The above estimation and robustness checks are repeated for this new regression. Again, the result of the semi-parametric model is quite robust.

[103] Jalan and Ravallion (2004) note that the cubic form is the minimum polynomial capturing high order non-linearity.

CHAPTER 5

POVERTY TRANSITIONS AND PERSISTENCE: A PERSPECTIVE FROM ASSETS

5.1 Introduction

There have been a large number of studies examining changes in household poverty status over time in rural China, from which two features are evident. Poverty has been reduced substantially over the past three decades (Chen and Ravallion, 2008), but it has remained persistent since the late 1990s (Ravallion and Chen, 2007). At the same time, many rural households moved into and out of poverty frequently, which indicates the existence of a transient component in poverty transitions (Jalan and Ravallion, 1998a, b; McCulloch and Calandrino, 2003).

A commonality across these studies is use of income or consumption as the indicator of household welfare or poverty status. However, both income and consumption-based poverty measures incur problems, which may challenge the above findings on poverty transitions in rural China. In particular, given the flow nature of income and consumption, the literature based on them provides only a snapshot of household well-being (Carter and Barrett, 2006, 2007; Moser and Felton, 2009) rather than delineating the underlying strategies exercised to manage livelihoods (Quisumbing and Baulch, 2009) or household abilities to resist risk and shocks (Tache and

Sjaastad, 2010). As a result, the existing income or consumption-based examination finds only *correlates* of poverty transitions and leaves unanswered the classic question of why some households appear as 'churning' poor, reflected by their volatile income and consumption, while others have sunk even deeper into the mire. In addition, measurement errors in income and consumption can upwardly bias income and consumption fluctuations (Baulch and Hoddinott, 2000) and hence inflate measured changes in household poverty status over time.

It is suggested that using household asset holdings instead of income and consumption may go some way towards resolving the aforementioned issues (Carter and Barrett, 2006, 2007). The literature on asset poverty suggests that the analysis of asset accumulation and its impact on household poverty status can complement income and consumption-based studies in at least two aspects. The asset-based method is not only able to reveal how households' long-run livelihoods and poverty status would change with less biased estimates (Carter and May, 2001; Carter and Barrett, 2007), but also extends our understanding of the multi-dimensional concept of poverty and the complexity of the processes underlying poverty reduction (Adato *et al.*, 2006; Addison *et al.*, 2009).

In order to better examine poverty transition and persistence in rural China, this chapter develops an econometric approach to investigate the conceptual framework of asset-based poverty measure by Carter and Barrett's (2006), which can overcome the problems in the previous empirical studies. Specifically, it contributes to the literature in four ways. First, it sheds new light on poverty transitions in rural China from a structural point of view, stressing the role of household asset dynamics.

Second, it addresses the ‘regime identification’ problem commonly seen in the literature on asset poverty (Carter and Barrett, 2006) by separating households into different accumulation regimes conditional on their underlying livelihood strategies. Third, it is the first empirical study establishing a *causal* effect running from less asset than the dynamic asset threshold to poverty measured by consumption expenditure, by taking into account the possibility that households might endogenously switch across accumulation regimes. Fourth, it distinguishes two different sources of persistent poverty: ‘genuine multiple-equilibrium poverty traps’ due to households’ behavioural responses to past experience of poverty, and ‘the club-convergence’ due to households’ observed and unobserved characteristics barricading poverty-exits. This allows us to address the ‘omitted relevant variables problems’ in the studies that utilise Carter and Barrett’s (2006) asset-based approach to examine poverty dynamics.

Our results reveal that assets play an important role in determining households’ long-run welfare and poverty status. Through 1989-2006, a dynamic asset threshold is identified that separates households into regimes of downward and upward mobility in terms of their agricultural asset holdings. Our estimation suggests a static causal link between falling into downward mobility and the probability of being poor. In addition, insufficient agricultural assets relative to the dynamic threshold also increase the probability of becoming poor in the long term and this impact could be further compounded by households’ behavioural responses to their past experience of poverty (the true state-dependence or ‘scarring effect’ of poverty). It is therefore argued that anti-poverty policy should pay more attention to helping poor rural households build up their agricultural assets in order to break this vicious circle and stimulate self-reinforcing growth.

The present chapter proceeds as follows. The next section elaborates on the steps of econometric modelling. Data and preliminary evidence are delineated in Section 5.3. Section 5.4 discusses the performance of the models in greater detail. We conclude and draw policy implications in Section 5.5.

5.2 Econometric strategy

We begin by empirically locating the dynamic asset threshold in household agricultural asset dynamics, based on which households are separated into different accumulation regimes leading to either high or low asset equilibria. Then, the impact of falling into the regime of downward mobility on the probability of poverty is investigated from static and dynamic aspects in Sections 5.2.2 and 5.2.3 respectively.

5.2.1 Identifying the dynamic asset threshold

The literature on asset poverty shows that if asset dynamics contain multiple equilibria, there might be a dynamic threshold which can separate households into different accumulation regimes (Zimmerman and Carter, 2003; Carter and Barrett, 2006). In the presence of locally increasing returns to assets, those below the dynamic threshold may sub-optimally backslide towards the lower equilibrium resulting in long-run lower incomes, while those above it may be able to approach the higher equilibrium and therefore escape from poverty (Lybbert *et al.*, 2004 for

Ethiopia; Adato *et al.*, 2006 for South Africa; Carter *et al.*, 2007 for Ethiopia and Honduras).

A critical drawback in the empirical literature drawing upon asset-based poverty measures is that they treat the dynamic asset threshold as being exogenous and identical for all households (Carter *et al.*, 2007; Lybbert and Carter, 2010).[104] This violates the assumption of the theoretical model that the dynamic asset threshold depends on households' various observed and unobserved characteristics (typically their innate abilities, such as learning and the capability of using assets efficiently to generate income) and underlying livelihood strategies.[105] Ignoring the endogenously determined asset threshold as the existing literature may overstate the number of households being caught in downward asset mobility and low-equilibrium poverty traps.

This chapter overcomes this shortcoming by using a Carter *et al.* (2007) type two-step procedure and letting the dynamic asset threshold be endogenously determined by our data.[106] In the first step, we employ Hansen's (1999) fixed-effects panel model to locate potential multiple structural breaks in household asset dynamics across which households' asset evolution might change. The growth rate of household agricultural assets from t to $t+1$ is expressed as follows:[107]

[104] The only exception is Santos and Barrett (2006).
[105] Theoretical models and the simulated results can be found in Barrett *et al.* (2008) and Carter and Ikegami (2009). Low-ability households appear to backslide easily, while those with high ability tend to converge to the high equilibrium. The medium-ability households are found to be more likely to bifurcate compared with the low- and high-ability households.
[106] The major difference between their study and the two-step approach implemented here is that Carter *et al.* (2007) applies Hansen's (2000) threshold estimation to their pooled cross sections and obtain identical estimators for split groups, while our approach employs Hansen (1999) threshold estimation for the balanced panel, which takes household-specific fixed effects into account, and provides different estimators for different sub-groups.
[107] Here we illustrate the case of only three structural breaks. One might include more.

$$
\begin{aligned}
g_{ht} = {} & \beta_A^1 A_{h(t-1)} I\left(A_{h(t-1)} \le \gamma_1\right) + \beta_A^2 A_{h(t-1)} I\left(\gamma_1 < A_{h(t-1)} \le \gamma_2\right) \\
& + \beta_A^3 A_{h(t-1)} I\left(\gamma_2 < A_{h(t-1)} \le \gamma_3\right) + \beta_A^4 A_{h(t-1)} I\left(\gamma_3 < A_{h(t-1)}\right) \\
& + \beta_Z Z_{ht} + \alpha_h + \mathrm{T}_t + \varepsilon_{ht}
\end{aligned}
\tag{5.1}
$$

where the potential break point is denoted by γ_i with $i \in (1,2,3)$; I is a binary indicator determining in which range the household would fall; $A_{h(t-1)}$ refers to the household agricultural assets at the beginning of the period *t*; Z_{ht}, α_h and T_t include households' idiosyncratic characteristics, fixed effects and time dummies in turn; error terms ε_{ht} satisfy the *iid* distribution with zero mean and a homoscedastic variance.[108] The searching procedure for γ_i follows Hansen's (1999) lease square approach minimising the sum of squared residuals. The *F*-type tests and the associated *p*-values for the significance of each $\hat{\gamma}_i$ are calculated based on his fixed regressor bootstrap.

Eq. (5.1) does not allow for varying coefficients of independent variables across structural breaks, but households may well change their accumulation behaviour in different asset regimes. To improve the description of household asset dynamics, in the second step, we regress the growth rates of agricultural assets on a number of covariates for each sub-group separated by $\hat{\gamma}_i$ with $i \in (1,2,3)$ derived in the first step. The set of regressions includes:

$$
g_{ht} = \begin{cases}
\theta_A^1 A_{h(t-1)} + \theta_Z^1 Z_h + \alpha_h^1 + \mathrm{T}_t^1 + \varepsilon_{ht} & \text{if } A_{h(t-1)} \le \hat{\gamma}_1 \\
\theta_A^2 A_{h(t-1)} + \theta_Z^2 Z_h + \alpha_h^2 + \mathrm{T}_t^2 + \varepsilon_{ht} & \text{if } \hat{\gamma}_1 < A_{h(t-1)} \le \hat{\gamma}_2 \\
\theta_A^3 A_{h(t-1)} + \theta_Z^3 Z_h + \alpha_h^3 + \mathrm{T}_t^3 + \varepsilon_{ht} & \text{if } \hat{\gamma}_2 < A_{h(t-1)} \le \hat{\gamma}_3 \\
\theta_A^4 A_{h(t-1)} + \theta_Z^4 Z_h + \alpha_h^4 + \mathrm{T}_t^4 + \varepsilon_{ht} & \text{if } \hat{\gamma}_3 < A_{h(t-1)}
\end{cases}
\tag{5.2}
$$

[108] Hansen (1999) notes that the estimation is not immune to the case of heteroskedastic errors. We will loosen this assumption using another model set-up in the following threshold estimation in Eq. (5.2).

where covariates are as same as in Eq. (5.1). The estimated coefficients $\left(\theta_A^i, \theta_Z^i, \alpha_h^i, T_t^i\right)$ with $i \in (1,2,3)$ capture households' different livelihood strategies conditional on the levels of their asset holdings. We calculate predicted asset growth rates based on observed covariates and estimated coefficients. The dynamic threshold is such that an asset level making the predicted asset growth rate equal or close to zero, while households lying left and right of it see negative and positive predicted growth rates, respectively. In other words, those with less asset than the dynamic asset threshold are shown to be downwardly mobile, while those owning sufficient assets to be above the threshold may be able to accumulate and so reach the high asset equilibrium. Hence, as noted by Carter and Barrett (2006), there should be a few households lying in the vicinity of the dynamic threshold, which has the appearance of an unstable equilibrium.

On identifying the dynamic asset threshold, we can proceed to investigate how falling below this asset threshold could affect households' probabilities of being (Section 5.2.2) and becoming poor (Section 5.2.3).

5.2.2 The impact of household asset holdings on poverty: A static examination

Although the empirics on asset poverty have documented an important role of some key asset holdings in determining household poverty status, they all neglect the possibility of endogenous asset accumulation. This concern arises if some unobservables simultaneously influence households' asset accumulation decisions as well as their poverty status measured by income or consumption. For example, a farm household with poor-quality land might be both income or consumption poor and reluctant to increase its investment in profitable agricultural asset accumulation, in terms of adopting advanced technology, or unable to plant certain high-yield or commercial crop varieties. Moreover, as revealed in Chapter 4, households' risk- and loss-aversion might simultaneously induce conservative consumption and investment strategies. Ignoring potential endogeneity in accumulation decisions makes estimates inconsistent and seriously biased and sometimes can even change the signs of estimated coefficients (Miranda and Rabe-Hesketh, 2006).

We therefore employ Miranda and Rabe-Hesketh's (2006) endogenous switching model which is free from endogeneity due to the unobserved heterogeneity and simultaneity. By controlling for endogeneity, our model captures a causal relationship running from households' asset status to poverty status.

The impact of insufficient asset holdings on the probability of suffering poverty measured by consumption is modelled by a system containing two correlated latent responses. Specifically, the household h makes decisions on agricultural asset accumulation at t:

$$\Pr(A_{ht} = 1) = \Phi(z'_{ht}\omega + \upsilon_{ht} > 0) \tag{5.3}$$

where household characteristics are included in z'_{ht} ; A_{ht} is a regime-switching indicator equalling one if the household falls into the downward mobility regime, that is, it owns fewer agricultural assets than the dynamic asset threshold identified in Section 5.2.1. Eq. (5.3) is termed the asset equation.

Meanwhile, h may experience consumption poverty. Its per capita consumption is denoted by a latent variable y^*_{ht}, where $y_{ht} = 1$ if y^*_{ht} is lower than the poverty line at the US$1.25/day adjusted to the rural-urban price gap in China. The poverty equation is therefore expressed by:

$$\Pr(y_{ht} = 1) = \Phi(x'_{ht}\beta + \theta A_{ht} + u_{ht} > 0) \tag{5.4}$$

where x'_{ht} includes a number of household characteristics; the endogenous dummy A_{ht} is defined the same as in Eq. (5.3).

In the presence of endogenous asset accumulation, the poverty and asset equations interact with each other through correlated residuals u_{ht} and υ_{ht}: they follow a bivariate normal distribution and are assumed to have the following structures:

$$u_{ht} = \lambda\zeta_{ht} + \tau_{ht} \tag{5.5}$$

$$\upsilon_{ht} = \zeta_{ht} + \varepsilon_{ht} \tag{5.6}$$

where ε_{ht}, τ_{ht} and ζ_{ht} are independently normally distributed with zero mean and variance one; u_{ht} and υ_{ht} are correlated through shared household-specific random intercepts ζ_{ht} with the correlation coefficient $\rho = \dfrac{\lambda}{\sqrt{2(\lambda^2 + 1)}}$. A significant non-zero ρ means some unobservables ζ_{ht} simultaneously influence households' asset and poverty status, that is, an endogenous choice of asset accumulation. The Maximum Likelihood (ML) estimation is applied to the above system and unobserved heterogeneity ζ_{ht} is integrated out by adaptive quadrature. These yield consistent and unbiased estimates of β and θ.[109] The causal relationship from inadequate assets relative to the dynamic threshold to consumption poverty is captured by a positive $\hat{\theta}$. The average marginal impact of falling below the dynamic asset threshold on the probability of consumption poverty is the difference between predicted conditional probabilities of consumption poverty: [110]

$$\begin{aligned} &E[\Pr(y_{ht}=1 \mid x'_{ht}, A_{ht}=1, \zeta_{ht})] - E[\Pr(y_{ht}=1 \mid x'_{ht}, A_{ht}=0, \zeta_{ht})] \\ &= \frac{1}{N}\sum_{h=1}^{N}\Phi\left(x'_{ht}\hat{\beta}+\hat{\theta}+\hat{\lambda}\hat{\zeta}_{ht}\right) - \frac{1}{N}\sum_{h=1}^{N}\Phi\left(x'_{ht}\hat{\beta}+\hat{\lambda}\hat{\zeta}_{ht}\right) \end{aligned} \tag{5.7}$$

A concern over the above endogenous switching model might come from the assumption that household-specific unobserved heterogeneity ζ_{ht} is uncorrelated with observed characteristics, i.e. a random-effects setting. In fact, this assumption may well be violated in the real world. Therefore, as a robustness check to the endogenous switching model, we implement a two-step control function (CF) approach motivated by Vella and Verbeek (1999) to address endogenous asset accumulation but with fixed effects. Specifically, the asset and poverty equations are expressed by Eq. (5.3) and (5.4) as before, but we no longer specify the composition of errors u_{ht} and υ_{ht}. Alternatively, in the first step, a standard random-effects probit model for the asset equation is estimated by ML. This yields the inverse Mills ratio $\delta_{ht} = \dfrac{\phi(-z'_{ht}\omega)}{1-\Phi(-z'_{ht}\omega)}$ and the generalised errors:

$$E(\tau_{ht} \mid A_{ht}, z'_{ht}, \varepsilon_{ht}) = A_{ht}E(\tau_{ht} \mid A_{ht}=1, z'_{ht}, \varepsilon_{ht}) + (1-A_{ht})E(\tau_{ht} \mid A_{ht}=0, z'_{ht}, \varepsilon_{ht})$$

---

[109] The estimates have to be re-scaled by $\dfrac{1}{\sqrt{\hat{\lambda}^2+1}}$ in order to serve as a rough comparison with the estimates derived from the following two-step CF estimators.

[110] $\hat{\zeta}_{ht}$ are posterior empirical Bayes predictions according to Skrondal and Rabe-Hesketh (2009).

In the second step, the poverty equation takes a linear probability specification with household-specific fixed effects and the above generalised error is included in the poverty equation as an additional regressor. By doing so, the household's poverty status is associated not only with its observed asset position, A_{ht}, but also with the factors influencing it to decide whether to accumulate, z'_{ht}:

$$\begin{aligned}
E(y_{ht} \mid x'_{ht}, A_{ht}, z'_{ht}) &= x'_{ht}\beta + \theta A_{ht} + E(\tau_{ht} \mid A_{ht}, z'_{ht}, \varepsilon_{ht}) \\
&= x'_{ht}\beta + \theta A_{ht} \\
&\quad + \left[A_{ht} E(\tau_{ht} \mid A_{ht} = 1, z'_{ht}, \varepsilon_{ht}) + (1 - A_{ht}) E(\tau_{ht} \mid A_{ht} = 0, z'_{ht}, \varepsilon_{ht})\right] \\
&= x'_{ht}\beta + \theta A_{ht} + \rho_{\tau\varepsilon}\sigma_{\tau}\left[A_{ht}\frac{\phi(-z'_{ht}\omega)}{1 - \Phi(-z'_{ht}\omega)} + (1 - A_{ht})\frac{-\phi(z'_{ht}\omega)}{\Phi(-z'_{ht}\omega)}\right]
\end{aligned}$$

The revised poverty equation is then estimated by OLS.[111] $\hat{\theta}$ reflects the impact of downward mobility of asset holdings on the probability of consumption poverty, after controlling for factors affecting households' accumulation decisions. Since we have assumed $\sigma_{\tau} = 1$ in Eq. (5.5), the estimated coefficient of the generalised error, $\hat{\rho}_{\tau\varepsilon}$, reflects the correlation between asset and poverty equations. In addition, as noted by Christiaesen *et al.* (2010), using fixed effects can also help purge the reverse causality running from household initial poverty to asset accumulation 'by controlling for the households' chronic poverty status'.

[111] Compared to OLS, if using the probit specification and ML in the second step, we can obtain consistent and relatively unbiased estimates (Vella and Verbeek, 1999), but at the cost of inappropriate distribution results for these estimates (Miranda and Rabe-Hesketh, 2006). However, using OLS and real values of per capita consumption as the dependent variable generates same signs of estimated coefficients derived from a probit set-up. The shortcoming of the linear probability poverty equation is that it is not suitable for calculating the marginal effect of assets, as the predicted probabilities are not necessarily within [0,1].

