Modelling Vulnerability in the UK

Sanghamitra Bandyopadhyay
and
Frank Cowell
University of Oxford
and
STICERD, London School of Economics

DARP 89
February 2007

The Toyota Centre
Suntory and Toyota International
Centres for Economics and Related
Disciplines
London School of Economics
Houghton Street
London WC2A 2A

(+44 020) 7955 6674

Abstract

In this paper we examine the concept of "vulnerability" (Townsend 1994) within the context of income mobility of the poor. We test for the dynamics of vulnerable households in the UK using Waves 1 - 12 of the British Household Panel Survey and find that, of three different types of risks that we test for, household-specific shocks and economy-wide aggregate shocks have the greatest impact on consumption, in comparison to shocks to the income stream. Quantile-specific estimates reveal specific quantiles, particularly those around the poverty line which are most susceptible to be vulnerable to shocks to the income stream. The estimates are found to be robust to household composition and year-specific shocks.

- JEL classification D1, D31, I32
- Keywords : income variability, vulnerability, income dynamics, BHPS

Distributional Analysis Research Programme

The Distributional Analysis Research Programme was established in 1993 with funding from the Economic and Social Research Council. It is located within the Suntory and Toyota International Centres for Economics and Related Disciplines (STICERD) at the London School of Economics and Political Science. The programme is directed by Frank Cowell. The Discussion Paper series is available free of charge. To subscribe to the DARP paper series, or for further information on the work of the Programme, please contact our Research Secretary, Leila Alberici on:

Telephone:	UK+20 7955 6674
Fax:	UK+20 7955 6951
Email:	l.alberici@lse.ac.uk
Web site:	http://sticerd.lse.ac.uk/DARP

1 Introduction

Households with volatile incomes are commonly encountered in developing and developed countries alike. This volatility is attributable to both idiosyncratic and aggregate risks and the potential economic disadvantage that it implies cannot be adequately captured by poverty measures or other static assessment criteria. It has also led to an interest in identifying households or individuals who are prone to being affected by such risks and who may, as a result, become poor: these are the *vulnerable*. The vulnerable are those who are unable to smooth their consumption in the light of idiosyncratic fluctuations to the income stream. In this paper we use a panel regression approach to identify the vulnerable in light of the different risks – both idiosyncratic and aggregate risks – faced by UK households using the British Household Panel Survey (BHPS). We also focus on specific subsets of the income distribution that may be particularly prone to these shocks, by estimating the dynamics for individual quantile groups within the income distribution.

The concept of economic vulnerability is not new, although the systematic treatment of measurement issues is fairly rent. Typically, the literature focuses on a quantile group of households in a given neighbourhood of the poverty line that are likely to experience volatile changes in their consumption levels in the event of a shock to their incomes. The theoretical framework and the empirical investigations take account of the economic risks and shocks that are likely to make households poor. The focus is different from that of studies measuring the extent of poverty and is closer to the mobility literature. The measurement of the vulnerability departs from the standard approach to mobility in two important respects: first, it focuses on the mobility of the particular households in the vicinity of the poverty line under the influence of economic risks and shocks; second it draws upon theories of risk in determining the nature of the shocks that make households vulnerable.

The recent literature on vulnerability uses recently available household-level datasets in Asia and Africa to identify what kind of shocks significantly affect households' consumption streams and welfare. The shocks are of three types. *Idiosyncratic* shocks are those that impinge directly upon the income stream; *aggregate* shocks are economy-wide and purely economic in nature (for example inflation); *household-specific* shocks are those involving significant changes in the household (such as the loss of an earning member of the family). It has become commonplace to think of these in terms of natural calamities within developing countries, but it is clear that all three types of shocks can affect the poor and the near-poor in developed countries as well.

A substantial econometric literature has addressed the effect of income shocks on the consumption stream, usually based on intertemporal choice models. There is a wide variety of models – usually based on some variant of the permanent income hypothesis – that seek to investigate the issue of consumption smoothing; most are. These include studies which measure the extent of consumption inequality (Blundell and Preston 1998, Deaton and Paxson 1994) and more direct tests of the presence of consumption smoothing in the face of income shocks (Japelli and Pistaferri 2006, Meghir and Pistaferri 2004). Further identification of the nature and the path of the shock itself has been addressed by a different literature (see Ramos and Schluter 2006) and is beyond the remit of this paper. The methods that we will employ are fashioned particularly to identify shocks that impinge upon households' welfare; the intent is to identify those who are prone to significant risks, irrespective of the nature of the shocks.

The empirical investigation in this paper uses the British Household Panel Survey (BHPS) to test for the existence of prominent risks affecting household consumption at a number of quantiles across the income distribution. We use a panel regression approach similar to that used in Amin et al. (2003) and Dercon and Krishnan (2002) – the focus of the paper is not to propose new empirical approaches but to identify location-specific dynamics of vulnerability. Different concepts of income exhibit different dynamics, particularly in the vicinity of the poverty line. The paper is set out as follows. Section 2 sets up the welfare framework from which we derive the empirical methodology for the identification of the vulnerable. Section 3 describes the data and the variables used for the analysis. Sections 4-6 present the results and Section 7 concludes.

2 Background: Who are the vulnerable?

The basic idea of vulnerability is related to a concept used extensively in the French-language social and economics literature – *précarité* (literally "precariousness") and sometimes translated as insecurity. To embody the concept of economic insecurity – vulnerability – within an appropriate analytical framework clearly requires the introduction of uncertainty, its effect on persons and households and their reactions to it. Such a modelling approach can be used to found the definition of vulnerability and the vulnerable on specific aspects of economic behaviour.

2.1 An economic approach

What aspects of economic behaviour? Take a simple, perhaps even naive, approach to the modelling of the economic welfare of individuals. The essential detail of this is set out in section 2.2 below but the main focus is as follows. An individual's well-being over time is determined by the flow of consumption enjoyed in each period. If we represent this using a conventional utility function (increasing in consumption of each period, quasiconcave) then it is immediate that (a) the person would prefer to avoid "extreme" consumption programmes – very high consumption in one period very low in another – and (b) the person is risk averse. Both conclusions follow from the conventional quasiconcavity assumption. But of course an individual's resources and needs are subject to fluctuation through time; furthermore they are subject to *unforeseen* fluctuation through time. So in this conventional model, faced with risks economic agents try to smooth consumption in order to maximise their economic welfare. If all the uncertainty about needs and resources could be represented in terms of a conventional risk model and there were efficient markets for risk, then a rational economic agent would purchase insurances so as to achieve the desired consumption smoothing over time and in each possible state of the world. Of course this level of abstraction is not entirely appropriate for modelling the circumstances faced by many people with low incomes and so it might asked whether this basic story still has something to offer.

Clearly for many types of uncertainty in life formal insurance contracts are not available; clearly too some individuals – typically those who are disadvantaged in some way – cannot or do not purchase insurance contracts, for a variety of reasons. Nevertheless, even in these circumstances, people arrange their affairs so as to cushion the economic effects of uncertainty in ways that mimic formal insurance and so achieve consumption smoothing, at least to some degree. This may be achieved by simply putting things by for a "rainy day" or by cooperation within the household or the community (Deaton 1997, Townsend 1994). Of course some people do not manage to do this cushioning effectively; as a consequence income shocks induce consumption shocks; consumption shocks in turn induce shocks to economic welfare; and, for these people, similar shocks to economic welfare arise from unforeseen changes in needs. Such shocks may lower the economic status of those who are already poor and may push others – those apparently not poor – down below the poverty line. It is these households who are of special concern to policy-makers concerned with "vulnerability."