5.2.3 Modelling poverty transitions and persistence: A dynamic examination

Carter and Barrett (2006) and Carter and Ikegami (2009) state that falling below the dynamic asset threshold indicates that households might be subject to *ex ante* chronic poverty as they may settle in a low-equilibrium and suffer low income for a long time in future. Their argument essentially invites a dynamic examination of the effect of households' previous experience of hardship on their current poverty status.

Following Islam and Shimeles (2006) and Bigsten and Shimeles (2008), the probability of becoming poor for the household h at time t takes a first-order Markov process and follows a normal distribution:

$$\Pr\left(y_{ht} = 1 \mid y_{h(t-1)}, y_{h(t-2)}, \ldots, y_{h0}, \widetilde{A}_{h(t-1)}, x'_{ht}, \alpha_h\right) = \Phi\left(\widetilde{A}_{h(t-1)}, x'_{ht}, \alpha_h, y_{h(t-1)}\right)$$

where $y_{ht} = 1$ indicates the household h is poor at t measured by its per capita consumption against the poverty line at US\$1.25/day; the control covariates include a Heckman-type endogeneity-corrected asset position in the previous period $\widetilde{A}_{h(t-1)} = \delta_{h(t-1)} A_{h(t-1)}$,[112] other observed household-specific characteristics x'_{ht} which

[112] Similar to the two-step CF estimation in Section 5.2.2, we estimate the asset equation Eq. (5.3) in a standard random-effects probit model and calculate the inverse Mills ratio at every time period, $\delta_{ht} = \frac{\phi\left(-z'_{h(t-1)}\omega\right)}{1-\Phi\left(-z'_{h(t-1)}\omega\right)}$. Because the inverse Mills ratio can also be understood as the hazard rate, $\delta_{h(t-1)}$ means the conditional probability of falling in downward mobility regime at *t-1* given that the household was not in the downward mobility regime in terms of asset holdings at *t-2*. Since the dependent variable is not 'specified' for the 'selection' of falling into downward mobility (i.e., y_{ht} is not restricted to 1 only if $A_{ht-1} = 1$, but may also be observed when $A_{ht-1} = 0$), we further multiply $A_{h(t-1)}$ to $\delta_{h(t-1)}$ to focus on the impact of falling in downward mobility of asset holdings, $A_{ht-1} = 1$, on the probability of becoming poor. By adjusting the asset variable by this two-step Heckman-type approach, factors affecting households' decisions on (not) accumulating assets may also influence their poverty status. To avoid multi-colinearity in estimating $\delta_{h(t-1)}$ and the coefficients of x'_{ht}, z'_{ht} further includes some variables not in x'_{ht}. In addition to the above method, one may use a dynamic system for asset and poverty equations to address endogenous selection of falling into downward mobility – for example, by using Stewart's (2007) bivariate dynamic probit model. Nevertheless, this

are assumed to be strictly exogenous, the latent heterogeneity α_h and the poverty status in the immediate past $y_{h(t-1)}$. The joint probability of the observed binary sequence for h conditional on all scenarios can be formulated as,

$$\begin{aligned}\Pr\left(y_{hT},\ldots,y_{h1},y_{h0} \mid \widetilde{A}_{h(t-1)},x'_h,\alpha_h\right) &= \Pr\left(y_{hT},\ldots,y_{ht},y_{h1} \mid y_{h0},\widetilde{A}_{h(t-1)},x'_{ht},\alpha_h\right) \\ &\quad \cdot \Pr\left(y_{h0} \mid \widetilde{A}_{h0},x'_{ht},\alpha_h\right) \\ &= \prod_{t=1}^{T}\Phi\left(y_{ht} \mid y_{ht-1},\widetilde{A}_{h(t-1)},x'_{ht},\alpha_h\right)\Phi\left(y_{h0} \mid \widetilde{A}_{h0},x'_{ht},\alpha_h\right)\end{aligned}$$

which clearly shows that a household's experience of poverty depends on its exposure to poverty in the immediate past as well as at the initial period.

This motivates our dynamic random-effects probit specification:

$$y_{ht} = \mathbf{1}\left(x'_{ht}\beta_1 + \beta_2\widetilde{A}_{h(t-1)} + \beta_3 y_{h(t-1)} + \alpha_h + u_{ht} > 0\right),\ t \in [1,T] \tag{5.8}$$

where x'_{ht} and $\widetilde{A}_{h(t-1)}$ are defined as before; the time-invariant household-specific heterogeneity α_h is independent with errors u_{ht} for all $t \geq 1$. Following Stewart's (2007) assumptions for a dynamic random-effects probit model, α_h is normally distributed[113] and $u_{ht}(t \geq 1)$ have an *iid* distribution $N\left(0,\sigma_u^2\right)$ as u_{h0}. The cross-period correlation for the composite error term (also known as the proportion of estimated error variance that can be explained by household-specific heterogeneity)

---

latter model requires uncorrelated disturbances as well as independent household-specific unobservables in asset and poverty regressions, which are relatively strong assumptions leading to weak exogenous selection of falling into downward asset mobility. In our empirical estimations, in addition to employing endogeneity-corrected asset position, we also implement Stewart's (2007) bivariate dynamic probit model. However, the GHK algorithm fails to get convergence.

[113] If normality is relaxed, the GHK algorithm for estimation is no longer valid. In this case, Islam and Shimeles (2006) assume that unobserved heterogeneity suggests different distributions with respective known probabilities (adding up to one) and use Hyslop's (1999) simulated maximum likelihood method.

holds constant, that is, $\lambda = Corr(\upsilon_{ht}, \upsilon_{hs}) = \frac{\sigma_e^2 - \sigma_u^2}{\sigma_e^2}$ where $\upsilon_{ht} = \alpha_h + u_{ht}$ and $t, s \in 1, \ldots, T; t \neq s$.

We explicitly model transitory shocks by the autocorrelated errors suggesting an $AR(1)$ process:

$$u_{ht} = \rho u_{h(t-1)} + \varepsilon_{ht},\ \varepsilon_{ht} \to i.i.d.\ N\left(0, \sigma_\varepsilon^2\right) \tag{5.9}$$

The aim of such a set-up is two-fold (Bigsten and Shimeles, 2008). The $AR(1)$ errors not only reflect the situation that transitory shocks may well affect households' welfare for a short period rather than merely a one-shot game, but are also 'an important means of reducing the effects of measurement error on coefficients' (Bigsten and Shimeles, 2008, p. 1579). This latter also makes our model more or less free from the problem of measurement errors.

Meanwhile, it could be the case that the start of observations is not exactly the start of households' poverty experience. This implies that the initial condition may correlate with households' unobserved characteristics and, therefore, be endogenously determined within the system. In the presence of endogenous initial poverty status, the existing literature would have overestimated the number being or becoming trapped in low equilibrium.

Our model overcomes this problem, which will be discussed in greater detail in Section 5.4.3.3, by taking Stewart's (2007) suggestion into account. Specifically, at the initial period, Heckman's (1981) reduced form of the marginal probability of y_{h0} given α_h is explicitly approximated by a static probit model,[114]

$$y_{h0} = \mathbf{1}\left(x'_{h0}\pi_1 + \pi_2 \widetilde{A}_{h0} + \zeta_h > 0\right) = \mathbf{1}\left(x'_{h0}\pi_1 + \pi_2 \widetilde{A}_{h0} + \theta\alpha_h + u_{h0} > 0\right) \qquad (5.10)$$

where ζ_h, which is orthogonally projected on $\theta\alpha_h + u_{h0}$, is assumed to be correlated with α_h, but uncorrelated with u_{ht} for all $t \geq 1$. In doing so, the household initial poverty status y_{h0} is associated with its heterogeneity α_h. The impact of the latter is captured by θ. Furthermore, the possible correlation between the latent heterogeneity (α_h) and observed household characteristics (x'_{ht} and $\widetilde{A}_{ht}$) is also taken into account. Adopting Mundlak (1978) and Chamberlain's (1984) specification, the household-specific heterogeneity is projected on households' intertemporal mean characteristics $\bar{x}'_h = \sum_{t=1}^{T} x_{ht}$:[115]

$$\alpha_h = a_0 + \bar{x}'_h a_1 + e_h \qquad (5.11)$$

with household-specific time-invariant effect $e_h \rightarrow N\left(0, \sigma_e^2\right)$. As a result, the distribution of α_h satisfies $N\left(a_0 + \bar{x}'_h a_1, \sigma_\alpha^2\right)$. Substituting Eq. (5.11) back into Eq. (5.10) yields the approximation of the initial condition:

$$y_{h0} = \mathbf{1}\left(z'_h \delta + \theta e_h + u_{h0} > 0\right) \qquad (5.12)$$

---

114 Hyslop (1999) mentions two ways of handling the correlation between α_h and observed characteristics. We adopt the non-linear probit model, which is more likely to 'provide a better fit' compared to linear ones (Hyslop, 1999, p. 1264). Alternatively, one may use a linear probability model which 'controls for an arbitrary correlation between the unobserved heterogeneity and the regressors' and is 'robust to the form of unobserved heterogeneity' (Hyslop, 1999, p. 1264).

115 Wooldridge (2005) provides an alternative projection assuming an arbitrary relation between household heterogeneity and the initial condition, $\alpha_h = a_0 + \bar{x}'_h a_1 + y_{h0} a_2 + e_h$. Substituting this into Eq. (5.8) yields the structural equation:

$$y_{ht} = \mathbf{1}\left(x'_{ht}\beta_1 + \beta_2 \widetilde{A}_{h(t-1)} + \beta_3 y_{h(t-1)} + \bar{x}'_h a_1 + y_{h0} a_2 + e_h + u_{ht} > 0\right)$$

It clearly indicates that the distribution of the sequence of outcomes is conditional on exogenous household characteristics as well as the initial observation of poverty status. The conditional maximum likelihood (CML) estimation is used in this case. Wooldridge's method will be used in the second-order dynamic probit model in Section 5.4.4.

where $z_h' = \left(x_{h0}', \widetilde{A}_{h0}, \overline{x}_h'\right)$. Substituting Eq. (5.11) into Eq. (5.8) gives the structural equation which will be used in estimation:

$$y_{ht} = \mathbf{1}\left(x_{ht}'\beta_1 + \beta_2 \widetilde{A}_{h(t-1)} + \beta_3 y_{h(t-1)} + \overline{x}_h' a_1 + e_h + u_{ht} > 0\right) \tag{5.13}$$

The co-existence of autocorrelation in error terms and the state-dependence of y_{ht} invalidates the simple Maximum Likelihood (ML) procedure, but invites the Maximum Simulated Likelihood (MSL) requiring a GHK algorithm to obtain consistent estimators.[116] In the empirical analysis in Section 5.5.4, we will employ four model specifications with different estimation methods:

i) the pooled dynamic probit model by OLS without random effects, $AR(1)$ errors and endogenously initial poverty status;

ii) the standard dynamic random-effects probit by ML with exogenous initial poverty status, but no $AR(1)$ errors (i.e., Eq. 5.13);

iii) the Heckman-type dynamic random-effects probit model by MSL with endogenous initial poverty status, but no $AR(1)$ errors (i.e., Eq. 5.12 and 5.13);

iv) the dynamic random-effects probit model by MSL with endogenously initial poverty status and $AR(1)$ errors (i.e., Eq. 5.9, 5.12 and 5.13).

The estimates based on these dynamic models allow us to purge the state-dependence of poverty over time. Following Cappellari and Jenkins (2004), we define the *aggregate* state-dependence (ASD) of poverty as the difference of the poverty

[116] See Stewart (2007) for technical details.

persistence probability (being poor in $t-1$ and t) and the entry probability (moving from non-poverty at $t-1$ to poverty at t):

$$\frac{\sum_{h\in\left(y_{h(t-1)}=1\right)} \Pr\left(y_{ht}=1 \mid y_{h(t-1)}=1\right)}{\sum_{h} y_{h(t-1)}} - \frac{\sum_{h\in\left(y_{h(t-1)}=0\right)} \Pr\left(y_{ht}=1 \mid y_{h(t-1)}=0\right)}{\sum_{h}\left(1-y_{h(t-1)}\right)} \tag{5.14}$$

where the probabilities as the numerators are obtained from estimating Eq. (5.13).

A household's ASD of poverty from *t-1* to *t* is a joint result of its observed characteristics, unobserved heterogeneity and behavioural responses to past exposure to poverty. Given ASD, our aim is to reveal to what extent households' responses to past poverty push them further down, i.e., the true state-dependence of poverty (TSD) excluding the impact of household observed characteristics and unobserved heterogeneity. Carter *et al.* (2007) and Carter and Barrett (2006) caution that the correlation between a household's unobserved characteristics and its initial condition may yield spurious evidence of state-dependence of poverty, which in turn would drive households to 'return to their original equilibrium attractor point' (Carter and Barrett, 2006, p. 194). This would complicate the conclusion of poverty traps in that households would be trapped 'not because of barriers to accumulation, but because they share intrinsic characteristics (for example, poor work ethic or a high discount rate) that place them in a low-level equilibrium "club" ' (Carter and Barrett, 2006, p. 194). The existing empirical literature ignores the relevant heterogeneity and might have overestimated the number being trapped (Carter and Barrett, 2006).

We adopt this Stewart (2007) definition of TSD to handle the above 'omitted relevant variable problem' confronted by former empirical studies. Controlling for observed and unobserved characteristics, TSD is calculated as the average partial effect (APE) of being poor compared to being non-poor at $t-1$ on current poverty at t:[117]

$$
\begin{aligned}
APE &= \hat{p}_{1t} - \hat{p}_{0t} \\
&= E\left[\Pr\left(y_{ht} = 1 \mid x'_{ht}, \widetilde{A}_{h(t-1)}, \alpha_h, y_{h(t-1)} = 1, y_{h0}\right)\right] \\
&\quad - E\left[\Pr\left(y_{ht} = 1 \mid x'_{ht}, \widetilde{A}_{h(t-1)}, \alpha_h, y_{h(t-1)} = 0, y_{h0}\right)\right] \\
&= \frac{1}{N}\sum_{h=1}^{N} \Phi\left[\left(x'_{ht}\hat{\beta}_1 + \hat{\beta}_2 \widetilde{A}_{h(t-1)} + \hat{\beta}_3 + \bar{x}'_h \hat{a}_1\right)\left(1-\hat{\lambda}\right)^{\frac{1}{2}}\right] \\
&\quad - \frac{1}{N}\sum_{h=1}^{N} \Phi\left[\left(x'_{ht}\hat{\beta}_1 + \hat{\beta}_2 \widetilde{A}_{h(t-1)} + \bar{x}'_h \hat{a}_1\right)\left(1-\hat{\lambda}\right)^{\frac{1}{2}}\right]
\end{aligned}
\tag{5.15}
$$

We also calculate the predicted conditional probability ratios (PPR) of poverty over non-poverty at $t-1$, $\frac{\hat{p}_{1t}}{\hat{p}_{0t}}$, to inform the severity of past poverty relative to non-poverty in increasing the probability of becoming poor. As shown in Eq. (5.15), we evaluate the partial effect of previous poverty for each household and then average across the sample.[118]

It is generally agreed that one cannot directly interpret the magnitude of coefficients in latent dependent models (Wooldridge, 2005). To enrich the discussion, we calculate marginal effects for each explanatory variable. For a continuous covariate x_k, the mean marginal effect across all households is the product of the estimated coefficient and the scale coefficient:

---

[117] Note that the estimates of pooled probit models cannot be compared directly with those of random-effects models, since they adopt distinct ways of normalization (Stewart, 2007). The former uses $\sigma_\upsilon^2 = 1$, while the latter employs $\sigma_u^2 = 1$. To make them comparable, Stewart (2007) suggests multiplying $\frac{\sigma_u}{\sigma_\upsilon} = \sqrt{1-\lambda}$ to random-effects estimators.

[118] The calculations of APE and PPR are different from the initial approach proposed by Stewart (2007) in that our results are, for one thing, time-variant, and more importantly, are the average values but rather for an average household with mean characteristics. Because Greene (2003) argues that the marginal effects for an average household with mean characteristics are less advisable and much information on households' differentiated characteristics would be lost, we follow Greene (2003) and calculate household-specific marginal effects of being poor at *t-1* and then take the average across all households.

$$\frac{\partial \Pr(y=1)}{\partial x_k} = \hat{\beta}_k \left[\frac{1}{N} \sum_{h=1}^{N} \phi \left(\overline{x}_h' \hat{\beta} (1-\hat{\lambda})^{\frac{1}{2}} \right) \right] \tag{5.16}$$

If x_k is a dichotomous variable, the average marginal effect is calculated by

$$\frac{\Delta \Pr(y=1)}{\Delta x_k} = \frac{1}{N} \sum_{h=1}^{N} \left[\Phi\left(\overline{x}_h' \hat{\beta} + \hat{\beta}_k\right)(1-\hat{\lambda})^{\frac{1}{2}} - \Phi\left(\overline{x}_h' \hat{\beta}\right)(1-\hat{\lambda})^{\frac{1}{2}} \right] \tag{5.17}$$

In sum, our model (in particular, the specification iv) carries two appealing strengths compared with standard dynamic random-effects probit models. First, it should be less influenced by measurement errors. More importantly, four sources of poverty persistence can be directly gauged, namely the true state-dependence due to households' behavioural responses induced by their past history of poverty, observed characteristics (typically insufficient assets compared to the dynamic asset threshold), unobserved heterogeneity handicapping escape, and transitory shocks.

5.3 Data and descriptive statistics

A balanced panel is derived containing 1441 rural households equally spread across seven provinces from coastal to inland China. The asset indices are constructed as in Chapter 4 using polychoric Principal Component Analysis. The distribution of household agricultural assets is given in Fig. A in Appendix. It shows multiple peaks and many of households appear to have gravitated at a lower asset level. The distribution of households' agricultural asset holdings gives rise to the possibility of multiple equilibria in asset dynamics which underlie Carter and Barrett's (2006) asset-based poverty traps.

The remainder of this section explores how rural households' poverty status changes over the sample period and demonstrates the importance of agricultural asset holdings and past poverty experience in determining current poverty.

5.3.1 Poverty transitions: Is past prologue?

Persistence and transitions of poverty co-exist in rural China (You, 2011). 15.05 percent of sample households were non-poor in every survey year and 2.87 percent were consistently poor. Among those who were poor in one round of the surveys, as shown in Table 5.1, 58.23 percent ended up in poverty again in the next round. By comparison, 80.49 percent of the non-poor were likely to retain their livelihood position in the next period. Meanwhile, there is also an evident poverty transition. 41.77 percent of previously poor households successfully moved out of deprivation, while only 19.51 percent of those who were non-poor slipped back into poverty.

Table 5.1 Probability transition matrix of consumption poverty (%), 1989-2006

t	*t+1* Poverty	Non-poverty	Total
Poverty	58.23	41.77	100
Non-poverty	19.51	80.49	100
Total	36.52	63.48	100

The above examination of mobility implicitly assumes that transitions across the US$1.25-a-day poverty line are independent of time durations. In reality however, the current shift of household position in consumption distribution is usually associated with the time it has spent at the previous position. Taking this into account, non-parametric survival estimates (Table 5.2) clearly point out strong negative duration-dependence associated with the rates of poverty exit and re-entry. For those who just started a non-poverty spell, 78.7 percent successfully remained above the poverty line, after spending one period in non-poverty, and their re-entry rate is 23.9

percent. After five periods in non-poverty, it has only a 1.6 percent likelihood of sliding into poverty in the next period. The exit rates are also negatively associated with the duration in poverty for those who just started a poverty spell. In other words, the longer the time spent in poverty, the lower the probability of escape for these households is becoming.[119]

Table 5.2 Survival and hazard functions of ins and outs of poverty

Time since the start of spell	Poverty re-entry Sur.(s.e.)	Exit (s.e.)	Poverty exit Sur. (s.e.)	Exit (s.e.)
1	1 (.)	. (.)	1 (.)	. (.)
2	0.787 (0.013)	0.239 (0.017)	0.779 (0.009)	0.249 (0.011)
3	0.709 (0.015)	0.104 (0.014)	0.626 (0.012)	0.217 (0.014)
4	0.680 (0.016)	0.041 (0.010)	0.517 (0.013)	0.191 (0.017)
5	0.667 (0.016)	0.019 (0.007)	0.314 (0.014)	0.490 (0.034)
6	0.657 (0.017)	0.016 (0.007)	0.207 (0.013)	0.408 (0.044)

Note: Kaplan-Meier estimates.

The above probability transition matrix and survival analyses reveal that households tend to hold their positions in the consumption distribution and hence continue in their previous (non-)poverty status. These findings raise questions regarding the driving forces behind this persistence and these transitions of poverty.

5.3.2 Poverty dynamics: Do assets matter?

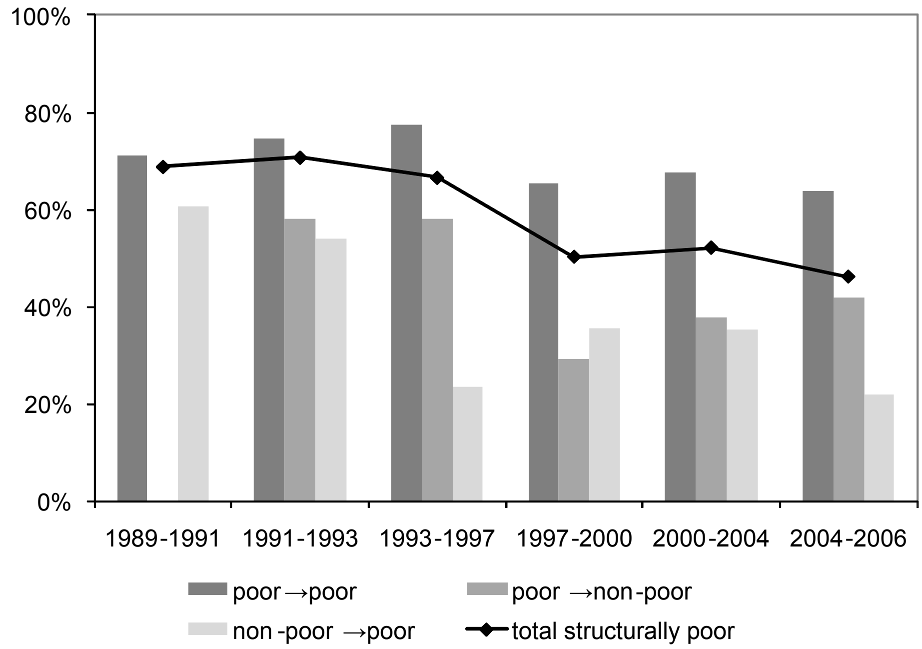
Assets appear to be an unneglectable driving force in poverty dynamics. By applying Carter and May's (2001) decomposition method to each sub-period containing two consecutive rounds of surveys, we demonstrate the important but largely under-stated structural feature underlying the poverty persistence and transitions in rural China in Fig. 5.1. In particular, we regress household log per capita consumption on a set of

[119] One may notice that after 3 periods in poverty, exit rates tend to increase, signalling an opportunity for the poor to escape at longer duration. You (2011) examines the impact of durations in poverty more carefully by a multivariate analysis and find that these increasing estimates are statistically insignificant. Detailed discussion can be found in You (2011).

household characteristics, including agricultural asset holdings, and household-specific time-invariant heterogeneity. Estimating this fixed-effect model yields predicted values of household log per capita consumption and the predicted error terms. A household is considered as structurally poor if its predicted consumption level is lower than the US$1.25-a-day poverty line, since its agricultural assets failed to lift its consumption up to the poverty line. Whatever a household is poor or rich measured by its observed consumption, it is deemed to experience entitlement losses (windfalls) if the predicted error terms are negative (positive).

As can be seen from Fig. 5.1, over 60 percent of the continuing poor (i.e., the 'poor→poor' group) in each sub-period did not have enough assets to lift their consumption up to the US$1.25-a-day poverty line. In the first sub-period, 60.5 percent of households who fell behind ('non-poor→poor') were structurally trapped. Over the full sample period, 84.4 percent of those structurally falling behind experienced entitlement losses.

Figure 5.1 The structural component in poverty dynamics



The above two kinds of structural poverty add up to the total structurally poor households among those being consumption poor in each sub-period. It can be seen that the proportion of total structurally poor, reflected by the line in Fig. 5.1, decreased from 69 in 1991 to about 50 percent at the end of 2000, but since than, has stagnated. Through 1989-2006, on average, around 60 percent of consumption poverty can be attributed to failures in agricultural asset accumulation in China. Meanwhile, for those who escaped in the second round of survey before 1997, nearly 60 percent can be attributed to structural mobility as their predicted consumption, given their asset holdings, was higher than the US$1.25-a-day poverty line. This proportion of structural upward mobility dropped to 29 percent between 1997 and 2000, but has risen continuously to 42 percent since 2000. Carter and May's (2001) decomposition of poverty dynamics clearly underscores the importance of assets in determining changes in household poverty status.

Nevertheless, their approach is essentially static and *ex post*, which fails to tell how many of the structurally poor would continue to suffer from hardship in the long term (Carter and Barrett, 2006). In the next section, we will identify the dynamic asset threshold and discuss how households' asset positions relative to this threshold would affect their long-run poverty status.

5.4 Estimation results and discussion

5.4.1 Multiple-equilibrium chronic poverty

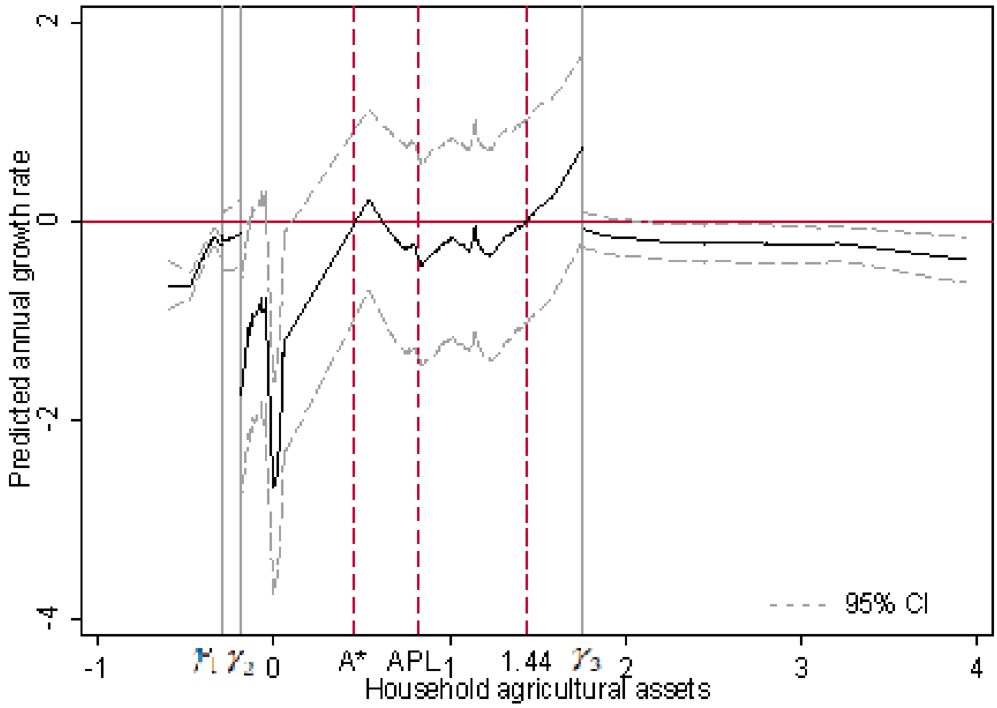
Following the searching procedures proposed in Section 5.2.1, the dynamics of household assets are shown in Fig. 5.2, where the horizontal and vertical axes measure the household asset level and the predicted asset growth rates respectively. A positive (negative) predicted growth rate indicates that the household would accumulate (deaccumulate) assets in the future.

Before continuing, it is useful to note that the decisions on whether to accumulate assets depend not only on households' existing asset levels at the time of decisions and other observed characteristics, but also on their unobserved innate abilities, such as cognition and ability to use assets efficiently. Carter and Ikegami's (2009) simulations based on Barrett *et al.*'s (2008) theoretical model suggest that the dynamic asset poverty threshold is contingent on households' innate ability. For some high-ability households, they would be able to accumulate assets even though finding themselves with very limited assets at hand. Thus, we introduce the following two bounds of the dynamic asset threshold. There may exist an asset level that even the most able household would not opt to accumulation should its assets fall below this level. We define this level as the *lower bound* of the dynamic asset threshold, A^*. In a situation by analogy, there may be an asset level that even the least able household would be able to accumulate assets if it is well-endowed with sufficient assets more than that level. We define such an asset level as the *higher bound* of the dynamic threshold.

In Fig 5.2, we find three structural breaks (γ_1 to γ_3) in households' asset dynamics with 1 percent significance levels. The lower bound of the dynamic asset threshold, A^*, is at 0.46 and the higher bound is 1.44.[120] Households in excess of 1.44 assets are more likely to converge to the higher asset equilibrium γ_3, while many of those with less asset than 0.46, experience negative predicted growth rates of assets and thus, would downwardly shift and settle in a low equilibrium around γ_2. In the range of [A^*, 1.44], it seems, from Fig. 5.2, that households have negative predicted growth rates of assets and also mobile downwards. However, because household abilities to accumulate assets are not reflected in Fig. 5.2, some high-ability households in this range would be able to accumulate assets, while some low-ability households would move downwards. In fact, we find that the fitted line of predicted asset growth rates crosses zero frequently in this domain if experimenting with narrower bandwidths. Also, the 95 percent confidence interval is wide, indicating that some have positive predicted asset growth and upwardly mobile, while some are subject to downward mobility in the future.

[120] Estimating Eq. (5.2) gives predicted growth rates of household agricultural assets. We employ lowess smoothing function with optimal bandwidth to obtain the fitted line of those predicted growth rates. We solve for the assets when the fitted line hits the horizontal axis. Among this set of asset levels, A^* is selected as such an asset level that predicted growth rates are negative (positive) in its left (right)-hand side.

Figure 5.2 Predicted annual growth rates of household agricultural assets



Note: a) The fitted line is achieved by LOWESS with optimal bandwidth.

b) APL denotes the static asset poverty line equivalent to US$1.25/day.

In the following empirical analysis, we focus only on the lower bound A^* and use it as the single dynamic asset threshold to separate households into different accumulation regimes, given that the proportion of those lying above 1.44 is too small to implement estimation: from 2.4 to 6.4 percent in different survey years.

The dynamic asset threshold, $A^* = 0.46$, is 55 percent of the static asset poverty line (APL=0.83).[121] Those falling below A^* face multiple equilibria: they would have been able to accumulate assets, but some factors placed them in the regime of downward mobility and trapped them in poverty in the long term. We term these

[121] Carter and Barrett (2006) argue that A^* can be either lower or higher than APL. The latter case is found in South Africa by Adato *et al.* (2006) which implies that the economy tends to be particularly ill-functioned for the poor's accumulation as all the currently structurally poor would be predicted to be trapped in low equilibrium in the long-term.

households the multiple-equilibrium chronic poor. By contrast, those lying above A^* would opt to accumulate and converge to the high equilibrium of assets, which lifts them out of poverty.

Comparing the total structurally poor's agricultural asset holdings with the dynamic asset threshold, roughly 80 percent of them fall below the threshold. These households are not only suffering low consumption, but also face the threat of falling into *ex ante* chronic poverty in the long term, as they would move downwards along the asset dynamics, and therefore would not have sufficient assets to sustain a higher consumption than the poverty line. Insufficient agricultural assets and accumulation might be a key reason for the increasing difficulty in further poverty reduction. The remainder of this section will measure to what extent fewer asset holdings relative to the dynamic threshold could affect the probability of poverty and investigate factors facilitating and barricading exits from poverty. We use the term 'asset poverty' to represent the situation where household falling below the dynamic asset threshold in the rest of this chapter.

5.4.2 The causal relationship between insufficient assets and consumption poverty

Table 5.3 gives the results from the estimation of the models presented by Section 5.2.2.[122] Asset accumulation is an endogenous choice since the correlation ρ (Row

[122] The asset equation does not include other kinds of assets as the poverty equation, but controls for the labour security and household business strategy. The former is constructed as Moser and Felton (2009). Specifically, we first construct an ordinal variable for household members' types of jobs and then, aggregate it for each household. The higher the value, the more secure the jobs are. The latter is an ordinal variable, with one to five representing from small-scale commerce to large-scale construction business. In the endogenous switching model, the independent variables in poverty and assets equations are not necessarily the same or different, since the correlation is modelled in the

16) is significantly different from zero. Having corrected households' endogenous switching across downward and upward mobility regimes of asset holdings, there is a significant impact from falling below the dynamic asset threshold on being poor (Row 1 and Column 1). This effect still holds even if controlling for household fixed effects (Row 1 and Column 2) such as preference, total wealth and quality of farm land. The above evidence indicates that owning less asset than the dynamic threshold can be causally related to falling into consumption poverty.

errors (Miranda and Rabe-Hesketh, 2006). However, in the two-step CF, labour security and household business strategies are weak instruments.

Table 5.3 The causal effect of asset holdings on the probability of remaining poor

Independent variable	Endogenous switching (1)	Two-step CF estimators (2)
Poverty Equation		
1. whether assets below the threshold	0.978 (0.175)***	0.752 (0.176)***
2. hh size	0.213 (0.015)***	0.084 (0.005)***
3. years of formal edu. of hh head	0.004 (0.004)	-0.006 (0.003)**
4. age of hh head	-0.004 (0.001)***	-0.005 (0.001)***
5. % male members	-0.179 (0.043)***	-0.058 (0.019)***
6. dependence ratio	0.362 (0.053)***	0.028 (0.020)
7. whether a specialised hh	-0.113 (0.038)***	0.008 (0.013)
8. land-on farm labour ratio	0.008 (0.007)	0.002 (0.002)
9. % having health insurance	-0.501 (0.047)***	-0.073 (0.015)***
10. % local off-farm employment	-0.041 (0.053)	0.018 (0.018)
11. village out-migration networks	0.773 (0.480)	-0.136 (0.156)
12. invst. in consumer durables	-0.017 (0.011)	-0.005 (0.005)
13. invst. in housing	0.014 (0.007)*	-0.001 (0.002)
14. business assets	-0.038 (0.016)**	-0.011 (0.006)*
15. human capital	-0.047 (0.005)***	-0.014 (0.002)**
16. ρ ($\rho_{\varepsilon\tau}$)	-0.550 (0.105)***	-0.362(0.085)***
Log-likelihood	-10475.580	
R^2		0.197
Asset Equation		
17. hh size	0.040 (0.013)***	0.025 (0.020)
18. years of formal edu. of hh head	-0.011 (0.005)**	-0.023 (0.010)**
19. age of hh head	0.005 (0.002)***	0.003 (0.004)
20. % male members	0.129 (0.047)***	0.166 (0.077)**
21. dependence ratio	-0.156 (0.057)***	-0.161 (0.086)*
22. whether a specialised hh	-0.123 (0.038)***	-0.045 (0.068)
23. land-on farm labour ratio	-0.006 (0.007)	-0.005 (0.010)
24. % local off-farm employment	0.097 (0.067)	0.168 (0.104)
25. village out-migration networks	-1.890 (0.456)***	-1.126 (0.636)*
26. labour security	-0.011 (0.004)***	-0.009 (0.006)
27. hh business strategy	0.003 (0.013)	-0.033 (0.019)*
Log-likelihood		-3860.803

Note: a) Year dummies are not reported.

b) ***, ** and * denote 1%, 5% and 10% significance levels.

c) Standard errors are in parentheses.

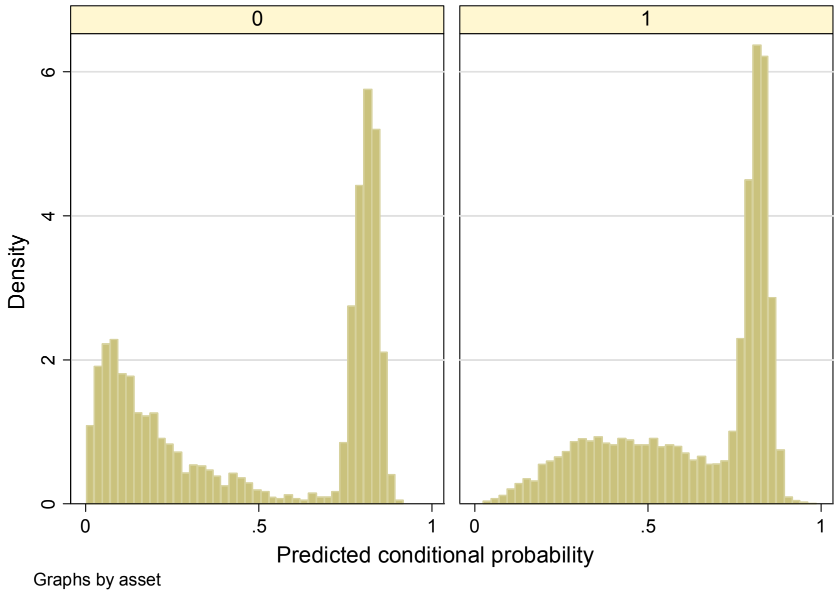
Based on the estimates of the endogenous switching model (Column 1 of Table 5.3), we further calculate predicted probabilities of poverty conditional on households' asset position compared to the dynamic asset threshold. It can be seen from Fig. 5.3 that some households are particularly vulnerable to poverty (the right-hand sides of the left histogram), although they are above the below the dynamic asset threshold.

This may be caused by the use of the lower bound of the dynamic asset threshold in our estimation.[123] For the remaining households among those whose assets are more than the threshold, the distribution of probabilities of being poor skews to the right (the left-hand side of the left histogram), while the opposite occurs for those lying below the threshold (the right histogram). According to this, one may infer that more households above the dynamic asset threshold face less likelihood of being poor compared with those falling below the threshold. Fig. 5.4 illustrates that the predicted probability of being poor for those in the downward mobility regime is consistently higher than that of those in the upward mobility regime in all survey years. Over time, the predicted probability of being poor if households fall below or above the dynamic asset threshold is 64.3 percent, and 49.5 percent if households' assets are in excess of the dynamic threshold. This means that when a household moves from the upward mobility regime to the downward mobility regime, the chance of it being consumption poor increases by 14.8 percent.[124]

[123] That is, some households' asset levels are slightly higher than A^*. Nevertheless, their characteristics, be they observed or unobserved, do not allow them to accumulate assets, and hence, increase the probability of falling into consumption poverty. We conjecture that, when the higher bound of the dynamic asset threshold is used, those who possess more assets than A^* but lower innate ability would be excluded, so that those households who have more assets but higher probability of being consumption poor would not have been observed. Unfortunately, given limited sample size lying above the higher bound of the dynamic threshold, we cannot simply use this higher bound of the threshold for estimation. Instead, the possible contribution of households' observed characteristics and unobserved heterogeneity will be examined by various dynamic probit models in Section 5.4.3.2 and 5.4.3.3 respectively.