Vulnerability interpreted in this way is the focus of the empirical investigation in this paper. The objectives are (1) to identify those who are unsuccessful at smoothing out consumption (and hence welfare) (2) to capture the economic and personal factors that predispose certain households and individuals to be vulnerable.

2.2 The underlying model

Each person has a multiperiod utility function:

$$\sum_{t=0}^{T} \delta^t u(c_t) \tag{1}$$

where c_t is consumption in period t, δ is a constant discount factor and u is the instantaneous utility function that captures the substitutability of consumption between periods and also the individual's attitude to risk. As far as risk preferences are concerned we focus on the standard constant relative risk aversion (CRRA) case

$$u(c_t) = \frac{1}{1-\rho} c_t^{1-\rho} \tag{2}$$

where ρ is the index of absolute risk aversion and of relative risk aversion.

If there were an efficient capital market and an efficient insurance market then the precise time path of incomes $(y_0, y_1, y_2, ...)$ would not be relevant to the economic agent, but only the present value of incomes A. Maximising (1) subject to

$$\sum_{t=0}^{T} p_t c_t \leq A, \tag{3}$$

where p_t the price of consumption at time t,.implies the following condition

$$\frac{u'(c_{t+1})}{u'(c_t)} = \frac{p_{t+1}}{\delta p_t} \tag{4}$$

where u' denotes the first derivative of u. Given the CRRA assumption (2) condition (4) yields

$$\left[\frac{c_{t+1}}{c_t}\right]^{-\rho} = \frac{p_{t+1}}{\delta p_t} \tag{5}$$

or equivalently

$$\Delta \log(c_t) = -\frac{\kappa_t}{\rho}. \tag{6}$$

Equation (6) forms the basis of the empirical strategy adopted in this paper.

2.3 The empirical strategy for measuring vulnerability.

The idea of vulnerability can be captured in an empirical translation of the model in 2.2. If there were no unforeseen income shocks then, given households' preferences represented by (2), efficient risk sharing by individuals in each household would imply exactly the relationship (6). But if there were unforeseen income shocks y_t the appropriate modification of 6 would be

$$\Delta \log (c_t) = \nu \Delta \log y_t - \frac{\kappa_t}{\rho}. \tag{7}$$

where the parameter ν captures the vulnerability of the economic agent to income shocks following the approach of Townsend (1994).[1] Household i is considered to be vulnerable if the coefficient associated with Δy_{it} is significant.[2]

Efficient risk sharing implies that household consumption tracks only aggregate consumption, but not income. One can test for full risk sharing and no risk sharing the hypotheses $\nu = 1$ and $\nu = 0$ respectively.[3] The empirical approach in this paper is to use a panel regression based on (7) in order to identify the impact of risks and therefore identify the vulnerable. First, we intend to identify the shocks themselves which characterise income risks.

[1] The approach used here is in the spirit of macro models that incorporate the impact of risks on consumption (Meghir and Pistaferri 2004, Japelli and Pistaferri 2006, Blundell and Preston 1998). The Townsend (1994) approach led to several developing-country studies where the risks which mattered the most tend to be idiosyncratic in nature alongside the economy-wide shocks, such as inflation. (Amin et al. 2003, Dercon and Krishnan 2002). Some of these studies have explicitly focused on the size of the effects of an income shock on the expected welfare of the household (Chaudhuri et al. 2002, Ligon and Schechter 2003). Our model is distinct from poverty-dynamics models that focus primarily on the mobility of the poor in terms of entry and exit rates, and on the identification of factors that trigger such transitions (Bane and Ellwood 1986, Jenkins 2000).

[2] In Amin et al. (2003) and Dercon and Krishnan (2002) the value of ν considered is typically between 0 and 1 for consumption smoothing not having taken place.

[3] Studies such as Amin et al. (2003) have a different interpretation of the ν coefficient. While the Townsend model only tests for ν taking values 1 or 0, Amin et al. (2003) and Dercon and Krishnan (2002) are more empirically geared to test for the impact of idiosyncratic and economic shocks on the consumption stream. Thus while from the Townsend point of view the interpretation of positive values of the ν coefficient is indicative of risk-sharing, from the Amin et al. (2003), or Dercon and Krishnan (2002) standpoint, one can assign the significance of the ν coefficient (positive in sign) as indicative of changes in consumption responding to income shocks i.e. an idiosyncratic risk. Their empirical formulation typically regresses changes in consumption on changes in incomes with time dummies accounting for the presence of economic or other kinds of shocks which perturb the natural relationship between changes in consumption and income.

This will be captured by using the household characteristics as regressors as well as dummies for the waves of the panel. We also wish to identify location-specific dynamics of the vulnerable in the income distribution – this is not revealed in a cross-section regression towards the mean. The standard regression approach reveals what is happening to households at the expected or average income. However, it is also important to observe what happens at particular quantiles in the distribution and thereby identifying where households are likely to be especially vulnerable than others. In particular, we will be interested in observing what happens to the households near the poverty line. The estimation strategy thus differ from the usual panel based studies undertaken with developing country data, but the parallels are obvious.

3 The British Household Panel Survey

The BHPS extends for 14 waves and follows the same representative sample of individuals over a period of 14 years from 1991 to 2004. Each annual interview round is called a wave: in our study we use 12 waves of data, and each wave is principally household-based, interviewing every adult member of sampled households. Each wave consists of over 5,500 households and over 10,000 individuals drawn from 250 areas of Great Britain. The samples of 1,500 households in each of Scotland and Wales were added to the main sample in 1999, and in 2001 a sample of 2,000 households was added in Northern Ireland.

Our principal variables of interest are those of consumption, income, and household characteristics. The following variables are used for the empirical study.

The following variables have been used for the analysis:

- Expenditure on food, per week per household.
- Household income, per household
- Number of children in household.
- Household size (i.e. number of individuals present in the household).
- Number of household members of employable age.

The data used for the estimation spreads over a span of 12 waves, of which 11 waves are available with the required data. Data on expenditure is however not available for Wave 7, so has been deleted from the analysis. Expenditure on durables is also only available for one wave, hence cannot be included in the analysis. The final wave-spread is there for Waves 1 to 6 and 8 to 12. Over the entire spread of the 11 waves, we have a complete panel with 1,659 individuals per wave. Waves 13 and 14 while currently available are not incorporated in dataset due to net income variables not being available as yet.

Some of the variables have had to be constructed given the nature of the variables provided by the BHPS. Household consumption is only available for food consumption (with very sparse data on fuel consumption). Household expenditure per week per household is multiplied by 4 to obtain monthly food consumption, and divided by household size to obtain per capita estimates. Income variables are defined in three different ways, detailed in (Bardasi and Jenkins 2004). There are three income definitions - monthly gross income, and two net income definitions – annual and weekly. Net annual income is provided over different time periods; for our study we have chosen income over the period 01.01.year to 31.12.year. Details of the derivation of net incomes in (Bardasi and Jenkins 2004) is provided in the Appendix. The three different definitions of income give us different perspectives on the income smoothing process – while the monthly per capita income allows for all the time-specific shocks, the net current income takes into account the household weekly income net of the local taxes, while net annual income does the same over the period of 12 months (net of taxes and annual pension contributions) and allows for some income smoothing to have taken place. The relative importance of each time horizon will reveal itself with the estimations, discussed in Sections 4 to 6.