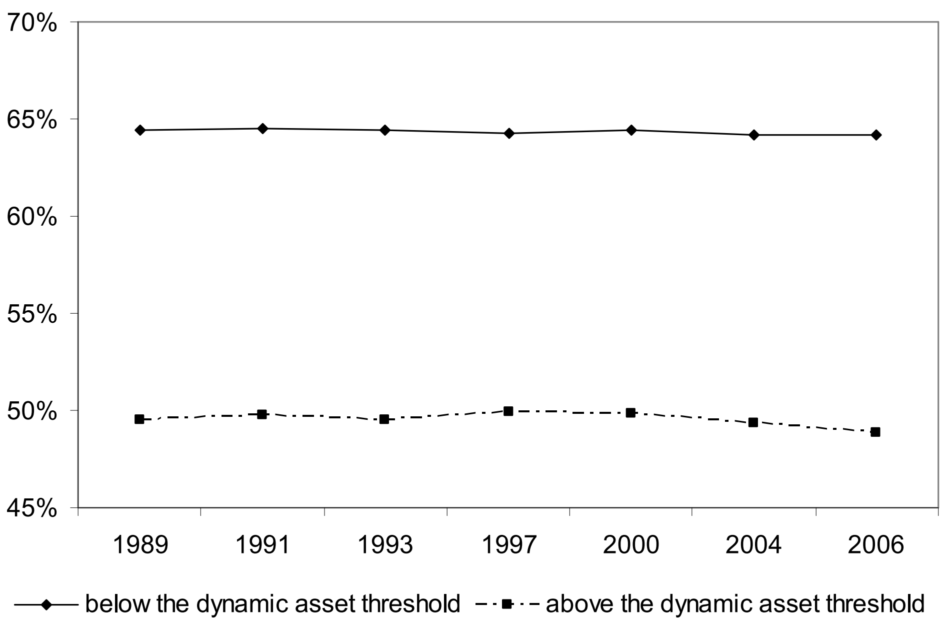
[124] This figure would have been higher if we could have used the higher bound of the dynamic asset threshold.

Figure 5.3 Distribution of predicted conditional probabilities of being poor, by asset status



Note: 0/1 represents lying above/below the dynamic asset threshold.

Figure 5.4 Mean predicted probability of poverty conditional on asset status



5.4.3 Unpacking the sources of poverty persistence over time

Using the dynamic random-effects probit model iv outlined in Section 5.2.3, this sub-section examines the impact of owning fewer agricultural assets than the dynamic threshold on the probability of becoming poor and a confluence of socioeconomic factors that may also change this probability. As robustness checks, three variations of the model specification, i to iii (i.e., the pooled probit model, the standard random-effects dynamic probit model and the Heckman estimator) are also reported.

We identify four sources of persistent poverty: the true state-dependence, unobserved heterogeneity, observed characteristics and transitory shocks. Based on the estimates in Table 5.4, they are discussed in turn in Sections 5.4.3.1 to 5.4.3.4.

5.4.3.1 The true state-dependence (TSD) of poverty

Poverty tends to beget poverty under all model specifications. According to Eq. (5.14), the ASD in the entire sample period is 38.72 percent. This stems from the households' genuine responses to past poverty as well as (observed and unobserved) heterogeneity. It is useful to distinguish between these asymmetric reasons for escape and descent as they suggest different policy implications (Ayllón, 2008). The TSD requires 'income-support policies' – for example, direct transfers of income or consumption credits to the least well-off. Ending the deprivation spinning off from individual heterogeneity calls for enhancing households' endowments in terms of improved access to financial credits, better education, skill-training and nutrition.

The TSD for the entire sample period is shown in Row 36 of Table 5.4. It accounted for over 70 percent of ASD in all model specifications. The extent of TSD decreases after controlling for unobserved household characteristics and measurement errors (Row 36 and Columns 8 and 1). Over the entire sample period, an average household is 2.66 times as likely to be poor at t as if they had been poor at $t-1$ (Row 37 and

Table 5.4 Dynamic probit models for the probability of poverty in rural China

Independent variables	Without time-invariant covariates				With time-invariant covariates			
	Pooled prob (1)	RE prob. (2)	Heckman (3)	AR(1) (4)	Pooled prob. (5)	RE prob. (6)	Heckman (7)	AR(1) (8)
State-dependence								
1. consumption poverty at *t-1*	0.927 (0.031)***	0.667 (0.045)***	0.569 (0.044)***	1.040 (0.056)***	0.852 (0.032)***	0.593 (0.045)***	0.500 (0.044)***	0.893 (0.062)***
Observed characteristics								
2. endogeneity-corrected asset status at *t-1*	0.414 (0.250)*	0.624 (0.291)**	0.710 (0.293)**	0.522 (0.266)**	0.564 (0.333)*	0.761 (0.352)**	0.800 (0.354)**	0.634 (0.348)*
3. hh size	0.261 (0.014)***	0.323 (0.017)***	0.336 (0.017)***	0.287 (0.017)***	0.292 (0.019)***	0.343 (0.021)***	0.351 (0.021)***	0.318 (0.021)***
4. age of hh head	-0.008 (0.001)***	-0.013 (0.002)***	-0.014 (0.002)***	-0.009 (0.002)***	-0.030 (0.003)***	-0.039 (0.004)***	-0.041 (0.004)***	-0.034 (0.004)***
5. % male members	-0.075 (0.050)	-0.119 (0.060)**	-0.118 (0.060)*	-0.100 (0.053)*	-0.223 (0.073)***	-0.235 (0.077)***	-0.237 (0.077)***	-0.250 (0.074)***
6. dependence ratio	0.423 (0.060)***	0.475 (0.069)***	0.484 (0.069)***	0.396 (0.062)***	0.178 (0.079)**	0.217 (0.084)***	0.223 (0.084)***	0.193 (0.080)**
7. whether a specialised hh	0.196 (0.033)***	0.282 (0.039)***	0.288 (0.039)***	0.260 (0.036)***	0.292 (0.041)***	0.334 (0.044)***	0.343 (0.044)***	0.348 (0.043)***
8. land-on farm labour ratio	0.014 (0.009)*	0.016 (0.009)*	0.016 (0.010)*	0.016 (0.009)*	0.016 (0.009)*	0.018 (0.010)*	0.018 (0.010)*	0.017 (0.010)*
9. % having medical insurance	-0.481 (0.049)***	-0.489 (0.056)***	-0.502 (0.057)***	-0.477 (0.052)***	-0.185 (0.063)***	-0.216 (0.066)***	-0.222 (0.066)***	-0.207 (0.065)***
10. % local off-farm employment	0.415 (0.055)***	0.548 (0.063)***	0.575 (0.063)***	0.455 (0.060)***	0.214 (0.070)***	0.301 (0.075)***	0.314 (0.076)***	0.244 (0.074)***

11. village out-migration networks	-0.782 (0.507)	-0.848 (0.563)	-0.852 (0.565)	-0.729 (0.534)	-0.780 (0.586)	-0.718 (0.618)	-0.660 (0.621)	-0.576 (0.608)
12. investment in consumer durables	-0.005 (0.013)	-0.013 (0.016)	-0.004 (0.016)	-0.003 (0.014)	-0.024 (0.019)	-0.028 (0.020)	-0.028 (0.020)	-0.030 (0.019)
13. investment in housing	0.010 (0.009)	0.009 (0.009)	0.006 (0.010)	0.005 (0.009)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)	-0.0003 (0.010)
14. business assets	-0.040 (0.020)**	-0.042 (0.022)*	-0.046 (0.022)**	-0.049 (0.021)**	-0.005 (0.023)	-0.016 (0.024)	-0.018 (0.025)	-0.020 (0.024)
15. human capital	-0.062 (0.005)***	-0.072 (0.006)***	-0.075 (0.006)***	-0.070 (0.006)***	-0.046 (0.006)***	-0.057 (0.007)***	-0.059 (0.007)***	-0.055 (0.007)***
16. a(endogeneity-corrected asset status)					-0.622 (0.541)	-0.892 (0.673)	-0.673 (0.677)	-0.581 (0.612)
17. a(hh size)					-0.086 (0.033)***	-0.102 (0.042)**	-0.082 (0.042)*	-0.088 (0.038)**
18. a(age of hh head)					0.028 (0.004)***	0.036 (0.004)***	0.038 (0.005)***	0.032 (0.004)***
19. a(% male members)					0.256 (0.106)**	0.269 (0.129)**	0.279 (0.131)**	0.297 (0.117)**
20. a(dependence ratio)					0.504 (0.147)***	0.626 (0.188)***	0.592 (0.188)***	0.482 (0.166)***
21. a(whether a specialised hh)					-0.641 (0.099)***	-0.782 (0.129)***	-0.790 (0.129)***	-0.726 (0.115)***
22. a(land-on farm labour ratio)					-0.006 (0.021)	-0.005 (0.028)	-0.003 (0.028)	-0.002 (0.024)
23. a(% having medical insurance)					-0.588 (0.107)***	-0.701 (0.134)***	-0.742 (0.134)***	-0.630 (0.122)***
24. a(% local off-farm employment)					-0.428 (0.164)***	-0.607 (0.215)***	-0.587 (0.215)***	-0.476 (0.190)**

25. a(village out-migration networks)					-0.482 (1.332)	-0.748 (1.729)	-1.079 (1.717)	-0.692 (1.513)
26. a(investment in consumer durables)					0.019 (0.029)	0.019 (0.036)	0.055 (0.036)	0.050 (0.032)
27. a(investment in housing)					0.072 (0.025)***	0.096 (0.033)***	0.052 (0.034)	0.049 (0.029)*
28. a(business assets)					-0.108 (0.045)**	-0.116 (0.058)**	-0.122 (0.059)**	-0.100 (0.052)*
29. a(human capital)					-0.024 (0.015)	-0.022 (0.019)	-0.031 (0.019)	-0.024 (0.017)
Unobserved heterogeneity								
30. θ			1.188 (0.168)***	1.608 (0.278)***			1.263 (0.179)***	1.571 (0.253)***
Transitory shocks								
31. ρ				-0.291 (0.027)***				-0.250 (0.031)***
32. λ		0.204 (0.026)	0.234 (0.025)***	0.133 (0.023)***		0.194 (0.024)	0.224 (0.023)***	0.153 (0.023)***
33. log-likelihood	-4513.37	-4477.34	-5312.46	-5279.74	-4376.79	-4339.28	-5170.24	-5151.75
34. Counterfactual $\hat{p}_1$	0.560	0.492	0.474	0.570	0.542	0.479	0.462	0.536
35. Counterfactual $\hat{p}_0$	0.219	0.269	0.292	0.214	0.249	0.297	0.313	0.254
36. APE (TSD): $\hat{p}_1 - \hat{p}_0$	0.341	0.223	0.182	0.356	0.293	0.182	0.149	0.282
37. PPR: $\hat{p}_1 / \hat{p}_0$	2.558	1.828	1.624	2.663	2.173	1.612	1.477	2.113

Note: a) Year dummies and the estimation for initial conditions are not reported. The small letter *a* represents the household intertemporal mean.

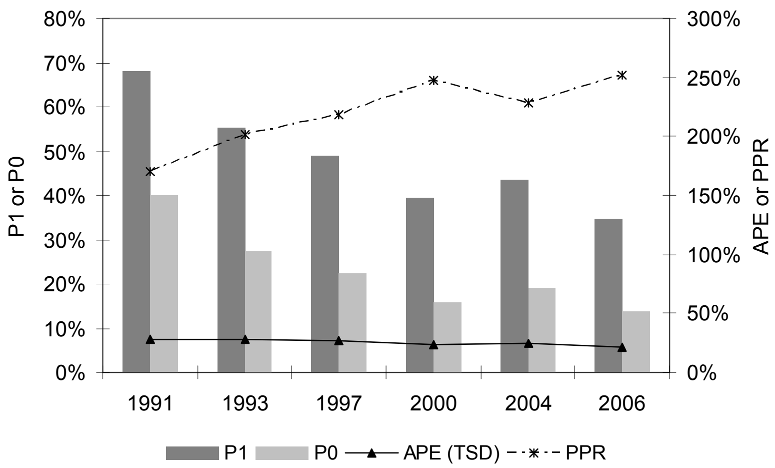
b) APE and PPR are comparable across specifications as the random-effects estimators have be multiplied by $\sqrt{1-\hat{\lambda}}$.

c) ***, ** and * denote 1%, 5% and 10% significance levels. Standard errors are in parentheses.

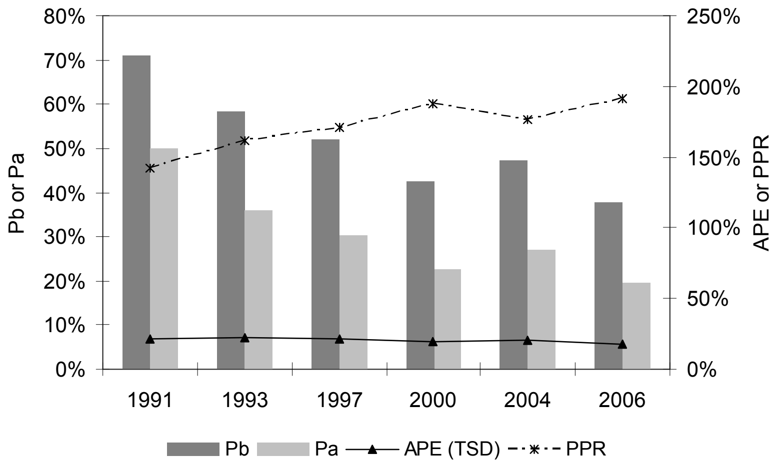
Column 4). This figure decreases to 2.11 times when further specifying the unobserved heterogeneity by the intertemporal mean characteristics (Row 37 and Column 8). We also calculate per-period TSD and PPR with respect to past poverty, based on the estimates in Column 8. The probability of becoming poor was higher for those who were poor at $t-1$ compared to the previously non-poor in every sub-period and the PPR grew rapidly to 2.5 at the end of 2006 (Fig. 5.5(a)). The per-period TSD only marginally decreased from 28.1 in 1991 to 20.9 percent in 2006.

Figure 5.5 The state dependence of poverty

(a) The effect of past poverty



(b) The effect of past asset status

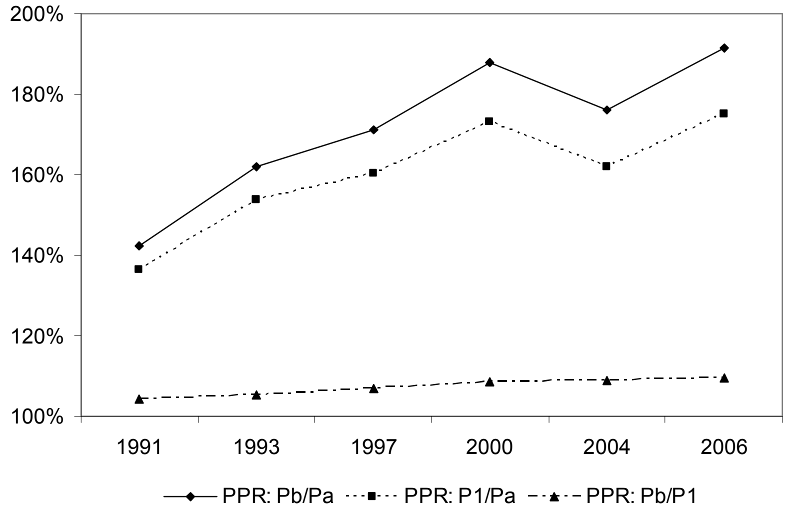


Note: p_1 (p_b) denotes consumption (asset) poverty at *t-1* and p_0 (p_a) denotes non-poverty at *t-1* accordingly.

In addition to past experience of poverty, we examine the impact of previous asset poverty on the probability of becoming poor. Based on Column 8, we calculate corresponding per-period TSD and PPR with respect to previous asset status. As shown in Fig. 5.5(b), in every sub-period, those falling below the dynamic asset threshold at $t-1$ are more likely to become poor compared to the previously asset-rich. Similar to the case of past poverty in Fig. 5.5(a), the PPR increased from 1.42 in 1991 to 2 in 2006 and TSD only slightly decreased from 21.1 to 18.1 in the same period. On average over time, households with the same characteristics are 1.72 times as likely to be poor at t as if they had not switched to the asset accumulation regime at $t-1$.

This analysis has documented the importance of past poverty and asset status on the probability of becoming poor. The present sub-section proceeds to compare the probability-increasing impacts of past consumption poverty and asset poverty by cross-calculating PPRs. The asset position compared to the dynamic threshold tends to be more vital in determining households' current consumption poverty status. The top line p_b / p_a in Fig. 5.6 is the same as the PPR with respect to past asset status in Fig. 5.5(b). Households are 1.72 times to be currently consumption poor if they had been asset poor at $t-1$ as if they had not been. The ratio p_1 / p_a suggests that, over time, they are on average 1.6 times as likely to be poor if they had been consumption poor at $t-1$ as if they had not been asset poor. Therefore, households are still 1.1 times as likely to be poor if they had been short of assets as if they had been in consumption poverty, as represented by the bottom line p_b / p_1. Moreover, this ratio is not only consistently higher than one, but also keeps increasing over time. This indicates an intensified effect of insufficient asset holdings on Chinese rural households' consumption poverty.

Figure 5.6 Comparative impacts of past consumption and asset poverty on the probability of current consumption poverty



Note: p_b (p_a) denote the probabilities of falling into consumption poverty at *t* if households were (not) asset poor at *t-1*. p_1 denotes the probability of consumption poverty at *t*.

The above evidence reveals a significant impact of past exposure to consumption and asset poverty on households' probabilities of becoming poor and lends support to the existence of 'scarring effects', captured by TSD, to past hardship, through which past consumption poverty can be transferred into the future. As argued by Carter and Barrett (2006), responding to past experience in poverty, households may change their behaviour, preferences, asset portfolios, livelihood strategies etc. For example, as found in Chapter 4, they may prefer conservative production activities to profitable but riskier asset accumulation, when faced with low consumption outcome. Moreover, as suggested by Fig. 5.6, a value of p_b / p_1 greater than one and its upward trend over time indicate that insufficient assets can generate increasingly more 'scarring effects' for households' future poverty status than simply being consumption poor.

In addition to these 'scarring effects', spell durations might be an alternative insidious conduit transferring poverty. Addison *et al.* (2009) note that different elapsed time duration spent in past poverty could also affect present outcomes. Empirically, the negative impact of the duration of spells of poverty on the possibility of exiting poverty has been documented in both developed countries (Spain, Italy, Russia, Sweden, Belgium and the UK[125]) and developing economies (rural Ethiopia by Bigsten and Shimeles, 2008). With regard to rural China, our survival analysis in Section 5.3.1 also provides evidence of negative duration dependence for both poverty-exit and re-entry rates.

In the presence of duration dependence, the identified positive relation between past and current poverty may be based on the fact that the poor experienced longer elapsed durations at $t-1$ and those having stayed in longer durations of past spells of poverty typically face greater probabilities of becoming poor at t. We test for this hypothesised channel by adding the duration of non-poverty spells for those who were not poor at $t-1$ to Column 8 in Table 5.4,[126] which is in line with Stewart's (2007) method in his analysis of employment participation. The estimated coefficient

[125] Using hazard rate models, relevant studies can be found, in turn, from Martín and Cowell (2006), Devicienti and Gualtieri (2007), Denisova (2007), Hansen and Walhlberg (2004), Maes (2008) and Devicienti (2002).

[126] In the interests of simplicity, we do not take the timing/order of past spells into account. When constructing the variable of duration, every past spell is treated equally whenever it occurred, i.e. the principle of 'universalism' in Calvo and Dercon (2009). Alternatively, Canto (2002) and Frederiksen *et al.* (2007) provide a better way of modelling recurrent spells, utilizing *n*-order Markov discrete-time duration models. Nevertheless, Arranz and Cantó (2008) show that both duration and accumulation of past spells could alter the probability of current poverty. In this stream, one may employ a sequence-sensitive aggregation assuming increasing distress for the most recent spell, as suggested by Calvo and Dercon (2009). Mendola *et al.* (2009) provide a path-dependent longitudinal poverty index increasing with both duration and the sequencing of poverty and non-poverty episodes.

of the duration variable is negative with the significance level at 1 percent, indicating that the longer time spent in non-poverty, the less likely is the household to fall into current poverty. Duration dependence does appear to be a possible channel and might result in over-estimated state-dependence of poverty. An extreme case with respect to duration dependence is that some households were poor in every survey year. Therefore, as a robustness check, we exclude those who were continuously poor and repeat the estimations and calculations. Results are shown in Table A in Appendix A. It can be seen that the above conclusions are unchanged.

To summarise, significant ASD underscores the persistence of poverty even after controlling for individual heterogeneity and measurement errors. Compared to past exposure to consumption poverty, insufficient assets relative to the dynamic asset threshold make households more likely to become poor. Substantial TSD in ASD implies that this continuing deprivation may be a result of 'scarring effects' brought about by past experience of consumption and/or asset poverty. Overall, poverty can propagate itself.

5.4.3.2 Household observed characteristics

A number of observed characteristics also contribute to the probability of households descending into consumption poverty. Table 5.5 computes the marginal effects of household observed characteristics based on the estimates in Column 8 of Table 5.4. The results indicate that family size and dependency ratio can significantly increase the probability of poverty-entry (Rows 1 and 4 in Table 5.5). By contrast, four kinds of factors are found capable of reducing the probability of becoming poor. The rest of this sub-section will discuss these latter findings in greater detail.

Table 5.5 Mean marginal effects on the probability of poverty

Independent variable	hh above the threshold	hh below the threshold
1. household size	6.340 (0.902)***	6.492 (0.924)***
2. age of household head	-0.042 (0.639)	-0.043 (0.065)
3. % male members	1.312 (2.247)	1.343 (2.530)
4. dependency ratio	18.611 (3.991)***	19.058 (4.087)***
5. whether a specialised farm hh	-10.265 (3.350)***	-11.128 (2.480)***
6. land-on farm labour ratio	0.409 (0.633)	0.419 (0.648)
7. % medical insurance	-23.077 (2.884)***	-23.631 (2.954)***
8. % local off-farm employment	-6.392 (2.815)***	-6.545 (2.931)***
9. village out-migration networks	-42.410 (38.494)	-43.429 (39.418)
10. investment in consumer durables	0.558 (0.703)	0.571 (0.720)
11. investment in housing	1.356 (0.761)*	1.338 (0.779)*
12. business assets	-3.306 (1.271)***	-3.385 (1.302)***
13. human capital	-2.175 (0.429)***	-2.228 (0.440)***

Note: a) Marginal effects are expressed by percentages.

b) Standard errors are in parentheses. They are computed by the Delta method and also multiplied by 100 in order to be comparable with marginal effects. *** and * represent 1% and 10% of significance levels.

i. Farmland

Being a 'specialised' farm household with more than 20*mu* of farmland may reduce the probability of falling into poverty by 10.3-11.1 percent (Row 5 in Table 5.5). A larger farm size can help households resist agricultural risk (in particular price and weather risk documented by Yang, 2007) by diversifying their crop variations. However, land rental markets in rural China have been underdeveloped and inefficient due to the state ownership and collective (re-)allocation of land (Brandt *et al.*, 2002), despite market liberalization in many other sectors. Rural households cannot trade their farm land freely, but have to abide by local governments' (re-)allocation according to the household labour force. This implies that, on the one hand, the poverty-reducing effect of large farm size might be enjoyed largely by those households endowed with more labour force in the medium term (prior to the next round of reallocation). On the other hand, those who have limited opportunities for off-farm employment and could have earned more income from enlarging agricultural production by acquiring more plots would have been prevented from specialising in agriculture, and thus, would not see significant reductions in the probability of poverty.

ii. Health insurance

Greater coverage of health insurance for household members appears to be the most prominent driving force in lowering the probability of entering poverty (Row 7 in Table 5.5).[127] It could reduce by 23 percent the probability of becoming poor for those lying above the dynamic asset threshold, while this marginal effect is marginally greater for those falling below the threshold (23.6 percent). This may lend some support to Barrett *et al.* (2008) and Carter and Ikegami's (2009) argument, based on their simulations for the theoretical model, that social protection could best facilitate the multiple-equilibrium chronically poor to escape, as it lowers the dynamic asset threshold for them and thereby encourages those facing multiple equilibria to adopt high-return technologies and production plans and accumulate towards higher equilibrium.

There might be two underlying mechanisms through which this movement takes place. Firstly, health insurance, especially the establishment of the New Cooperative Medical Scheme (NCMS) in 2003, may reduce financial risk faced with rural households, which is widely seen as one of the driving forces of poverty (e.g.,

[127] The discussion on the probability-reducing impact of health insurance and off-farm employment on poverty should be read with caution. Although treated strictly exogenously in our analysis, both variables may be endogenous. It could be the case that wealthier or well-educated households are more likely to afford the health insurance and engage in off-farm activities and these households are also more able to get rid of previous poverty.

Gustafsson and Li, 2004; Hu *et al.*, 2008).[128] Secondly, wider coverage of health insurance improves rural residents' health status by enhancing rural residents' use of preventive care (Lei and Lin, 2009), and hence, sustains their labour productivity. This in turn may serve as part of productive safety nets which function to prevent households from falling below the dynamic asset threshold.

iii. Off-farm employment and household business assets

Village out-migration networks seem to have the largest poverty-reducing effect, with 42.4-43.4 percent less chance of becoming consumption poor for an additional 10 percent increase in village out-migration (Row 9 in Table 5.5). However, this impact appears statistically insignificant, which is the opposite to Giles and Murtazashvili (2010) who use the RCRE data set and find statistical significance. The reason may be that the share of village out-migration in our data is much lower than in Giles and Murtazashvili (2010).[129] Local off-farm employment, on the other hand, suggests a statistically significant marginal effect (Row 8 in Table 5.5); a 10 percent increase in it reduces the probability of falling into poverty by 6.4-6.5 percent.

In order to take advantages of the poverty-alleviating effect of off-farm employment, policies might do well to relax rural households' liquidity constraints on finance

[128] However, this positive effect of health insurance needs to be treated with a great deal of caution. Many studies do not directly find decreasing out-of-pocket medical expenditure under the NCMS (e.g., Wagstaff *et al.*, 2009b; Lei and Lin, 2009), largely because hospitals are inclined to over-prescribe and over-provide expensive services to NCMS participants (Lei and Lin, 2009; Sun *et al.*, 2009a; Yip and Hsiao, 2009). Wagstaff *et al.* (2009a) also underline the non-decreasing nature of out-of-pocket payments per outpatient visit and in-patient stay.

[129] Our indicator of village out-migration is calculated as the share of individuals living and temporarily working outside of their home villages (less than six months) in the village total population. In comparison, Giles and Murtazashvili (2010) define out-migration as the share of those living and working, either temporarily or permanently, outside their home county in the village working age adults.

(Uchida *et al.*, 2009), unblock labour and land transfers across villages (Bowlus and Sicular, 2003), and provide educational support (Brosig *et al.*, 2009). They could encourage households' shift from on-farm to off-farm activities. However, this does not mean that agriculture is no longer important. For one thing, agricultural growth has long been a driving force of poverty reduction in rural China (Montalvo and Ravallion, 2010; Christiaensen *et al.*, 2010), while household business has only a trivial impact on reducing the chance of becoming poor (3.3-3.4 percent in Row 12 of Table 5.5). For another, employment in non-agricultural sectors appears to reduce poverty through assisting agricultural production rather than household business. Take out-migration for instance; although households may loose some on-farm workforce, remittances can loosen financial constraints on agricultural production (Rozelle *et al.*, 1999b; Taylor *et al.*, 2003), stimulate agricultural productivity (Rozelle *et al.*, 1999a) and improve rural households' livelihoods by increasing investments in housing and consumer durables (de Brauw and Rozelle, 2008a). It is nevertheless less likely to stimulate investment in household business capitals and inventory (Taylor *et al.*, 2003; de Brauw and Rozelle, 2008a).

iv. Human capital

More human capital in terms of weighted years of education reduces the probability of becoming poor (Row 13 in Table 5.5). Apparently, the magnitude of the poverty-reducing effect of human capital is not substantial (roughly 2.2 percent). However, it is better understood through its 'spillover' effects on households' other capabilities.

Specifically, human capital not only allows households to make better use of assets to generate income, particularly from non-agricultural production (Yang, 2004), but also increases the likelihood of obtaining off-farm jobs (Zhang *et al.*, 2002; Glauben *et al.*, 2008) and returns to off-farm employment. For example, de Brauw and Rozelle (2008b) estimate the average returns of one year of education to rural residents' off-farm wages at 6.4 percent. Given these spillover mechanisms, one may suppose that the actual marginal effect of human capital could surpass 2.2 percent.

However, it should be mentioned that, although increasing, for a long time Chinese labour market and wage policy have kept the private returns to education low compared to that of other countries (15-20 percent for the US in Heckman, 2005) and of physical capital in China (20 percent in Chow, 1993). This discourages individual investment in education and skill training. Moreover, our analysis does not point to what educational level or kind of training could help the poor better. This invites further investigation.

5.4.3.3 Unobserved heterogeneity and endogenously initial poverty

In addition to a range of observed characteristics, unobservables may also influence household poverty status (Row 30 in Table 5.4). In effect, 15.3 percent of the error variance can be attributed to household heterogeneity (Row 32 and Column 8). In the right panel of Table 5.4, we try to identify some of the unobserved time-invariant heterogeneity by including household-specific intertemporal mean characteristics. Compared to Columns 1-4, inclusion of the intertemporal mean (Columns 5-8) fits our models better as log-likelihoods are larger (Row 33). TSD and PPR in Columns 5-8 decrease (Rows 36-37) and many of the intertemporal mean characteristics are statistically significant (Rows 17-21, 23-24, and 27-28). These findings imply that unobserved heterogeneity does matter. Controlling for it improves the accuracy of estimates of transitions in and out of poverty.

Furthermore, the existing literature on asset poverty traps shares the 'omitted relevant variables problem' (Carter and Barrett, 2006), associated with ignorance of possible correlations between household-specific heterogeneity and initial poverty status. Specifically, downward mobility may not only be due to observed difficulties in asset accumulation as households fall below the dynamic threshold, but also be due to intrinsic and impassable barriers such as handicaps and 'low work ethic' (e.g., the bad attitude about work or work commitment). In this case, one may arrive at the conclusion of a spurious poverty trap which is actually a low-level equilibrium 'club' (Carter and Barrett, 2006). Because existing empirical studies fail to distinguish between genuine poverty traps (TSD) and club convergence, they may have over-stated the number of the dynamically poor in the long term.

We address this problem by allowing for correlation between household unobserved heterogeneity and initial poverty status (Columns 3, 4, 7 and 8), which is captured by $\hat{\vartheta}$ (Row 30). The unobserved heterogeneity appears to be an important contributor to households' initial poverty status, as $\hat{\vartheta}$ is significantly positive. Comparing Columns 6-8 with Column 4, both TSD and PPR (Row 36, 37) decline when we gradually control for some specified unobserved heterogeneity, endogenous initial poverty status and measurement errors as $AR(1)$ residuals. This confirms Carter and Barrett's (2006) argument on possible overstatement of genuine multiple-equilibrium poverty traps in the existing empirics. Nevertheless, the magnitude of TSD still remains substantial in ASD in Column 8, pointing to the presence of genuine poverty traps due to the 'scarring effects' of past poverty alone, as discussed in Section 5.4.3.1.

Overall, the impact of household heterogeneity on poverty transitions and persistence can be confirmed in our analysis. Pertinent policy implications would include providing social protection in the form of health insurance, increasing off-farm job opportunities and improving care of the elderly through provision of pensions for rural residents.

5.4.3.4 Transitory shocks

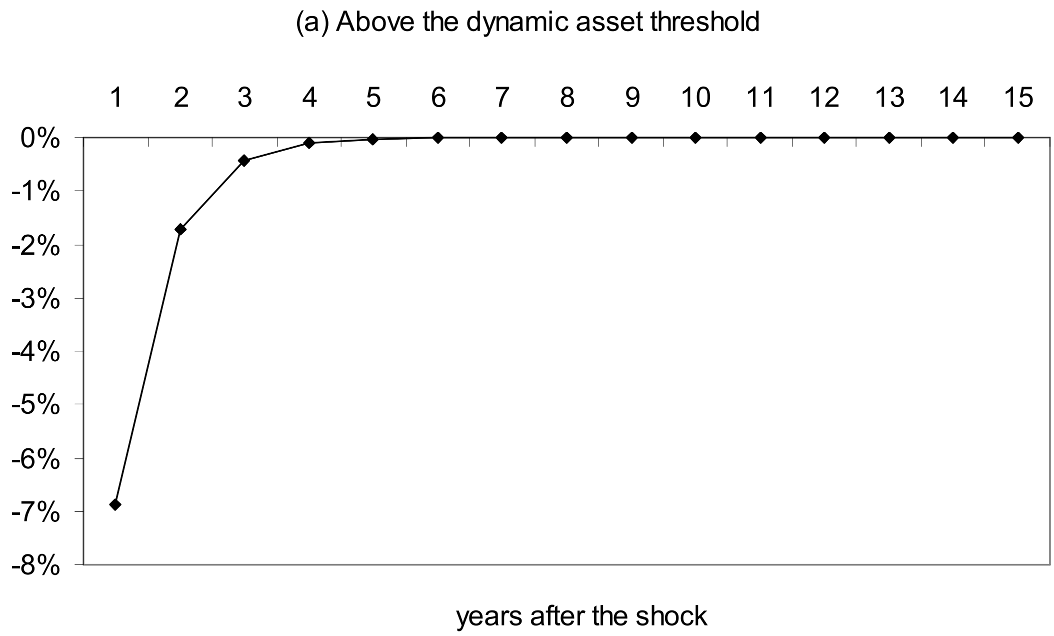
Comparing Columns 3 and 4 (and Columns 7 and 8), the inclusion of $AR(1)$ error terms considerably accentuates the persistence of poverty as TSD (Row 36) increases substantially. Such a tendency implies that TSD may have been underestimated in the presence of transitory shocks, including measurement errors, in existing studies (Bigsten and Shimeles, 2008).

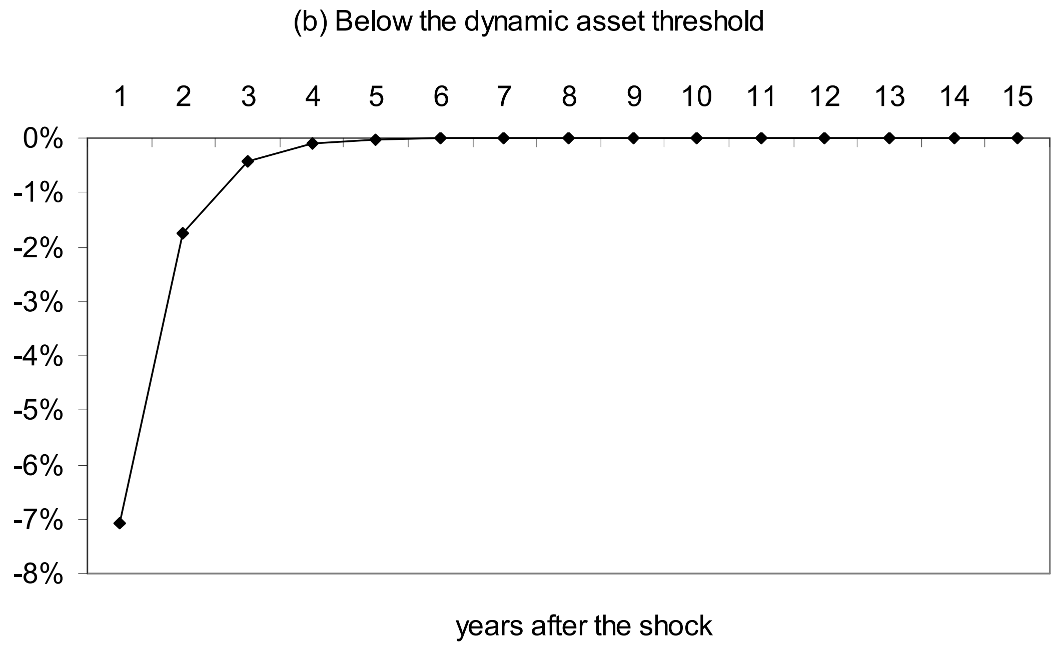
Significant negative $\hat{\rho}$ (Row 31) suggests that transitory shocks are negatively correlated in all cases, implying that favourable shocks facilitating household asset accumulation and increasing their consumption could reduce the probability of sliding into poverty.[130] However, as pointed out by Bigsten and Shimeles (2008), the estimated coefficient of ρ being less than one indicates that the appreciated impact of positive shocks tends to dissipate over time. For example, we suppose there is one unit of favourable shock at the initial period. Others things being equal, Fig. 5.7 (a) and (b) show that the probability of becoming poor would decline by 7 percent at the

[130] An extreme example of a 'favourable shock' could be if the household wins a lottery.

end of the first year after the realisation of this shock, but would quickly drop to 1.7 percent after two years. The poverty-alleviating effect of a unit of favourable shock is predicted to practically disappear after four years. Also, there is no systematic difference in the marginal effects of favourable transitory shocks between those below (Fig. 5.7b) and above the dynamic asset threshold (Fig. 5.7a).

Figure 5.7 Simulated impacts of positive transitory shocks on the probability of becoming poor, by household asset position





Under adverse shocks, both subsets confront greater chances of slipping into long-run low welfare. Negative shocks on their own would increase the probability of being poor by lowering household consumption, but this poverty-increasing effect would be almost zero after four years. Nevertheless, considering the strong TSD of poverty, distress caused by a large adverse shock in the recent past may well change household behaviour and thereby increase the chance of staying in poverty in the future. In this sense, transitory shocks may shape a gnawing long-run 'vicious circle' for households, especially those below or just slightly above the dynamic asset threshold. Breaking this vicious circle calls for income-supporting policies as well as social protection that helps households mitigate the effects of adverse shocks – for example, by providing more off-farm employment and health insurance as discussed in Section 5.4.3.2.