Table 1 presents the summary statistics for the variables we will be using for the estimation of vulnerability dynamics, estimated in 2000 prices. The most notable characteristics observed is that the dynamics of level values of consumption and income do not follow the same trajectory as that of the inter-temporal changes of the same variable. As our model presented earlier discusses, our main focus will involve tracking the dynamics of the changes in consumption and that of income. The second half of the table presents the summary statistics of the truncated sample. The truncations are performed on the basis of outliers of the changes in household consumption - we truncate households for which changes in inter-temporal consumption exceed +/-1. It is clear from the right-hand side of the table that truncation does not remove the most extreme values of any variables other than dlxpfoodmnpc00, the variable used to condition the truncation.

	FULL SAMPLE $N = 16590$				TRUNCATED SAMPLE $N = 14786$			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
xpfoodmnpc00	8.9533	4.1596	0	45.377	9.2325	4.1554	0	45.377
mnincpc00	566.99	457.37	0	22365	585.80	469.11	0	22365
hhnetipc00	157.81	183.55	-13.000	5204.9	163.05	189.09	-13.000	5204.93
hhynetipc00	8047.1	8958.4	0	287593	8312.6	9238.2	0	287593
dlxpfoodmnpc00	-0.13744	0.60173	-3.5814	2.8594	0.029968	0.23407	-0.98083	0.94497
dlmnincpc00	0.048732	0.36686	-7.0221	3.9442	0.050573	0.36707	-7.0221	3.9442
dlhhnetipc00	0.039956	1.0124	-9.6245	9.9385	0.039991	1.0296	-9.6245	9.9385
dlhhynetipc00	0.92673	0.075408	0.81730	1.0313	0.93867	0.069520	0.8173	1.0313
hhsize	2.6573	1.4415	1	10	2.6565	1.4461	1	10
nkids	0.75069	1.1045	0	7	0.75023	1.1051	0	7
nwage	1.1425	1.1757	0	7	1.1338	1.1822	0	7

Table 1: Summary statistics

3.1 The cross-section unit of study

The BHPS matches persons across waves and not households, thus presenting itself as a possible difficulty for using the data as a longitudinal panel. This however, is surmountable in that one can match households by the individual (i.e. personal) identity numbers. Again, tracking individuals as opposed to just households, is our preferred cross-section unit, as household compositions change over the waves (due to a household member leaving the household, or due to the interviewee not being available while survey was being undertaken). Our unit of consumption and income is that of the person, having taken into account household compositions. In tracking individual consumption and income we are also avoiding possible problems with economies of scale with large households. This however will be discussed when dealing with equivalised quantities.

4 Vulnerability − a first look

Our first set of estimates involve estimating the following structure, in the same spirit as estimated in Townsend (1994) and Amin et al. (2003). First we estimate the simplest model based on the CRRA specification (2) using the following:

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \varepsilon_{it} \tag{8}$$

where $c_t := C_t/n$,denotes per-capita consumption of the household in wave t, y_{it} is household income per capita at wave t, and W_t is a wave dummy, which equals one for observations at wave t, zero otherwise. t varies from 1 to 11, wave 1 corresponds to $t = 1$, wave 7 is dropped from analysis, and wave 12 corresponds to $t = 11$. The coefficient ϕ_t captures the coefficient $\frac{1}{\alpha}\kappa_t$ in equation (7). We also assume the error term to be uncorrelated with the RHS variables and to have zero mean. Let us assume the following dynamic structure:

$$\begin{aligned} \operatorname{var}(\varepsilon_{ht}) &= \sigma_h^2 \\ \operatorname{cov}(\varepsilon_{ht}, \varepsilon_{jt}) &= 0 \\ \operatorname{cov}(\varepsilon_{ht}, \varepsilon_{ht'}) &= 0 \end{aligned}$$

$$\sigma_h^2 = \exp\left(\sum_j \beta_j z_{hj}\right)$$

The error term can be expected to vary across households, because of heterogeneity in household size, consumption and income. The heteroscedasticity of the error term assumption is motivated by tests performed such as the White test (by regressing the square of the residuals on household characteristics and their squares and cross-products for each wave), where some heteroscedasticity is revealed. We estimate the above taking into account the heteroscedastic nature of the error term using standard GLS, where the vector z_{hj} is estimated by postulating that individual household variance depends upon a number of observable household characteristics (household size, number of children) using the expression above. However, diagnostic tests performed on the residuals using standard panel data methods (i.e. allowing for a homoscedastic error term) do not suggest a strong presence of heteroscedasticity; nevertheless we use GLS methods for estimation along with standard panel methods. Taking inter-temporal differences (i.e. of the regressand and principal regressor, Δc_{it} and Δy_{it}) eliminates a source of correlation across time periods and there is little evidence of correlation of the differences across time periods.[4] The GLS method used takes into account any residual correlation across panels that may still remain after the first-differencing. Equation (8) is estimated both under fixed-effects and under random-effects assumptions for the standard panel model.

We estimate two sets of regressions. First, we run an empirical application of the Townsend model (8).

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \varepsilon_{it}$$

[4] The correlation coefficients between Δc_{it} and Δc_{it-1}, and Δy_{it} and Δy_{it-1} are not significant anywhere nor do we obtain a consistently significant Dickey-Fuller test.

household characteristics which may be representative of household shocks, and thereby determine the smoothing relationship.

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \gamma X_{it} + \varepsilon_{it} \tag{9}$$

While this model tests for a different specification of the utility function (namely, the CRRA specification), it empirically also lends itself better to the statistical problems which medium-to-long run time series data present. Differencing renders the variables as stationary, thus preventing any spurious co-trending from accounting for a positive and significant smoothing coefficient.

The following table presents our results of estimating equation 9 using panel estimation methods with the three different definitions of income. Here we consider the CRRA specification of the utility function, where the dependent variable is differences in log-consumption and the principal right hand side variable is differences in log-incomes, presented in Table 2. We find that the ν coefficient is significant under some specifications. Columns 1 and 2 present the results using the monthly income (per capita) variable, for both fixed and random effects – the ν coefficient is positive and significant. A large number of wave dummies are positive and significant, with exception of Wave 2 which is negative. This result repeats itself for specifications with all other income definitions – columns 3 and 4 present regressions with net current income as the income variable, and columns 5 and 6 with net annual household income – we find that in all cases, the ν coefficient is either weakly significant or not significant. Wave 2 continues to be negative and strongly significant, while wave 8 and 11 is also consistently positive and significant. In addition, waves 3, 4 and 5 also show up to be strongly significant under most specifications.

We can now summarise our findings under some broad generalisations:

- We find waves 2 (negative), wave 8 and 11 (positive) to be strongly significant. The effect of economy-wide shocks is therefore clear. Of the other waves 3, 4 and 5 also show up as positive and significant under certain specifications.