5.4.3.5 Summary of sources of persistent poverty over time

Section 5.4.3 identifies four sources of poverty persistence and discusses the extent to which each influences the probability of falling into poverty. It is useful to point out that the marginal effects should be understood as short- or medium-run effects given the inclusion of lagged poverty $y_{h(t-1)}$. Bigsten and Shimeles (2008) note that in the long-run steady-state when $y_{ht} = y_{h(t-1)}$, the marginal effect for an independent variable $x_{k,ht}$ should be up-scaled to $\frac{\hat{\beta}_k}{1-\hat{\beta}_3}$ under the specification of linear probability. In other words, both poverty-increasing and alleviating effects will be exacerbated 3.4 times in our analysis.

At the same time, two caveats remain. First, the dynamic models *per se*, whatever the specifications they take, do not exclude the possibility of continuing spells of poverty during the entire sample period. This may lead to over-prediction of the estimators, especially the state-dependence estimator. It also means our model is unable to examine how these factors affect re-entering poverty in a discrete series of poverty spells. Stewart (2007) suggests using a bivariate version of the model presented in Section 5.2.3 to address this problem, but this has been left for future research.

Second, Hyslop (1999) notes that time-invariant heterogeneity cannot reveal the effects of transitory unobserved factors on poverty, so the prediction of observed households' poverty status may be largely imprecise. We test for this conjecture in our sample by predicting households' poverty sequences using model specifications of Eq. (5.5) and (5.6). The analysis does find significant underprediction of sequences with transitions of consumption poverty as well as overprediction of continuing consumption poverty spells.[131] To address this problem, Hyslop (1999) provides an alternative specification, but again this goes beyond the scope of this chapter.

5.4.4 Insufficient assets as a conduit of becoming poor

The analysis so far has examined how poverty and asset status in the immediate past affect the probability of current poverty. In this sub-section, we further investigate whether assets that are insufficient compared to the dynamic threshold serve as a conduit of transferring past hardship into current poverty. This is done by adopting Stewart's (2007) second-order dynamic probit models. Results are presented in Table 5.6.

[131] For example, we compare the observed and the predicted poverty transitions using predictions based on estimates of standard random-effects probit (Column 6). On the one hand, the observed share of households with at least three transitions into and out of poverty is 24 percent, while 13 percent in prediction of our model. On the other hand, the share of households with at most two transitions into and out of poverty increases from the observed 30 percent to predicted 54 percent.

Table 5.6 Estimation of the 2nd-order dynamic probit model

Independent variable	Pooled OLS (1)	Wooldridge (2005) CML (2)
1. PL	0.444 (0.045)***	0.416 (0.054)***
2. PH	0.293 (0.088)***	0.264 (0.094)***
3. LP	-0.109 (0.094)	-0.110 (0.096)
4. LL	-0.129 (0.114)	0.133 (0.116)
5. HH	0.339 (0.174)*	0.352 (0.178)**
6. LH	0.356 (0.194)*	0.375 (0.198)*
7. poverty at *t-2*	0.238 (0.042)***	0.270 (0.055)***
8. poverty at *t-1*	0.787 (0.087)***	0.749 (0.096)***
9. endogeneity-corrected asset status at *t-2*	0.191 (0.598)	0.189 (0.607)
10. endogeneity-corrected asset status at *t-1*	1.483 (0.990)	1.566 (1.011)
11. hh size	0.329 (0.022)***	0.337 (0.024)***
12. hh age	-0.004 (0.005)	-0.004 (0.005)
13. % male members	-0.294 (0.083)***	-0.303 (0.085)***
14. dependence ratio	0.038 (0.090)	0.040 (0.092)
15. whether a specialised hh	0.008 (0.072)	0.010 (0.073)
16. land-on farm labour ratio	0.019 (0.010)*	0.019 (0.010)*
17. % medical insurance	-0.034 (0.071)	-0.038 (0.072)
18. % local off-farm employment	-0.073 (0.094)	-0.073 (0.095)
19. village out-migration networks	0.215 (0.647)	0.255 (0.655)
20. investment in consumer durables	-0.018 (0.022)	-0.018 (0.022)
21. investment in housing	0.005 (0.011)	0.005 (0.011)
22. business assets	-0.015 (0.026)	-0.015 (0.027)
23. human capital	-0.075 (0.009)***	-0.078 (0.010)***
24. a(endogeneity-corrected asset status)	-0.931 (0.768)	-0.948 (0.792)
25. a(hhsize)	-0.127 (0.039)***	-0.125 (0.041)***
26. a(hhage)	0.005 (0.006)	0.005 (0.006)
27. a(% male members)	0.320 (0.124)***	0.332 (0.129)***
28. a(dependence ratio)	0.427 (0.172)**	0.449 (0.180)**
29. a(whether a specialised hh)	-0.247 (0.143)*	-0.270 (0.149)*
30. a(land-on farm labour ratio)	-0.012 (0.024)	-0.012 (0.025)
31. a(% medical insurance)	-0.796 (0.129)***	-0.829 (0.138)***
32. a(% local off-farm employment)	-0.265 (0.194)	-0.274 (0.203)
33. a(village out-migration networks)	-2.274 (1.573)	-2.396 (1.645)
34. a(investment in consumer durables)	0.019 (0.033)	0.020 (0.035)
35. a(investment in housing)	0.035 (0.029)	0.037 (0.030)
36. a(business assets)	-0.106 (0.052)**	-0.112 (0.055)**
37. a(human capital)	-0.002 (0.018)	-0.003 (0.019)
38. λ		0.037 (0.038)
39. log-likelihood	-3361.731	-3361.101
40. APE (TSD): PL	0.130	0.118
41. APE (TSD): PH	0.091	0.078
42. PPR: PL	1.826	1.750
43. PPR: PH	1.464	1.410

Note: Time dummies in the pooled OLS are not reported.

We treat the initial poverty status exogenously by pooling all households and applying OLS, but consider endogenous initial conditions by using Wooldridge (2005) method. Specifically, the probability of poverty at t is regressed as:

$$y_{ht} = \mathbf{1}\left(x'_{ht}\beta_1 + \beta_2\widetilde{A}_{h(t-1)} + \beta_3\widetilde{A}_{h(t-2)} + \beta_4 y_{h(t-1)} + \beta_5 y_{h(t-2)} + D'\beta_6 + \alpha_h + u_{ht} > 0\right) \quad (5.18)$$

where $D' = \{PL, PH, LP, LL, HH, LH, HP, HL\}$ with the first letter denotes households' poverty or asset status at *t-2* and the second letter denotes households' poverty or asset status at *t-1*; P represents falling into poverty and H represents lying higher than the dynamic asset threshold; other variables are defined as in Section 5.2.3. Different from Eq. (5.11), household heterogeneity is projected on households' intertemporal mean characteristics as well as the initial conditions:

$$\alpha_h = a_0 + \bar{x}'_h a_1 + y_{h0}a_2 + y_{h1}a_3 + e_h \quad (5.19)$$

Substituting this into Eq. (5.18) yields the structural equation:

$$y_{ht} = \mathbf{1}\begin{pmatrix} x'_{ht}\beta_1 + \beta_2\widetilde{A}_{h(t-1)} + \beta_3\widetilde{A}_{h(t-2)} + \beta_4 y_{h(t-1)} + \beta_5 y_{h(t-2)} \\ + \bar{x}'_h a_1 + y_{h0}a_2 + y_{h1}a_3 + e_h + u_{ht} > 0 \end{pmatrix} \quad (5.20)$$

Eq. (5.20) indicates that the distribution of the sequence of outcomes is conditional on exogenous household characteristics as well as the initial observation of poverty status. The conditional maximum likelihood (CML) estimation is used in this case.

As seen in Table 5.6, households' poverty experiences at $t-2$ (Rows 1-2) significantly increase the probability of being currently poor, no matter whether or not they were below or above the dynamic asset threshold at $t-1$. Furthermore, the magnitude of this negative impact of past poverty experience is significantly different for those lying below and above the asset threshold.[132] Specifically, for

[132] The *p*-values of Wald test of equal estimated coefficients (Rows 1-2) are 11.0% for Column 1 and 11.2% for Column 2.

those having been poor at $t-2$, possessing less asset than the dynamic asset threshold at $t-1$ would bring 34 percent greater likelihood for them to become currently poor at t compared to those owning more assets than the threshold at $t-1$ (Row 42 minus Row 43 in Column 2). In addition, the TSD for households above the dynamic threshold is 4 percent lower than that of those falling below the threshold (Row 40 minus Row 41 in Column 2). These findings suggest that insufficient assets may act as a channel through which past poverty could be more easily transferred to current poverty.

5.5 Concluding remarks

The work reported in this chapter has identified a dynamic asset threshold for rural Chinese households during the period 1989-2006 and explored the contributing factors of the probability of falling into poverty (measured by consumption expenditure) conditional on their position in the distribution of agricultural asset holdings. In dealing with this latter issue, our model explicitly accounts for the true state-dependence of poverty, household unobserved heterogeneity and transitory shocks. Three particular findings can be summarised as follows.

First, the analysis finds a dynamic asset threshold separating households into downward and upward mobility regimes in terms of their agricultural asset holdings. The former group may become trapped with low equilibrium assets and therefore suffer long-run low income, while the latter group has the potential means to escape. However, the threshold appears highly contingent on heterogeneous household characteristics, especially for those with medium innate abilities.

Second, using a static endogenous switching model, we find a significant impact of falling below the dynamic asset threshold on suffering consumption poverty. A causal link running from insufficient agricultural assets to consumption poverty is likely to exist. Stimulating household asset accumulation is essential to minimising the chances of being poor.

Third, the estimation of various dynamic models indicates that poverty can be compounded due to strong true state-dependence and insufficient asset holdings, which act as a conduit in transferring past distress of hardship into current poverty. It is therefore of paramount importance to help households re-establish agricultural asset accumulation and become upwardly mobile after a spell of poverty, in order to break this 'vicious cycle'. With regard to specific policy implications, an extended health insurance scheme for rural households appears to be the most important and efficient recipe for helping them to escape from expenditure-based poverty. Nevertheless, given the potential problems of the NCMS, to what extent such a scheme may actually work remains in doubt. A more viable approach may to promote self-insurance through building households' assets and thereby increasing and stabilising their incomes. Off-farm employment is another pivotal contributor to poverty-exit, but our analysis does not exclude further examination of its role. For example, Shi *et al.* (2007) find that households with limited assets find it easier to work for other farm households' agricultural production, and seldom engage in the local non-agricultural and self-employment and migration which promote entrepreneurship and are usually more profitable, because of the high transaction or sink costs involved in pursuing such high-return livelihood strategies (Mohapatra *et al.*, 2007). Future research is needed to sub-divide off-farm employment into different categories and examine which would reduce the probability of consumption poverty more for Chinese rural households.

Appendix Supplementary figure and table

Figure A Distribution of household agricultural assets, 1989-2006

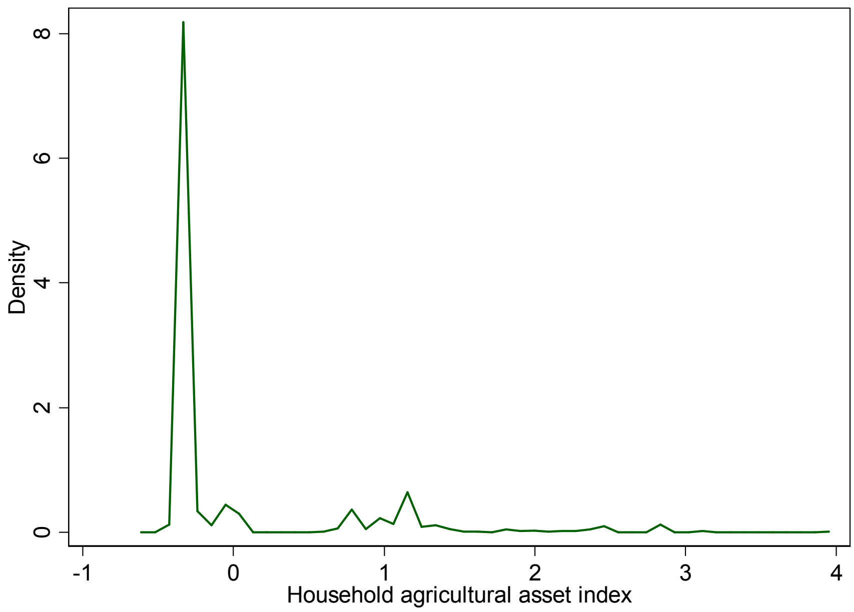


Table A Dynamic probit models for the probability of poverty in rural China, excluding continuing spells

Independent variables	Without time-invariant covariates				With time-invariant covariates			
	Pooled prob. (1)	RE prob. (2)	Heckman (3)	AR(1) (4)	Pooled prob. (5)	RE prob. (6)	Heckman (7)	AR(1) (8)
State dependence								
1. poverty at *t-1*	0.927 (0.031)***	0.667 (0.045)***	0.563 (0.043)***	1.001 (0.056)***	0.852 (0.032)***	0.593 (0.045)***	0.481 (0.044)***	0.835 (0.065)***
Observed characteristics								
2. endogeneity-corrected asset status at *t-1*	0.414 (0.250)*	0.624 (0.291)**	0.669 (0.288)**	0.533 (0.264)**	0.564 (0.333)*	0.761 (0.352)**	0.772 (0.354)**	0.645 (0.350)*
3. hh size	0.261 (0.014)***	0.323 (0.017)***	0.328 (0.017)***	0.285 (0.017)***	0.292 (0.019)***	0.343 (0.021)***	0.349 (0.021)***	0.321 (0.021)***
4. hh age	-0.008 (0.001)***	-0.013 (0.002)***	-0.120 (0.002)***	-0.008 (0.002)***	-0.030 (0.003)***	-0.039 (0.004)***	-0.041 (0.004)***	-0.035 (0.004)***
5. % male members	-0.075 (0.050)	-0.119 (0.060)**	-0.100 (0.059)*	-0.084 (0.053)	-0.223 (0.073)***	-0.235 (0.077)***	-0.235 (0.077)***	-0.251 (0.074)***
6. dependence ratio	0.423 (0.060)***	0.475 (0.069)***	0.467 (0.068)***	0.384 (0.062)***	0.178 (0.079)**	0.217 (0.084)***	0.225 (0.084)***	0.198 (0.081)**
7. whether a specialised hh	0.196 (0.033)***	0.282 (0.039)***	0.279 (0.038)***	0.255 (0.036)***	0.292 (0.041)***	0.334 (0.044)***	0.340 (0.044)***	0.345 (0.044)***
8. land-on farm labour ratio	0.014 (0.009)*	0.016 (0.009)*	0.015 (0.009)	0.014 (0.009)	0.016 (0.009)*	0.018 (0.010)*	0.016 (0.010)	0.015 (0.010)
9. % medical insurance	-0.481 (0.049)***	-0.489 (0.056)***	-0.497 (0.056)***	-0.467 (0.052)***	-0.185 (0.063)***	-0.216 (0.066)***	-0.219 (0.066)***	-0.206 (0.065)***

10. % local off-farm employment	0.415 (0.055)***	0.548 (0.063)***	0.602 (0.063)***	0.489 (0.060)***	0.214 (0.070)***	0.301 (0.075)***	0.317 (0.075)***	0.253 (0.074)***
11. village out-migration networks	-0.782 (0.507)	-0.849 (0.563)	-0.737 (0.559)	-0.570 (0.530)	-0.780 (0.586)	-0.718 (0.618)	-0.643 (0.618)	-0.534 (0.608)
12. investment in consumer durables	-0.006 (0.013)	-0.013 (0.016)	-0.005 (0.016)	-0.006 (0.014)	-0.024 (0.019)	-0.028 (0.020)	-0.029 (0.020)	-0.030 (0.020)
13. investment in housing	0.010 (0.009)	0.009 (0.009)	0.006 (0.009)	0.006 (0.009)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)	-0.0001 (0.010)
14. business assets	-0.040 (0.020)**	-0.042 (0.022)*	-0.048 (0.022)**	-0.052 (0.021)**	-0.005 (0.023)	-0.016 (0.024)	-0.016 (0.025)	-0.020 (0.024)
15. human capital	-0.062 (0.005)***	-0.072 (0.006)***	-0.076 (0.006)***	-0.073 (0.006)***	-0.046 (0.006)***	-0.057 (0.007)***	-0.059 (0.007)***	-0.056 (0.007)***
16. a(endogeneity-corrected asset status)					-0.622 (0.541)	-0.892 (0.673)	-0.520 (0.656)	-0.438 (0.603)
17. a(hh size)					-0.086 (0.033)***	-0.102 (0.042)**	-0.098 (0.041)**	-0.100 (0.037)***
18. a(hh age)					0.028 (0.004)***	0.036 (0.004)***	0.041 (0.004)***	0.035 (0.004)***
19. a(% male members)					0.256 (0.106)**	0.269 (0.129)**	0.282 (0.127)**	0.302 (0.116)***
20. a(dependence ratio)					0.504 (0.147)***	0.626 (0.188)***	0.420 (0.180)**	0.356 (0.162)**
21. a(whether a specialised hh)					-0.641 (0.099)***	-0.782 (0.129)***	-0.800 (0.123)***	-0.735 (0.112)***
22. a(land-on farm labour ratio)					-0.006 (0.021)	-0.005 (0.028)	-0.005 (0.026)	-0.004 (0.023)
23. a(% medical insurance)					-0.588 (0.107)***	-0.701 (0.134)***	-0.672 (0.129)***	-0.576 (0.119)***

24. a(% local off-farm employment)					-0.428 (0.164)***	-0.607 (0.215)***	-0.530 (0.205)***	-0.431 (0.185)**
25. a(village out-migration networks)					-0.482 (1.332)	-0.748 (1.729)	0.141 (1.634)	0.094 (1.464)
26. a(investment in consumer durables)					0.019 (0.029)	0.019 (0.036)	0.043 (0.035)	0.037 (0.032)
27. a(investment in housing)					0.072 (0.025)***	0.096 (0.033)*	0.056 (0.032)*	0.056 (0.029)**
28. a(business assets)					-0.108 (0.045)**	-0.116 (0.058)**	-0.125 (0.056)**	-0.104 (0.051)**
29. a(human capital)					-0.024 (0.015)	-0.022 (0.019)	-0.030 (0.018)	-0.025 (0.017)
Unobserved heterogeneity								
30. θ			1.317 (0.220)***	1.776 (0.369)***			1.485 (0.247)***	1.812 (0.345)***
Transitory shocks								
31. ρ				-0.275 (0.027)***				-0.224 (0.034)***
32. λ		0.204 (0.026)***	0.180 (0.024)***	0.100 (0.021)***		0.194 (0.024)***	0.172 (0.023)***	0.119 (0.022)***
33. log-likelihood	-4513.372	-4477.336	-5185.100	-5157.021	-4376.787	-4339.277	-5036.308	-5022.856
34. Counterfactual $\hat{p}_1$	0.560	0.492	0.458	0.552	0.542	0.479	0.447	0.515
35. Counterfactual $\hat{p}_0$	0.219	0.269	0.269	0.207	0.249	0.297	0.301	0.250
36. APE (TSD): $\hat{p}_1 - \hat{p}_0$	0.341	0.223	0.189	0.346	0.293	0.182	0.147	0.265
37. PPR: $\hat{p}_1 / \hat{p}_0$	2.558	1.828	1.702	2.671	2.173	1.612	1.487	2.061

Note: See Table 5.4.

CHAPTER 6

CONCLUSION

This thesis has contributed to the existing literature on development in rural China by providing new insights into better understanding and measure rural households' welfare and poverty status in times of radical economic reform, social changes and increasing uncertainty. In pursuit of this objective, three substantive chapters have been organised to address different issues.

Chapter 3 has examined the welfare losses which could be confronted by *all* rural households due to increasing uncertainties in their lives. Recent literature has identified the importance of an individual's relative position, social comparisons and aspirations for an urban and hedonistic lifestyle in forming their subjective sense of well-being in both rural and urban China. This chapter complements the research into subjective perceptions by quantifying households' vulnerability as uncertain welfare due to growing inequality and volatility of households' consumption flows. The analysis has found that, during the period 1989-2006, rural households' welfare losses grew despite the nation-wide increase in economic prosperity and substantial poverty reduction. Among sub-groups, farmers appear to have suffered most. This welfare loss, according to our decomposition, is mainly driven by the inequality component. Primary education and health insurance are likely to alleviate this welfare loss, while diversification from agriculture has a relatively limited effect. In general, China's entrenched 'growth' oriented policy does not appear to have been entirely successful in reducing the dangers of lost welfare for rural households.

Chapters 4 and 5, then focused on *poor* households' long-term well-being in relation to their asset holdings. Despite significant poverty reduction over the last three decades in rural China, the poverty remaining has been persistent since the late 1990s. Stagnation of income growth has been a particular problem for many of the poor. Yet existing studies tend to neglect the underlying causes of this persistence of poverty, especially those which may be structural and long-term.

Given the paucity of empirical studies, Chapter 4 aimed to gain new insights into the persistence of poverty, stressing the long-run influences of shocks and risk on households' asset holdings. The analysis found that households have a proclivity towards holding substantial unproductive precautionary savings in the hope of coping with consumption shortfalls brought about by negative shocks. In addition, such households tend to be loss- and risk-averse and so are predisposed to specialise in low-risk low-return agriculture when faced with *ex-ante* credit constraints and possibly poor welfare outcomes if the production plans should prove unsuccessful. Overall, household responses to uninsured shocks and risk cause deficiencies and inefficiencies of investment in agricultural asset accumulation. As a result, some households are likely to be trapped in low-equilibrium asset poverty in the long-term. Results indicate the importance of establishing productive safety nets for rural households, which would benefit both the currently poor's livelihood and improve their possibilities of escaping the low-equilibrium asset traps.

Based on Chapter 4's identification of risk-induced persistent poverty, Chapter 5 examined how much this kind of poverty explains rural poverty transitions. This chapter used an asset-based approach to shed new light on household poverty transitions and persistence in rural China. It found a dynamic asset threshold separating households into different accumulation regimes leading to divergent pathways in the future. More specifically, the static analysis found a causal relationship between falling below the dynamic asset threshold and the probability of being poor. Over time, there is strong true state-dependence of poverty: households' past experience in poverty may alter their preferences and behaviour and hence, makes them more likely to be poor in the future. Insufficient assets relative to the asset threshold serve as a channel transmitting this state-dependence. Favourable transitory shocks could facilitate poverty-exit, but this effect dissipates over time. Off-farm employment and health insurance play pivotal roles in assisting households to escape.

The results in the three substantive chapters carry a number of policy implications. The provision of social safety nets appears to be a potent means to improve rural households' well-being and bail out the poor. Health insurance and financial credits could cushion poorer households against shocks and risk and remove hurdles to poorer households such as credit constrains.

We also found that both local off-farm employment and out-migration could improve households' well-being. More importantly, the latter could not only increase the remaining households' living standards, but also dampen households' strong precautionary savings. Hence, it could allow households to invest more in profitable asset accumulation and add chances to their escape from poverty.

Of particular note is the fact that both safety nets policies and off-farm employment are not only useful for the currently poor, but also such proactive approaches would reduce the could-be poor. They could lift households' living standards and promote self-reinforcing growth and escape from poverty via households' asset accumulation in the long-term.

Nevertheless, much remains to be learnt. The findings in the thesis are by no means definitive. In particular, the welfare loss to rural households revealed by Chapter 3 is virtually a static measure. It may well be exacerbated by the accumulated distress of low utility in the past. Future research is required to extend the static framework intertemporally.

Chapter 4 emphasised the paramount importance of establishing effective production safety nets for rural households, especially extending the coverage of health insurance. However, this may spawn other problems such as moral hazard and adverse selection which may blunt the effectiveness of larger coverage of insurance. This is an interesting area for further investigation.

The dynamic model used in Chapter 5 to examine poverty transitions, did not deal adequately with the problem of non-random attrition in the genuine panel. Thus, the estimated strong persistence of poverty may be over- or under-stated. Further investigation of this could be done using Cappellari and Jenkins's (2004) method to explicitly model the probability of individual retention.

To recap, as the Human Development Report (2010, p. 25) remarks, 'thinking clearly about the future requires looking critically at the past'. Despite 33 years of economic reforms in rural China and the associated huge and multi-dimensional progress that has been made, threats that endanger household welfare and further poverty reduction still remain. This thesis has investigated these threats from the perspectives of utility and asset holdings and assessed their impact on households' long-term well-being. Based on the empirical analysis, policy implications have been suggested with the hope of better informing the policies aimed at improving human development and fighting against poverty.

REFERENCE

Adato, M., Carter, M. R. and May, J. (2006) Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data. *Journal of Development Studies* 42, 226-247

Addison, T., Hulme, D. and Kanbur, R. (2009) Poverty dynamics: Measurement and understanding from an interdisciplinary perspective. *Poverty Dynamics: Interdisciplinary Perspectives*, R. Addison, D. Hulme and R. Kanbur (eds.). Oxford University Press. Oxford, UK

Akay, A., Martinsson, P. and Medhin, H. (2010) Does relative position matter in poor societies? Resources For The Future Discussion Paper Series, EfD DP 10-05

Alderman, H., Hoddinott, J. and Kinsey, B. (2006) Long-term consequences of early childhood malnutrition. *Oxford Economic Papers* 58, 450-474

Antman, F. and McKenzie, D. (2007) Poverty traps and nonlinear income dynamics with measurement error and individual heterogeneity. *Journal of Development Studies* 43, 1057-1083

Arellano, M. and Honoré, B. E. (2001) Panel data models: Some recent developments. In *Handbook of Econometrics*, Vol. 5, J. Heckman and E. Leamer (eds.). Amsterdam: Elsevier Science Publishers B.V.

Arranz, J. M. and Cantó, O. (2008) Measuring effect of spell recurrence on poverty dynamics. *Paper presented at the Conference of Frontiers of Poverty Analysis*, UNU-WIDER, Helsinki.

Ayllón, S. (2008) Modelling poverty transitions in Spain: Do attrition and initial conditions really matter? *IRISS Working Paper Series*, No. 2008-08, INSTEAD.

Barnett, B. J., Barrett, C. B. and Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development* 36, 1766-1785

Barrett, C. B., Carter, M., and Ikegami, M. (2008) Poverty traps and social protection. Cornell University Working Paper series. Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1141881

Barrett, C. B., Marenya, P. P., Mcpeak, J., Marten, B., Murithi, F., Oluoch-Kosura, W., Place, F., Randrianarisoa, J. C., Rasambainarivo, J. and Wangila, J. (2006) Welfare dynamics in rural Kenya and Madagascar. *Journal of Development Studies* 42, 248-277

Baulch, B. and Hoddinott, J. (2000) Economic mobility and poverty dynamics in developing countries. *Journal of Development Studies* 36, 1-24

Benjamin, D., Brandt, L. and Rozelle, S. (2000) Aging, wellbeing, and social security in rural Northern China. *Population and Development Review* 26, 89-116

Benjamin, D., Brandt, L. and Fan, J. (2003) Ceaseless toil? Health and labor supply of the elderly in rural China. *William Davidson Institute Working Paper*, No. 579

Benjamin, D., Brandt, L. and Giles J. (2005) The evolution of income inequality in rural China. *Economic Development and Cultural Change* 53, 769-824

Benjamin, D., Brandt, L., Giles, J. and Wang, S. (2008) Income inequality during China's economic transition. *China's Great Economic Transformation*, L. Brandt and T. G. Rawski (eds.). Cambridge University Press. Cambridge, UK

Bigsten, A. and Shimeles, A. (2008) Poverty transition and persistence in Ethiopia: 1994-2004. *World Development* 36, 1559-1584

Blundell, R. and Bond, S. (1998) Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 11-143

Bowlus, A. J. and Sicular, T. (2003) Moving towards markets? Labor allocation in rural China. *Journal of Development Economics* 71, 561-583

Bramall, C. (2001) The quality of China's household income surveys. *China Quarterly* 167, 689-705

Brandt, L and Holz, C. A. (2006) Spatial price differences in China: estimates and implications. *Economic Development and Cultural Change* 55, 43-86

Brandt, L., Huang, J., Li, G. and Rozelle, S. (2002) Land rights in rural China: facts, fictions and issues. *The China Journal* 47, 67-97

Brosig, S., Glauben, T., Herzfeld, T. and Wang, X. (2009) Persistence of full- and part-time farming in Southern China. *China Economic Review* 20, 360-371

Brown, P. H., Bulte, E. and Zhang, X. (2010) Position spending and status seeking in rural China. IFPRI Discussion Paper No. 00983

Cai, F. (2004) The aging trend and pension reform in China: Challenges and options. *China & World Economy* 12, 36-49

Cai, F. (2010) Chinese rural reform in 30 years: An analysis in terms of institutional economics. *Frontiers of Economics in China* 5, 150-168

Cai, F., Park, A. and Zhao, Y. (2008) The Chinese labour market in the reform era. *China's Great Economic Transformation*, Loren Brandt and Thomas Rawski, (eds.), Cambridge University Press. Cambridge, UK

Cai, H., Chen, Y., Fang, H. and Zhou, L. (2009) Microinsurance, trust and economic development: Evidence from a randomized natural field experiment. *NBER Working Paper Series*, No. 15396

Calvo, C. and Dercon, S. (2005) Measuring individual vulnerability. *Department of Economics Discussion Paper Series, Oxford University,* No. 229

Calvo, C. and Dercon, S. (2009) Chronic poverty and all that: The measurement of poverty over time. *Poverty Dynamics: Interdisciplinary Perspectives*, R. Addison, D. Hulme and R. Kanbur (eds.). Oxford University Press. Oxford, UK

Cantó, O. (2002) Climbing out of poverty, falling back in: Low income stability in Spain. *Applied Economics* 34, 1903-1916

Cao, S., Wang, X. and Wang, G. (2009) Lessons learned from China's fall into the poverty trap. *Journal of Policy Modeling* 31, 298-307

Cappellari, L. and Jenkins, S.P. (2004) Modelling low income transitions. *Journal of Applied Econometrics* 19, 593-610

Carter, M. R. and Barrett, C. B. (2006) The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of Development Studies* 42, 178-199

Carter, M. R. and Barrett, C. B. (2007) Asset thresholds and social protection: A 'think-piece'. *IDS Bulletin* 38, 34-38

Carter, M. R. and Ikegami, M. (2009) Looking forward: Theory-based measures of chronic poverty and vulnerability. *Poverty Dynamics: Interdisciplinary Perspectives*, R. Addison, D. Hulme and R. Kanbur (eds.). Oxford University Press. Oxford, UK

Carter, M. R., Little, P. D., Mogues, T. and Negatu, W. (2007) Poverty traps and natural disasters in Ethiopia and Honduras. *World Development* 35, 835-865

Carter, M. R. and May, J. (2001) One kind of freedom: Poverty dynamics in post-apartheid South Africa. *World Development* 29, 1987-2006

Chamberlain, G. (1980) Analysis of covariance with qualitative data. *The Review of Economics and Statistics* 47, 225-238

Chamberlain, G. (1984) Panel data. *Handbook of Econometrics* 2, Z. Griliches and M. D. Intrilligator (eds.). Amsterdam: Elsevier Science Publishers B.V.

Chen, S. and Ravallion, M. (1996) Data in transition: assessing rural living standards in southern China. *China Economic Review* 7, 23-56

Chen, S. and Ravallion, M. (2008) China is poorer than we thought, but no less successful in the fight against poverty. *World Bank Policy Research Working Paper*, No. 4621

Chen, S. and Wang, Y. (2001) China's growth and poverty reduction: trends between 1990 and 1999. *World Bank Policy Research Working Paper*, No. 2651

Chow, G.C. (1993) Capital formation and economic growth in China. *Quarterly Journal of Economics* 108, 809-842

Christiaensen, L. J., Pan, L. and Wang, S. (2010) Drivers of poverty reduction in lagging regions: Evidence from rural western China. *UNU-WIDER Working Paper*, No. 2010/35

Clarke, D. and Dercon, S. (2009) Insurance, credit and safety nets for the poor in a world of risk. *UN/DESA Working Paper*, No. 81

de Brauw, A. and Giles, J. (2008) Migrant labor markets and the welfare of rural households in the developing world: Evidence from China. *The World Bank Policy Research Working Paper*, No. 4585

de Brauw, A. and Rozelle, S. (2008a) Migration and household investment in rural China. *China Economic Review* 19, 320-335

de Brauw, A. and Rozelle, S. (2008b) Reconciling the returns to education in off-farm wage employment in rural China. *Review of Development Economics* 12, 57-71

de Janvry, A., Sadoulet, E. and Zhu, N. (2005) The role of non-farm incomes in reducing rural poverty and inequality in China. UC Berkeley: Department of Agricultural and Resource Economics, UCB. *CUDARE Working Paper* No. 1001. Available at http://escholarship.org/uc/item/7ts2z766 de Janvry, A. and Sadoulet, E. (2006) Progress in modelling of rural households' behaviour under market failures. In Economic Studies in Inequality, Social Exclusion and Well-being, A. de Janvry and R. Kanbur (eds.). Springer US.

Dercon, S. (1996) Risk, crop choice, and savings: Evidence from Tanzania. *Economic Development and Cultural Change* 44, 485-513

Dercon, S. (1998) Wealth, risk and activity choice: Cattle in Western Tanzania. *Journal of Development Economics* 55, 1-42

Dercon, S. (2004) Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics* 74, 309-329

Dercon, S. (2005) Vulnerability: A micro perspective. *Paper presented at the ABCDE for Europe. Amsterdam, The World Bank*

Dercon, S. (2006) Risk, growth and poverty: What do we know, what do we need to know? *QEH Working Paper Series*, No. 148

Dercon, S. (2009) Fate and fear: Risk and its consequences in Africa. *Journal of African Economies* 17, 97-127

Dercon, S. and Christiaesen, L. (2010) Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, DOI: 10.1016/j.jdeveco.2010.08.003

Dercon, S., Hoddinott, J. and Woldehanna, T. (2005) Shocks and consumption in 15 Ethiopian villages, 1999-2004. *Journal of African Economies* 14, 559-585

Dercon, S. and Shapiro, J.S. (2007) Moving on, staying behind, getting lost: Lessons on poverty mobility from longitudinal data. *Oxford CSAE Working Paper*, No. GPRG-WPS-075

Démurger, S., Fournier, M. and Yang, W. (2010) Rural households decisions towards income diversification: Evidence from a township in northern China. *China Economic Review* 21, Suppl. 1, s32-s44

Denisova, I. A. (2007) Entry to and exit from poverty in Russia: Evidence from longitudinal data. *Centre for Economic and Financial Research (CEFIR) Working Paper*, No. w0098

Devicientik, F. (2002) Poverty persistence in Britain: A multivariate analysis using the BHPS, 1991-1997. *Journal of Economics* Suppl. 9, 307-340

Devicientik, F. and Gualtieri, V. (2007) The dynamics and persistence of poverty: Evidence from Italy. *LABOR Working Paper*, No. 63, the Collegio Carlo Alberto.

Dollar, D. (2007) Poverty, inequality and social disparities during China's economic reform. *The World Bank Policy Research Working Paper*, No. 4253

Dong, F. and Featherstone, A. M. (2006) Technical and scale efficiencies for Chinese Rural Credit Cooperatives: A bootstrapping approach in data envelopment analysis. *Journal of Chinese Economic and Business Studies* 4, 57-75

Duclos, J. Y., Araar, A. and Giles, J. (2010) Chronic and transient poverty: Measurement and estimation, with evidence from China. *Journal of Development Economics* 91, 266-277

Elbers, C. and Gunning, J.W. (2003) Vulnerability in a stochastic dynamic model. *Tinbergen Institute Discussion Paper*, No. 2003-070/2

Elbers, C., Gunning, J. W. and Kinsey, B. (2007) Growth and risk: Methodology and micro evidence. *The World Bank Economic Review* 21, 1-20

Fafchamps, M. (2003) Rural Poverty, Risk, and Development. Elgar Publishing. Cheltenham and Northampton.

Fafchamps, M. (2009) Vulnerability, risk management, and agricultural development. In The AERC Conference on Agriculture and Development Mombasa, Kenya.

Fafchamps, M. and Shilpi, F. (2008) Subjective welfare, isolation and relative consumption. *Journal of Development Economics* 86, 43-60

Filmer, D. and Pritchett, L.H. (2001) Estimating wealth effects without expenditure data–or tears: An application to educational enrolments in states of India. *Demography* 38, 115-132

Foster, A. D. and Rosenzweig, M. R. (2010) Microeconomics of technology adoption. *Economic Growth Centre Discussion Paper*, No. 984

Foster, J, Greer, J. and Thorbecke, E. (1984) A class of decomposable poverty measures. *Econometrica* 52, 761-765

Frederiksen, A., Honoré, B. E. and Hu, L. (2007) Discrete time duration models with group-level heterogeneity. *Journal of Econometrics* 141, 1014-1043

Gaiha, R. and Imai, K. (2008) Measuring vulnerability and poverty: Estimates for rural India. *UNU-WIDER Research Paper*, No. 2008/40

Ghatak, S. and Seale Jr, J. (2001) Supply response and risk in Chinese agriculture. *Journal of Development Studies* 37, 141-150

Giesbert, L. and Schindler, K. (2010) Assets, shocks, and poverty traps in rural Mozambique. DIW Berlin Discussion Papers, No. 1073

Giles, J. (2006) Is life more risky in the open? Household risk-coping and the opening of China's labor markets. *Journal of Development Economics* 81, 25-60

Giles, J. and Murtazashvili, I. (2010) A control function approach to estimating dynamic probit models with endogenous regressor, with an application to the study of poverty persistence in China. *The World Bank Policy Research Working Paper*, No. 5400

Giles, J. and Yoo, K. (2007) Precautionary behavior, migrant networks and household consumption decisions: An empirical analysis using household panel data from rural China. *The Review of Economics and Statistics* 89, 534-551

Glauben, T., Herzfeld, T. and Wang X. (2008) Labor market participation of Chinese agricultural households: Empirical evidence from Zhejiang province. *Food Policy* 33, 329-340

Goh, C., Luo, X. and Zhu, N. (2009) Income growth, inequality and poverty reduction: A case study of eight provinces in China. *China Economic Review* 20, 485-496

Greene, W. (2003) *Econometric Analysis.* Prentice Hall, New Jersey.