- Across the results we find that the number of employable age in household to be significantly negatively associated with changes in consumption. The number of children in the family have also shown up as significantly negatively associated with changes in consumption.

	dlmnincpc		dlhhnetipc		dlhhynetipc	
dlxpfoodmnpc	F	R	F	R	F	R
dlincomepc	0.02851*	0.03251*	-0.00335	-0.00339	-0.00533‡	-0.00489‡
dwave2	-1.97258*	-1.98955*	-1.96579*	-1.98591*	-1.97178*	-1.98848*
dwave3	0.06501*	0.04862*	0.07229*	0.05293*	0.06600*	0.04963*
dwave4	0.05790*	0.04452*	0.06455*	0.04840*	0.05909*	0.04578*
dwave5	0.05108*	0.03860*	0.05951*	0.04437*	0.05319*	0.04112*
dwave6	0.03137†	0.01888	0.04003*	0.02454‡	0.03330†	0.02111
dwave8	0.09090*	0.08192*	0.09764*	0.08594*	0.09317*	0.08469*
dwave9	0.02340‡	0.01785	0.03191†	0.02357‡	0.02351‡	0.01882
dwave10	0.02749†	0.02438‡	0.03556†	0.02982†	0.02888†	0.02710‡
dwave11	0.03504*	0.03348*	0.04103*	0.03709*	0.03762*	0.03490†
nkids	-0.04598*	-0.00318	-0.05002*	-0.00397	-0.05118*	-0.00380
nwage	-0.06196*	-0.0111*	-0.06338*	-0.01128*	-0.06497*	-0.01148*
conts	0.09581*	0.01121	0.09381*	0.00929	0.10223*	0.01235
Notes	$*$: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 2: Vulnerability model with CRRA specification, all incomes

- We also observe that gross monthly income per capita definition exposes the lack of consumption smoothing the most – for this definition, the ν coefficient is significant for most specifications. Of the two net income definitions, net monthly income (compared to net annual income) again, reveals ν coefficient to be significant, though not as pervasively as the gross (monthly) income definition.

5 Locating the vulnerable

Clearly not all cases where an individual's or household's current consumption is responsive to current income should be characterised as vulnerability. There are obviously instances where well-off agents respond to surprise positive income shocks by boosting their consumption; we would not normally think of them as vulnerable consumers. Furthermore, there may be very poor agents who have little choice but to tie current consumption to current income; however, for them there is no danger of "slipping into poverty" – they are there already. To obtain a clearer idea of the dynamics in the neighbourhood of the poverty line and to compare dynamics in specific parts of the distribution we adopt the following procedure. Specify a set of intervals

$$I_j := [q_j, q_{j+1})$$

where $0 \leq q_j < q_{j+1} < 1$ and let them define a set of location-specific subsamples on which to estimate the model (7) using one of two methods. First, consider the households' starting positions in the income distribution according to whether they fall into interval I_j by rank in the initial wave, Second, identify households that at some point in time have contact with I_j. Section 5.1 uses the first method for fixed quantile groups throughout the income distribution; section 5.2 compares the results for each of the two methods to examine the performance of the vulnerability model in the neighbourhood of the poverty line where the neighbourhood intervals I_j are determined relative to the poverty line.

5.1 Location within the distribution

We begin by taking the following fixed quantile groups as key "starter intervals": 20-40, 40-50, 50-60, 60-70 and 70-80 where, for example the 20-40 group includes all households who start at or above the 20th centile, but below the 40th centile. Tables 3 and 4 present results across the quantile groups for the fixed-effects specification[5] using, respectively, gross and net monthly income per capita. In every group the ν coefficient is significant for gross income but not for net income. For the gross-income model wave dummies are especially important in the 20-40 and 70-80 groups but not in the neighbourhood of the median; but for the net-income version the wave dummies are not significant at the bottom of the distribution (20-40 group) although they are still important at the top (70-80 group). Both the number of children and the number of employable aged household members matter for the gross-income version of the model for the lower groups 20-40, 50-60 and 60-70.[6]

[5] We have estimated both fixed effects and random effects versions of the models, and present those of the fixed effects (FE) only. For all the variants of the model and all subsamples tested for, the Hausman test performed does not indicate a significant difference between the two models' estimates. It is however the case that for some models the household characteristics are significant only under the FE specifications, as opposed to the random effects models, even though the Hausman test is not significant. Noting that the Hausman test tests for a null of no difference between FE and RE models, we therefore present the fixed effects models' estimates. The GLS estimates for all the models that have been estimated are either presented in the Appendix, or not presented due to their results being very similar to the panel results.

[6] In the case of household net *annual* incomes the ν coefficient is significant for the 40-50, 50-60 and 70-80 groups. The number of children, and number of employable members

I_j :	**20%-40%**	**40%-50%**	**50%-60%**	**60%-70%**	**70%-80%**
dlmnincpc	0.03318‡	0.04847†	0.05369‡	0.12001*	0.11419*
dwave2	-1.92746*	-1.90004*	-1.82901*	-1.90651*	-1.93907*
dwave3	0.07960*	0.03464	0.03970	0.04675	0.08743†
dwave4	0.07983*	0.04800	0.09558†	0.06523	0.10904*
dwave5	0.06900†	0.04076	0.07640‡	0.03775	0.07203‡
dwave6	0.08133*	0.05327	0.02825	0.03853	0.05307
dwave8	0.08013*	0.07833†	0.15527*	0.06741	0.12110*
dwave9	0.03820	0.02018	-0.01777	0.00067	0.01993
dwave10	0.05816†	0.02641	0.06534	0.00950	0.01531
dwave11	0.06563†	0.04680	0.02299	-0.00904	0.08378†
nkids	-0.06413*	-0.03371	-0.09264*	-0.08328†	-0.01696
nwage	-0.08621*	-0.02712	-0.07763*	-0.09083*	-0.06239*
const	0.10036*	0.02676	0.11077†	0.11993†	0.03190
Notes.	$*$: Significant at the 1% level				
	$\dagger$: Significant at the 5% level				
	$\ddagger$: Significant at the 10% level				

Table 3: Vulnerability model for selected quantile groups; gross monthly percapita income

We run the same model using the GLS specification for all three income definitions; results are presented in the Appendix. We observe the same dynamics as observed with the panel regression specification. What is notable though is that the level of significance of the vulnerability coefficient improves for the gross monthly income definition results. Also notable is that while panel regressions with the monthly net income definition do not exhibit significant vulnerability for any of the quantiles, for the GLS estimates 20-40 and 50-60 groups exhibit significant vulnerability dynamics. The GLS results and panel regression results for using the annual net income model are identical, though the level of significance of vulnerability coefficient is stronger for a few quantiles.

5.2 Location at the poverty threshold

To focus upon what happens on the threshold of poverty we use two versions of the "poverty zone," an interval I^* defined relative to the poverty line. Let the proportion of households with incomes below 60% of the median be q^* and

of family show up as significant for the quantiles of 20-40 and 40-50, and 70-80 only. The wave dummies only show up as significant strongly for the 20-40 quantile.

I_j :	**20%-40%**	**40%-50%**	**50%-60%**	**60%-70%**	**70%-80%**
dlhhnetipc	0.006902	0.00103	0.00984	-0.00199	-0.01132
dwave2	-2.0077*	-1.97913*	-2.02330*	-2.00585*	-1.86091*
dwave3	0.08456†	0.08476†	0.08408†	0.08513†	0.13950*
dwave4	0.03253	0.08474†	0.06562‡	0.06896‡	0.13286*
dwave5	0.04755	0.06051‡	0.05123	0.07447‡	0.14357*
dwave6	0.049712	0.07761†	0.03763	0.05186	0.06637
dwave8	0.082042*	0.11743*	0.08726†	0.10419*	0.12032
dwave9	0.03779	0.05206	0.04545	-0.00915	0.08078‡
dwave10	0.014789	0.06074‡	0.03821	0.02459	0.08471‡
dwave11	0.035767	0.04172	0.04694	0.06474‡	0.11387†
nkids	-0.071218*	-0.04362‡	-0.00712	-0.10113*	-0.12786*
nwage	-0.070181*	-0.04286†	-0.06565*	-0.10491*	-0.10774*
cons	0.03349	0.05842	0.05846	0.13628*	0.05815
Notes.	$*$: Significant at the 1% level				
	†: Significant at the 5% level				
	‡: Significant at the 10% level				

Table 4: Vulnerability model for selected quantiles; household monthly net income only

take two separate 20% neighbourhoods of this value, $I^*_{\text{sym}} = [q^* - 0.1, q^* + 0.1)$ and $I^*_{\text{asym}} = [q^* - 0.15, q^* + 0.05)$. [7] For each version of the poverty zone I^* we estimate the model for both the "starts in poverty zone" case (*sipz*), where the household was initially in I^*, and for the "ever in poverty zone" (*eipz*) case, where the household is in I^* for at least one year covered by the panel.