Guimaraes, R. J. R. (2007) Searching for the vulnerable: A review of the concepts and assessments of vulnerability related to poverty. *The European Journal of Development Research* 19, 234-250

Gustafsson, B. and Li, S. (2004) Expenditures on education and health care and poverty in rural China. *China Economic Review* 15, 292-301

Hansen, B. E. (1999) Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics* 93, 345-368

Hansen, B. E. (2000) Sampling splitting and threshold estimation. *Econometrica* 68, 575-603

Hansen, J. and Walhlberg, R. (2004) Poverty persistence in Sweden. *IZA Discussion Paper*, No. 1209

Heckman, J. J. (1981) Statistical models for discrete panel data. *Structural Analysis of Discrete Data*, C. Manski and D. McFadden (eds.). MIT Press. Cambridge, Massachusetts

Heckman, J. J. (2005) China's human capital investment. *China Economic Review* 16, 50-70

Hebel, J. (2003) Social welfare in rural China. *Journal of Peasant Studies* 30, 224-251

Ho, C., Ho, W. A. and Li, D. (2010) Consumption fluctuations and welfare: Evidence from China. *World Development* 38, 1315-1327

Hoddinott, J. (2006) Shocks and their consequences across and within households in rural Zimbabwe. *Journal of Development Studies* 42, 301-321

Hoogeveen, J. G. M. (2001) Income risk, consumption security and the poor. *Oxford Development Studies* 30, 105-121

Honoré, B. E. (1992) Trimmed LAD and least squares estimation of truncated and censored regression models with fixed effects. *Econometrica* 60, 533-565

Honoré, B. E. (2008) On marginal effects in semiparametric censored regression models. Department of Economics Working Paper Series, Princeton University. Available at SSRN: http://ssrn.com/abstract=1394384

Hu, S., Tang, S., Liu, Y., Zhao, Y., Escobar, M. and de Ferranti, D. (2008) Reform of how health care is paid for in China: Challenges and opportunities. *The Lancet* 372, 1846-1853

Huang, J., Lin, J. Y. and Rozelle, S. (2003) What will make Chinese agriculture more productive? *How Far Across the River? Chinese Policy Reform at the Millennium*, N. C. Hope, D. T. Yang and M. Y. Li (eds.). Stanford University Press. Stanford, California

Huang, J., Zhang, Q. and Rozelle, S. (2008) Economic growth, the nature of growth and poverty reduction in rural China. *China Economic Journal* 1, 107-122

Human Development Report (2010), United Nations Development Programme, Washington D. C.

Hyslop, D. R. (1999) State dependence, serial correlation and heterogeneity in intertemporal labour force participation of married women. *Econometrica* 67, 1255-1294

Imai, K., Wang, X. and Kang, W. (2010) Poverty and vulnerability in rural China: Effects of taxation. *Journal of Chinese Economic and Business Studies* 8, 399-425

Islam, N. and Shimeles, A. (2006) Poverty dynamics in Ethiopia: State dependence and transitory shocks. Göteborg University, *mimeo*.

Jacoby, H. G., Li, G. and Rozelle, S. (2002) Hazards of expropriation: Tenure insecurity and investment in rural China. *American Economic Review* 92, 1420-1447

Jalan, J. and Ravallion, M. (1998a) Transient poverty in post reform rural China. *Journal of Comparative Economics* 26, 338-357

Jalan, J. and Ravallion, M. (1998b) Determinants of transient and chronic poverty: Evidence from rural China. *World Bank Policy Research Working Paper*, No. 1936

Jalan, J. and Ravallion, M. (1999) Are the poor less well insured? Evidence on vulnerability to income risk in rural China. *Journal of Development Economics 58,* 61-81

Jalan, J. and Ravallion, M. (2001) Behaviour responses to risk in rural China. *Journal of Development Economics* 66, 23-49

Jalan, J. and Ravallion, M. (2002) Geographic poverty traps? A micro model of consumption growth in rural China. *Journal of Applied Econometrics* 17, 329-346

Jalan, J. and Ravallion, M. (2005) Household income dynamics in rural China. *Insurance Against Poverty*, Stephen Dercon (ed.), Oxford University Press, Oxford, UK.

Kanbur, R. and Zhang, X. (2005) Fifty years of regional inequality in China: A journey through central planning, reform, and openness. *Review of Development Economics* 9, 87-106

Khan, A. R., Griffin, K. and Riskin, C. (1999) Income distribution in urban China during the period of economic reform and globalization. *The American Economic Review* 89, 296-300

Knight, J. (2008) Reform, growth and inequality in China. *Asian Economic Policy Review* 3, 140-158

Knight, J., Li, S. and Deng, Q. (2009a) Education and the Poverty Trap in Rural China: Setting the Trap. *Oxford Development Studies* 37, 311-332

Knight, J., Song, L. and Gunatilaka, R. (2009b) Subjective well-being and its determinants in rural China. *China Economic Review* 20, 635-649

Knight, J., Li, G. and Deng, Q. (2010) Education and the poverty trap in rural China: Closing the trap. *Oxford Development Studies* 38, 1-24

Kolenikov, S. and Angeles, G. (2009) Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer? *Review of Income and Wealth* 55, 128-156

Lee, J. and Swada, Y. (2010) Precautionary savings under liquidity constraints: Evidence From rural Pakistan. *Journal of Development Economics* 91, 77-86

Lei, X. and Lin, W. (2009) The new cooperative medical scheme in rural China: Does more coverage mean more service and better health? *Health Economics* 18, 25-46

Ligon, E. (2007) Dynamics, risk and vulnerability. *Unpublished manuscript.*

Ligon, E. and Schechter, L. (2002) Measuring vulnerability: The director's cut. *UNU-WIDER Discussion Paper*, No. 86

Ligon, E. and Schechter, L. (2003) Measuring vulnerability. *Economic Journal* 113, C95-C102

Ligon, E. and Schechter, L. (2004) Evaluating different approaches to estimating vulnerability. *World Bank Social Protection Discussion Paper Series*, No. 0410

Lin, J. Y. (1992) Rural reforms and agricultural growth in China. *American Economic Review* 82, 34-51

Liu, Y., Hisao, W. C. and Eggleston, K. (1999) Equity in health and health care: The Chinese experience. *Social Sciences & Medicine* 49, 1349-1356

Liverpool, L. S. O. and Winter-Nelson, A. (2010) Poverty status and the impact of formal credit on technology use and wellbeing among Ethiopian smallholders. *World Development* 38, 541-554

Lokshin, M. (2006). Difference-based semiparametric estimation of partial linear regression models. *The Stata Journal* 6, 377-383

Lybbert, T. J. and Carter, M. (2010) Who smooth what? Asset smoothing versus consumption smoothing in Burkina Faso. UC-Davis Working Paper

Lybbert, T. J., Barrett, C. B., Desta, S. and Coppock, D. L. (2004) Stochastic wealth dynamics and risk management among a poor population. *The Economic Journal* 114, 750-777

Lybbert, T. J. and Barnett, B. J. (2010) Risk-taking behaviour in the presence of nonconvex asset dynamics. *Economic Inquiry*, DOI: 10.1111/j.1465-7295.2009.00198.x

Maes, M. (2008) Poverty persistence among Belgian elderly: True or spurious? *ISER Working Paper Series*, No. 2008-24

Mankiw, N. G., Romer, D. and Weil, D. N. (1992) A contribution to the empirics of economic growth. *The Quarterly Journal of Economics* 107, 407-437

Martín, E. B. and Cowell, F. (2006) Static and dynamic poverty in Spain, 1993-2000. *LSE STICERD, Distributional Analysis Research Programme*, Paper No. 77

Mendola, D., Bustetta, A. and Milito, A. M. (2009) How much should we care about consecutive spells of poverty? Proposal of a new index. *Paper presented at the BHPS-2009 Conference*, University of Essex.

McCulloch, N. and Calandrino, M. (2003) Vulnerability and chronic poverty in rural Sichuan. *World Development* 31, 611-628

McDonald, J. F. and Moffitt, R. A. (1980) The uses of tobit analysis. *The Review of Economics and Statistics* 62, 318-321

McKenzie, D. J. and Woodruff, C. (2006) Do entry costs provide an empirical basis for poverty traps? Evidence from Mexican microenterprises. *Economic Development and Cultural Change* 55, 3-42

Mesnard, A. and Ravallion, M. (2001) Is inequality bad for business? A nonlinear microeconomic model of wealth effects on self-employment. *The World Bank Policy Research Working Paper* No. 2527

Minten, B. and Barnett, B. J. (2008) Agricultural technology, productivity, and poverty in Madagascar. *World Development* 36, 797-822

Miranda, A. and Rabe-Hesketh, S. (2006) Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables. *The Stata Journal* 6, 285-308

Mohapatra, S., Rozelle, S. and Goodhue, R. (2007) The rise of self-employment in rural China: Development or distress? *World Development* 35, 163-181

Montalvo, J. G. and Ravallion, M. (2010) The pattern of growth and poverty reduction in China. *Journal of Comparative Economics* 38, 2-16

Morduch, J. (1995) Income smoothing and consumption smoothing. *The Journal of Economic Perspectives* 9, 103-114

Moser, C. and Felton, A. (2009) The construction of an asset index measuring asset accumulation in Ecuador. *Poverty Dynamics: Interdisciplinary Perspectives*, R. Addison, D. Hulme and R. Kanbur (eds.). Oxford University Press. Oxford, UK

Mundlak, Y. (1978) On the pooling of time series and cross section data. *Econometrica* 46, 69–85

National Human Development Report (NHDR): China Human Development Report 2005. United Nations Development Programme China Office, Beijing, China.

Norton, E. C., Wang, H. and Ai, C. (2004) Computing interaction effects and standard errors in logit and probit models. *The Stata Journal* 4, 154-167

Pang, L, de Brauw, A. and Rozelle, S. (2004) Working until you drop: The elderly of rural China. *The China Journal* 52, 73-94

Park, A. (2006) Risk and household grain management in developing countries. *The Economic Journal* 116, 1088-1115

Park, A. and Ren, C. (2001) Microfinance with Chinese characteristics. *World Development* 29, 39-62

Quisumbing, A. and Baulch, B. (2009) Assets and poverty traps in rural Bangladesh. *Chronic Poverty Research Centre Working Paper*, No. 143

Ravallion, M. (2005) Growth, inequality & poverty: Looking beyond averages. *World Development* 29, 1803-1815

Ravallion, M. (2009) Are there lessons for Africa from China's success against poverty. *World Development* 37, 303-313

Ravallion, M. and Chaudhuri, S. (1997) Risk and village India: Comment. *Econometrica* 65, 171-84

Ravallion, M. and Chen, S. (2003) Measuring pro-poor growth. *Economic Letters* 78, 93-99

Ravallion, M. and Chen, S. (2007) China's uneven progress against poverty. *Journal of Development Economics* 82, 1-42

Ravallion, M., Chen, S. and Sangraula, P. (2008) Dollar a day revisited. *World Bank Policy Research Working Paper*, No. 4620

Ravallion, M. and Jalan, J. (1999) China's lagging poor areas. *The American Economic Review, Papers and Preceedings* 89, 301-305

Ren, C., Liao, C. and Huang, L. (1989) The income and expense survey in Chinese urban households. Chinese Statistical Press, Beijing

Rosenzweig, M. R. and Binswanger, H. P. (1993) Weather risk and the composition and profitability of agricultural investments. *The Economic Journal* 103, 56-78

Rosenzweig, M. R. and Wolpin, K. I. (1993) Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investment in bullocks in India. *The Journal of Political Economy* 101, 223-244

Rozelle, S., Guo, L., Shen, M., Hughart, A. and Giles, J. (1999a) Leaving China's farms: Survey results of new paths and remaining hurdles to rural migration. *The China Quarterly* 158, 367-393

Rozelle, S., Taylor, E. and de Brauw A. (1999b) Migration, remittances, and agricultural productivity in China. *American Economic Review* 89, 287-291

Rui, L. and Xi, Z. (2010) Econometric analysis of credit constraints of Chinese rural households and welfare loss. *Applied Economics* 42, 1615-1625

Sahn, D. and Stifel, D. (2003) Exploring alternative measures of welfare in the absence of expenditure data. *Review of Income and Wealth* 49, 463-489

Santos, P. and Barrett, C.B. (2006) Heterogeneous wealth dynamics: On the roles of risk and ability. *Mimeo*. Available at SSRN: http://ssrn.com/abstract=998549

Schechter, L. (2006) Vulnerability as a measure of chronic poverty. *Paper presented at the Workshop on Concepts and Methods for Analysing Poverty, University of Manchester.*

Shi, X., Heerink, N. and Qu, F. (2007) Choices between different off-farm employment sub-categories: An empirical analysis for Jiangxi province, China. *China Economic Review* 18, 438-455

Shorrocks, A.F. (1983) Ranking income distributions. *Econometrica* 50, 3-17

Sicular, T., Yue, X., Gustafsson, B. and Li, S. (2007) The urban-rural income gap and inequality in China. *Review of Income and Wealth*, 53, 93-126

Skoufias, E. and Quisumbing, A. R. (2005) Consumption insurance and vulnerability to poverty: A synthesis of the evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia. *The European Journal of Development Research* 17, 24-58

Skrondal, A. and Rabe-Hesketh, S. (2009) Prediction in multilevel generalized linear models. *Journal of the Royal Statistical Society* 172, 659-687

State Council (2007) China's poverty relief and development report. CPAD, the State Council, Beijing

Stewart, M.B. (2007) The interrelated dynamics of unemployment and low-wage employment. *Journal of Applied Econometrics* 22, 511-531

Sun, X., Jackson, S., Garmichael, G.A. and Sleigh, A.C. (2009a) Prescribing behaviour of village doctors under China's new cooperative medical scheme. *Social Science & Medicine* 68, 1775-1779

Sun, X., Jackson, S., Garmichael, G.A. and Sleigh, A.C. (2009b) Catastrophic medical payment and financial protection in rural China: Evidence from the new cooperative medical scheme in Shandong province. *Health Economics* 18, 103-119

Tache, B. and Sjaastad, E. (2010) Pastoralists' conceptions of poverty: An analysis of traditional and conventional indicators from Borana, Ethiopia. *World Development* 38, 1168-1178

Taylor, J. E., Rozelle, S. and de Brauw, A. (2003) Migration and incomes in source communities: A new economics of migration perspective from China. *Economic Development and Cultural Change* 52, 75-101

Thorbecke, E. (2004) Conceptual and measurement issues in poverty analysis. *UNU-WIDER Discussion Paper*, No. 2004/04

Uchida, E., Rozelle, S. and Xu, J. (2009) Conservation payments, liquidity constraints and off-farm labour: Impact of the Grain for Green Program on rural households in China. *American Journal of Agricultural Economics* 91, 70-86

Vella, F. and Verbeek, M. (1999) Estimating and interpreting models with endogenous treatment effects. *Journal of Business and Economic Statistics* 17, 473-478

Wagstaff, A. and Lindelow, M. (2008) Can insurance increase financial risk? The curious case of health insurance in China. *Journal of Health Economics* 27, 990-1005

Wagstaff, A., Lindelow, M., Jun, G., Ling, X. and Juncheng, Q. (2009a) Extending health insurance to the rural population: An impact evaluation of China's new cooperative medical scheme. *Journal of Health Economics* 28, 1-19

Wagstaff, A., Yip, W., Lindelow, M. and Hsiao, W. (2009b) China's health system and its reform: A review of recent studies. *Health Economics* 18, 7-23

Wan, G. (2004) Accounting for income inequality in rural China: A regression-based approach. *Journal of Comparative Economics* 32, 348-363

Wan, G. (2007) Regional income inequality in rural China, 1985-2002: Trends, causes and policy implications. *UNU-WIDER Research Paper*, No. 2007/05

Wan, G. and Cheng, E. (2001) Effects of land fragmentation and returns to scale in the Chinese farming sector. *Applied Economics* 33, 183-194

Wan, G., Lu, M. and Chen, Z. (2006) The inequality-growth nexus in the short and long runs. *UNU-WIDER Research Paper*, No. 2006/92

Wan, G. and Zhou, Z. (2005) Income inequality in rural China: Regression-based decomposition using household data. *Review of Development Economics* 9, 107-120

Wang, H, Zhang, L. and Hsiao, W. (2006) Ill health and its potential influence on household consumptions in rural China. *Health Policy* 78, 167-177

Wang, G. (2005) A policy study on the poverty reduction program of RPC: Trends and challenges. CPAD, The State Council, Beijing

Whalley, J. and Yue, X. (2009) Rural income volatility and inequality in China. *CESifo Economic Studies* 55, 648-668

World Bank (2009) From poor areas to poor people: China's evolving poverty reduction agenda. Poverty Reduction and Economic Management Department, East Asia and Pacific Region, The World Bank.

Wooldridge, J. M. (2002) Econometric analysis of cross section and panel data. MIT Press. Cambridge, Massachusetts

Wooldridge, J. M. (2005) Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 20, 39-54

Xu, X. (2008) Consumption risk-sharing in China. *Economica* 75, 326-341

Yang, D. T. (2004) Education and allocative efficiency: Household income growth during rural reforms in China. *Journal of Development Economics* 74, 137-162

Yang, W. (2007) Institutional reforms, agricultural risks and agro-industrial diversification in rural China. *Journal of the Asia Pacific Economy* 12, 386-402

Yang, W. (2009) Economic structural changes and rural income: Evidence from Chinese provinces during the reform period. *China Economic Review* 20, 742-753

Yao, S. (2000) Economic development and poverty reduction in China over 20 years of reforms. *Economic Development and Cultural Change* 48, 447-474

Yao, S., Zhang, Z. and Hanmer, L. (2004) Growing inequality and poverty in China. *China Economic Review* 15, 145-163

Yip, W. and Hsiao, W. (2009) China's health care reform: A tentative assessment. *China Economic Review* 20, 613-619

You, J. (2011) Evaluating poverty persistence and transition: a spell-approach to rural China. *Applied Economics Letters*, DOI: 10.1080/13504851.2010.537625

Zhang, L., Huang, J. and Rozelle, S. (2002) Employment, emerging labour markets, and the role of education in rural China. *China Economic Review* 13, 313-328

Zhang, Y. and Wan, G. (2006a) Poverty reduction in China: trends and causes. *UNU-WIDER Research Paper*, No. 2006/152

Zhang, Y. and Wan, G. (2006b) An empirical analysis of household vulnerability in rural China. *Journal of the Asia Pacific Economy* 11, 196-212

Zhang, Y. and Wan, G. (2006c) The impact of growth and inequality on rural poverty in China. *Journal of Comparative Economics* 34, 694-712

Zhang, Y. and Wan, G. (2009) How precisely can we estimate vulnerability to poverty? *Oxford Development Studies* 37, 277-287

Zhao, Y. (2003) The role of migrant networks in labour migration: The case of China. *Contemporary Economic Policy* 21, 500-511

Zimmerman, F. J. and Carter, M. R. (2003) Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of Development Economics* 71, 233-260