Tables 5 and 6 present the results using both interpretations of the poverty zone (I^*_{sym} and I^*_{asym}) for the *sipz* and *eipz* cases respectively. For the monthly *gross* income definition the ν coefficient is significant, particularly for the *eipz* case.[8] By contrast, the monthly *net* income definition produces rather different dynamics. While the *sipz* case show no signs of consumption smoothing

[7] So if, for example, we use the starter-interval approach and the poverty line is at the 26th percentile, the "symmetric around the poverty line" subsample includes households between the 16th and 36th percentiles and the "symmetric around the poverty line" subsample includes households between 11th and 31st percentiles. Given that each wave has 1659 pids, there are 345 pids per wave in the subsample.

[8] For the *eipz* case the ν coefficient is significant for both fixed and random effects specifications (with the same level of significance). While the number of employable household members is strongly significant in both specifications, the number of children is so for the random effects specification only.

for either I^*_{sym} or I^*_{asym} (i.e. the income coefficient is not significant), this is not true for the *eipz* case – the ν coefficient is significant. The results for annual net income are very similar to those for monthly net income: no significant relationship between changes in income and in consumption, except for I^*_{asym} in the *eipz* case. The number of employable household members and the number of children in family are significant and negative everywhere. There is clearly a difference in the impact of the wave dummies as between I^*_{sym} or I^*_{asym}, although Wave 2 is strongly significant in all specifications.[9]

	mnincpc		hhnetipc		hhynetipc	
I^* :	sym	asym	sym	asym	sym	asym
dlmnincpc	0.03595†	0.03291†	0.00460	0.00859	0.00009	-0.00323
dwave2	-1.97733*	-2.01541*	-2.02700*	-2.05541*	-1.98453*	-2.07215*
dwave3	0.07342†	0.04874	0.06852†	0.06638†	0.06500†	0.03447
dwave4	0.02601	0.01527	0.01237	0.03083	0.05843‡	0.01896
dwave5	0.06695†	0.05921‡	0.03828	0.06664†	0.03568	0.00025
dwave6	0.04079	0.02832	0.03925	0.03909	0.02976	-0.00038
dwave8	0.08388*	0.07503†	0.05353	0.06552†	0.07725†	0.03169
dwave9	0.00949	0.02488	0.01120	0.02863	0.00702	-0.02827
dwave10	0.03855	0.01955	-0.00088	0.02148	0.01776	-0.01400
dwave11	0.00718	-0.00956	0.02491	0.03895	0.02492	-0.02951
nkids	-0.07929*	-0.07325*	-0.07082*	-0.05769*	-0.06527*	-0.05332*
nwage	-0.08468*	-0.08620*	-0.07695*	-0.07185*	-0.07293*	-0.06954*
cons	0.20139*	0.24685*	0.19105*	0.16880*	0.17439*	0.19952*
Notes.	$*$: Significant at the 1% level					
	$\dagger$: Significant at the 5% level					
	$\ddagger$: Significant at the 10% level					

Table 5: Vulnerability model for sipz case, symmetric and asymmetric samples

[9] GLS estimates for the *sipz* model are very similar to the panel regression results - the vulnerability coefficient is significant for the monthly gross income definition, but not so for the net monthly and net annual income definitions. While wave dummies are significant for most models, the household characteristics are not significant for the net income definitions.

	mnincpc		hhnetipc		hhynetipc	
I^* :	sym	asym	sym	asym	sym	asym
dlmnincpc	0.06039*	0.07853*	0.00818	0.00021	0.01012‡	0.00937
dwave2	-2.05154*	-2.06623*	-2.01978*	-2.06528*	(dropped)	(dropped)
dwave3	0.01455	0.00778	0.04731	0.01878	0.11298*	0.04140
dwave4	0.01155	0.00063	0.06830‡	0.04629	0.12587*	0.07445†
dwave5	0.04382	0.01781	0.06781‡	0.07773†	0.12716*	0.06963†
dwave6	0.02562	0.01516	0.06876‡	0.07250†	0.11228*	0.03511
dwave8	0.03632	0.01098	0.08685†	0.07940†	0.15301*	0.11749*
dwave9	-0.00679	-0.00150	0.03641	0.03885	0.09101*	0.04265
dwave10	0.01802	-0.00810	0.04353	0.03738	0.09241*	0.02647
dwave11	-0.00830	-0.02390	0.07340†	0.06271‡	0.09082*	0.01760
nkids	-0.05871*	-0.06157*	-0.07621*	-0.08210*	-0.06875*	-0.07449*
nwage	-0.07050*	-0.07045*	-0.09070*	-0.11258*	-0.06836*	-0.06982*
cons	0.17543*	0.21910*	0.19249*	0.25823*	0.11197*	0.18737*
Notes.	$*$: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 6: Vulnerability model for eipz case, symmetric and asymmetric samples

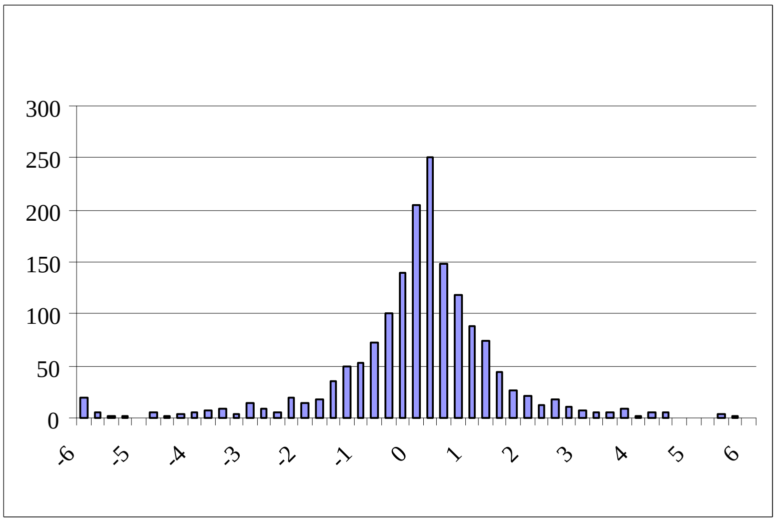

Figure 1: Frequency distribution of ν_i estimates, monthly gross income

In terms of vulnerability, does it matter what we mean when we speak of households "near the poverty line"? Perhaps surprisingly, the answer is that the estimates are robust to the choice of definition. Although there are slight differences between the symmetric and asymmetric poverty-zone subsamples, the vulnerability dynamics turn out to be much the same. Although the *eipz* definition allows for a larger group of households to be considered– anyone who has ever been in the 20% neighbourhood – again the conclusions based on the s*ipz* still hold good although the ν coefficient is larger for the *eipz* definition, both for the monthly gross income definition.. What does make a difference is the definition of income,, gross or not, for each definition of "near the poverty line."

5.3 Individual vulnerability

For a close-up view of the dynamics of vulnerability of individual households we use a household-specific version of the standard model

$$\Delta \ln c_{it} = \nu_i \Delta \ln y_{it} + \phi_t W_t + \gamma X_{it} + \varepsilon_{it} \tag{10}$$

– contrast (10) with (9). In principle this would enable us to to identify which particular households are most susceptible to the shocks discussed earlier. What is more useful for us, however, is to examine the distribution of individual ν_i coefficients, using the plots in Figures 1 to 5.

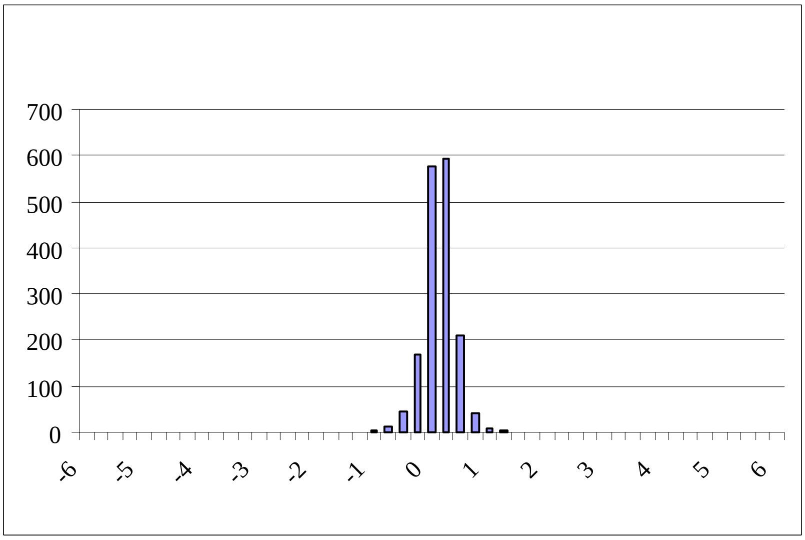

Figure 2: Frequency distribution of ν_i estimates: net monthly income

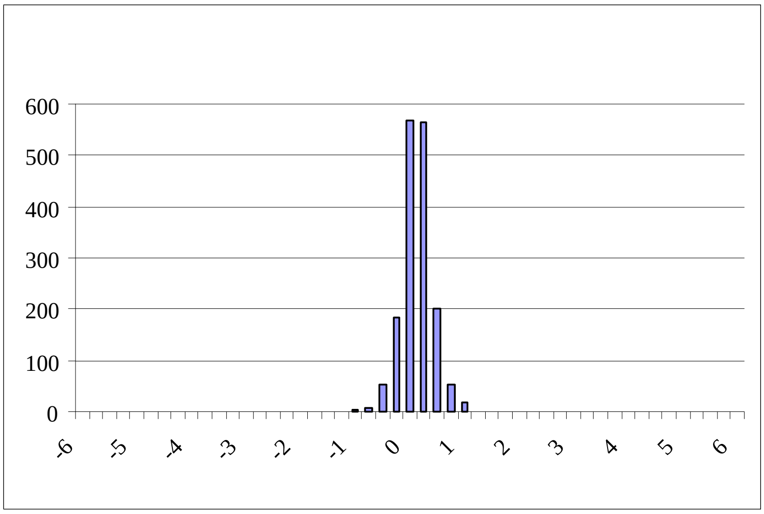

Figure 3: Frequency distribution of ν_i estimates: net annual income

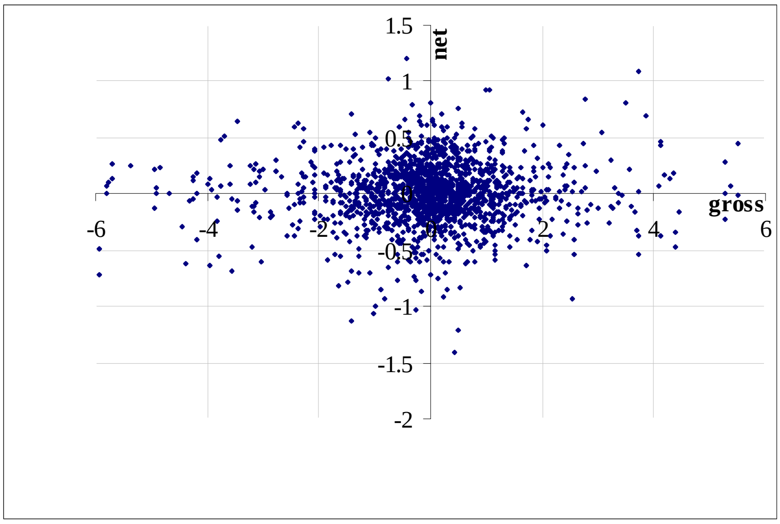

Figure 4: Scatter-plots of ν_i estimates: gross versus net monthly income

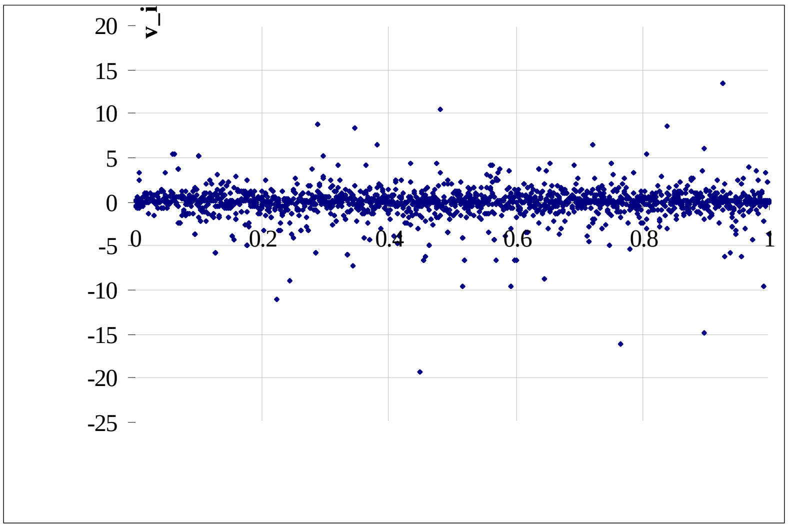

Figure 5: Distribution of ν_i estimates by quantile position: gross monthly income

Figure 1 presents the plots of the ν_is using gross monthly income as the income variable, while Figures 2 and 3 present the corresponding results for the net income model.[10] The plots reveal the greater spread of the monthly income model which confirms our finding from the general panel regression model (in section 4) that vulnerability is more evident if one uses the gross income definition than either of the net-income definitions; furthermore when imputations are made to derive annual net incomes, the estimates are even less spread out. This is also borne out by Figure 4 where we observe that, for the majority of households, the vulnerability coefficient for the net-income model is smaller than that for the gross-income model.

Finally, from Figure 5.confirms the result from section 5.1 vulnerability is not confined to one particular part of the income distribution.

6 Vulnerability and individual welfare

Vulnerability is supposed to be about the wellbeing of individuals, as we discussed in section 2. The relationship of individual wellbeing to household incomes will depend among other things on economies of scale within the household. In the analysis of section 4 we have implicitly made an extreme assumption – that such economies of scale are absent. We now put that right by introducing a simplified version of household scale economies into the basic vulnerability model. This modification has two effects: first it alters the imputed values for consumption and income at a given moment and, second, it alters the dynamic relationship from which the vulnerability estimates are derived. The reason for this second effect is that, for each household i household size m_{it} varies through time so that the scale-economies effect, if present, will also vary.

6.1 A modified model

In order to examine a variety of possible relationships between household income and individual welfare it is useful to have a flexible form for the scale-economy effect. We adopt the standard version of Buhmann et al. (1988) so that equivalent income is defined as

$$y_{it}^e = \frac{m_{it} y_{it}}{m_{it}^{\theta}} = \frac{y_{it}}{m_{it}^{\theta - 1}}, \tag{11}$$

[10] Cases where ν_i significantly different from zero amount to 9.7% of the sample for the gross income definition, and 4.6% with the net income definition. A similar percentage of the number of households with the vulnerability coefficient significantly different from zero are observed in the Amin et al. (2003) study on Bangladesh households.

where $0 \leq \theta \leq 1$ and y_{it} is again income per head. The parameter θ captures the strength of the scale-economies effect: the case $\theta = 0$ corresponds to the case where there are extreme household economies of scale – a many-person household can live as as cheaply as a single person; the case $\theta = 1$ is where there are no implied household economies of scale and equivalised income is just per-capita income again.

We can now re-write the consumption-income relationship as

$$\Delta \ln c_{it}^e = \nu_i \Delta \ln y_{it}^e + \phi_t W_t + \gamma X_{it} + \varepsilon_{it} \tag{12}$$

One might expect to find different values of θ to affect the nature of the relationship between changes in log consumption and changes in log income. From (12) we have

$$\Delta \ln c_{it} = \nu_i \Delta \ln y_{it} - [1-\theta]\,[1-\nu_i]\,\Delta \ln m_{it} + \phi_t W_t + \gamma X_{it} + \varepsilon_{it} \tag{13}$$

From (13) it is clear that the relationship between θ and the estimated value of v will depend on the nature of the correlation between household size and per-capita income. However it is difficult to draw a priori general conclusions about the nature of the variation in household composition and its likely impact on the relationship between changes in income and consumption. For example, $\Delta \ln m_{it}$ may be attributable to an additional earner in the household or to a household member, such as an older child, who sporadically adds to the household size for a short period of time, affecting consumption (by increasing expenses) and not necessarily adding to household income.

6.2 Vulnerability and the scale-economy effect

To examine the scale-economy effect on the dynamic relationship between income and consumption we run the model (12) for a number of values of the parameter θ. We already have the results for $\theta = 1$ (from section 4) and we complement these with results for $\theta = 0.5$ and $\theta = 0$; we also equivalise consumption using the same deflator as used for income. Tables 7 to 9 present the fixed-effects panel regressions for the three income definitions where the vulnerable are assumed to be in 20% subsamples drawn around the poverty line. The results for the three values of θ are presented in decreasing order so that economies of scale are increasing as one reads from left to right across each table;[11] the column $\theta = 1$ in Tables 7 to 9 corresponds to a column in Tables 5 and 6.

[11] The explanatory variables used are as for the model presented in section 4 and include dummies for waves 2 to 11.

θ :	symmetric 1.0	0.5	0.0	asymmetric 1.0	0.5	0.0
dlmnincpc	0.03595†	0.04706*	0.07658*	0.03291†	0.04198*	0.09113*
dwave2	-1.97733*	-2.03261*	-2.07890*	-2.01541*	-2.03003*	-2.06729*
dwave3	0.07342†	0.04024‡	0.02135	0.04874	0.05747†	0.04430‡
dwave4	0.02601	0.04643‡	0.00209	0.01527	0.05797†	-0.01411
dwave5	0.06695†	0.04894†	0.01894	0.05921‡	0.05987	0.02617
dwave6	0.04079	0.00947	-0.02767	0.02832	0.02979	-0.02829
dwave8	0.08388*	0.09331*	0.04639†	0.07503†	0.09413*	0.06027†
dwave9	0.00949	0.01261	-0.02625	0.02488	0.02731	-0.03288
dwave10	0.03855	0.02337	-0.01462	0.01955	0.03973‡	0.00718
dwave11	0.00718	0.05619†	0.00757	-0.00956	0.06004†	0.01145
nkids	-0.07929*	-0.01530	0.02343	-0.07325*	-0.02557‡	0.03497†
nwage	-0.08468*	-0.02300‡	0.00561	-0.08620*	-0.02300‡	0.01949
const	0.20139*	0.01360	-0.00281	0.24685*	0.01201	-0.01480
Notes.	$*$: Significant at the 1% level					
	$\dagger$: Significant at the 5% level					
	$\ddagger$: Significant at the 10% level					

Table 7: Vulnerablity model: equivalised monthly gross income

In the modified model (12) it is clear once again that the ν coefficient is significant for gross income (Table 7) but not for net income, monthly or annual (Tables 8 and 9); this conclusion applies to both symmetric and asymmetric samples.[12] Furthermore for gross income waves 2 and 8 are particularly significant. Clearly the conclusions drawn from the simple per-capita model discussed in sections 4 and 5 are robust to changing the assumptions about scale economies.[13]

Now let us examine in more detail the effect of altering the assumed size of scale economies as captured by the parameter θ. The most striking result is that, for each implementation of the gross-income model, as the value of θ decreases, the level of significance of the vulnerability coefficient improves and the size of the coefficient also increases. We also find that, with few exceptions, the significance of the household characteristics (which both relate to household size) and of the wave dummies drops with increasing economies of scale.[14] The effect of θ on the size and significance of the

[12]It also holds whether or not household characteristics are included as regressors.

[13]We carried out a further robustness test, discussed in Appendix C

[14]There principal exception to this is the case of net monthly income for values of θ between 0 and 0.5

	symmetric			asymmetric		
θ :	**1.0**	**0.5**	**0.0**	**1.0**	**0.5**	**0.0**
dlhhnetipc	0.00460	0.00086	-0.00011	0.00859	-0.00251	-0.00469
dwave2	-2.02700*	-2.10767*	-2.12709*	-2.05541*	-2.09426*	-2.13198*
dwave3	0.06852†	0.04324‡	0.01745	0.06638	0.07477*	0.02910
dwave4	0.01237	0.02527	0.02906	0.03083	0.05237†	0.00702
dwave5	0.03828	0.03910‡	0.00959	0.06664†	0.06129*	0.00607
dwave6	0.03925	0.02662	0.00035	0.03909	0.03827‡	-0.02078
dwave8	0.05353	0.05752†	0.03433	0.06552†	0.06507*	0.03243
dwave9	0.01120	0.03098	0.00076	0.02863	0.05350†	0.00740
dwave10	-0.00088	0.00906	-0.00845	0.02148	0.04542†	-0.01600
dwave11	0.02491	0.03886‡	0.01272	0.03895	0.05527†	0.02814
nkids	-0.07082*	-0.02428‡	0.00752	-0.05769*	-0.03130†	0.04903*
nwage	-0.07695*	-0.02473†	0.04216*	-0.07185*	-0.01921‡	0.07996*
const	0.19105*	0.04957‡	-0.04500‡	0.16880*	0.03162	-0.10973*
Notes.	∗: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 8: Vulnerablity model: equivalised monthly net income

coefficients of the Wave dummies depends on the income definition. Of the two types of subsamples around the poverty line, the asymmetric sample around the poverty reveals the greater sensitivity to household characteristics and economy-wide shocks.

7 Conclusion

Are UK households "vulnerable"? In this paper we have addressed this question by attaching to vulnerability the standard economic meaning in terms of income and consumption risk that has been developed in the recent literature. Panel regression methods are used to identify those households for which income instability is translated into instability of consumption and welfare. This reveals that vulnerability is associated with year-specific dummies that capture aggregate shocks to the economy; the size and composition of the household which affect vulnerability dynamics are important, but they may either magnify or offset the effect of the income fluctuations. Above all, however, the income definition is crucial: expenditure changes significantly track income changes when "income" means monthly gross income; but the

	symmetric			asymmetric		
θ :	**1.0**	**0.5**	**0.0**	**1.0**	**0.5**	**0.0**
dlhhynetipc	0.00009	-0.00039	0.00083	-0.00323	0.00157	0.00076
dwave2	-1.98453*	-2.09503*	-2.06424*	-2.07215*	-2.10378*	-2.07559*
dwave3	0.06500†	0.03855‡	0.01417	0.03447	0.02971	0.03460
dwave4	0.05843‡	0.03131	0.02897	0.01896	0.04003‡	0.04654†
dwave5	0.03568	0.02085	0.01523	0.00025	0.01185	0.01422
dwave6	0.02976	0.03390	0.01627	-0.00038	0.01676	0.02840
dwave8	0.07725†	0.04527†	0.03148	0.03169	0.04015‡	0.04382‡
dwave9	0.00702	0.01268	0.00336	-0.02827	-0.00170	0.01535
dwave10	0.01776	0.01365	-0.02425	-0.01400	0.00602	-0.01034
dwave11	0.02492	0.01911	0.01263	-0.02951	0.01606	0.02426
nkids	-0.06527*	-0.01162	0.01917	-0.05332*	-0.01726	0.01367
nwage	-0.07293*	-0.01940‡	0.01052	-0.06954*	-0.02662†	0.00845
const	0.17439*	0.03938	-0.01664	0.19952*	0.05979†	-0.02066
Notes.	∗: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 9: Vulnerability model for equivalised incomes; household annual net income only.

vulnerability relationship defined for net income is less clear.

It is tempting to interpret vulnerability in terms of the income-consumption relationship within one particular part of the distribution, but this may be a mistake. The subsamples in the zone around the poverty line – symmetric and asymmetric – certainly exhibit vulnerability although the pattern differs somewhat depending on the way the poverty zone is defined and whether we pose the question in terms of *sipz* ("starts in poverty zone") or *eipz* ("ever in poverty zone"). But there is evidence of vulnerability well away from the poverty zone too as a detailed analysis of quantile groups and of individual-household vulnerability reveals.

The estimated relationships are robust to assumptions about household economies of scale and to the elimination of outliers from the data. Vulnerability is not just an artefact of model specification.

References

Amin, S., A. S. Rai, and G. Topa (2003). Does microcredit reach the poor and vulnerable? evidence from northern Bangladesh. *Journal of Development Economics 70*, 59–82.

Bane, M. J. and D. T. Ellwood (1986). Slipping into and out of poverty: The dynamics of spells. *Journal of Human Resources 21*, 1–23.

Bardasi, E. and S. P. Jenkins (2004). Documentation for derived current and annual net household income variables. mimeo, Institute for Social and Economic Research, University of Essex, Colchester CO4 3SQ.

Blundell, R. and I. Preston (1998). Consumption inequality and income uncertainty. *Quarterly Journal of Economics 113*, 603–639.

Buhmann, B., L. Rainwater, G. Schmaus, and T. Smeeding (1988). Equivalence scales, well-being, inequality and poverty: Sensitivity estimatesacross ten countries using the Luxembourg Income Study (LIS) database. *Review of Income and Wealth 34*, 115–142.

Chaudhuri, S., J. Jalan, and S. Suryahadi (2002). Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia. Department of Economics Discussion Paper Series 0102-52, Columbia University, New York, NY 10027.

Deaton, A. and C. Paxson (1994). Intertemporal choice and inequality. *Journal of Political Economy 102*, 437–467.

Deaton, A. S. (1997). *The Analysis of Household Surveys.* Baltimore, Maryland: Johns Hopkins Press for the World Bank.

Dercon, S. and P. Krishnan (2002). Vulnerability, seasonality and poverty in Ethiopia. *Journal of Development Studies 36*, 25–53.

Japelli, T. and L. Pistaferri (2006). Intertemporal choice and consumption mobility. *Journal of the European Economic Association 4*, 75–115.

Jenkins, S. (2000). Modelling household income dynamics. *Journal of Population Economics 12*, 529–567.

Ligon, E. and L. Schechter (2003). Measuring vulnerability. *Economic Journal. 113*, C95–C102.

Meghir, C. and L. Pistaferri (2004). Income variance dynamics and heterogeneity. *Econometrica. 72*, 1–32.

Ramos, X. and R. Schluter (2006). Subjective income expectations and income risk. IZA Discussion Paper 1950, Institute for the Study of Labor (IZA).

Townsend, R. M. (1994). Risk and insurance in village India. *Econometrica 62*, 539–591.

A Net incomes

In this section we discuss the derivation of the estimates of net income, as described in Bardasi and Jenkins (2004). The following definitions are provided.

- Total household net income = Total household labour income

+Total household investment
+Total household pension income
+Total household benefit income
+Total household transfer income
+Local Taxes.

- Total household labour income is estimated in the following manner:

Total household labour income = Total household gross labour earnings - Deductions, where

Total household gross labour earnings = Head of household (hoh): gross earnings from employment

+Spouse of hoh (where present): gross earnings from employment
+Hoh: gross earnings from self employment
+Spouse of hoh (where present): gross earnings from self employment
+Other gross labour income (earnings of other household members + occasional earnings of head & spouse if they have no main job).

Deductions: Income tax + national insurance contributions + pension contributions of all household members.

The definition of annual net household income is very similar to that for the current net household income variable, except for the following exceptions. First, local taxes are not deducted from income. Second, it is related to the income reference period. Annual net income refer to the 12 months interval up to September 1 of the year of the relevant interview wave. For example the wave 6 annual income variables refer to the period 01.09.95 until 31.08.96. Third, annual net income does not include earnings from a second job (whereas they are included in current net income).

A.1 Legend of Variables

The variables used in the empirical analysis are the following:

xpfoodmnpc: expenditure on food, monthly, per capita

mnincpc: monthly income, gross, per capita

hhnetipc: monthly income, net, per capita

hhynetipc: annual income, net, per capita

dlxpfoodmnpc: changes in log expenditure, monthly, per capita, between time t and $t-1$.

dlmnincpc: changes in log income, monthly gross, per capita, between time t and $t-1$.

dlhhnetipc: changes in log income, monthly net, per capita, between time t and $t-1$.

dlhhynetipc: changes in log income, annual net, per capita, between time t and $t-1$.

nkids: number of children in household

nwage: number of employable members of household.

All variables used are estimated at 2000 prices.

B Robustness: GLS estimates

As a further check on our approach using fixed-effect panel regressions we also estimated the model using GLS, to account for heteroscedastic errors. The interesting feature observed with the GLS estimates is that there are some instances where we observe significant vulnerability in certain groups that did not exhibit vulnerability before. This is for the net incomes cases; both monthly and annual net income cases. In Table 10 we observe the same results as we did for the panel regressions; the vulnerability coefficient associated with monthly gross income has a greater level of significance compared to that observed in the panel regressions. In Table 11, we have results with the monthly *net* income variable - groups 20-40 and 50-60 exhibit significant vulnerability, which had shown up as weakly significant with the panel regressions. Likewise, for the *annual net* income results in Table 12 we observe some weakly significant vulnerability at the upper groups of 50-60, 60-70 and 70-80.

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dlmnincpc	0.02237†	0.02803†	0.04237*	0.04939*	0.05190*
dwave2	-2.03994*	-2.0219*	-2.05912*	-2.0439*	-2.04523*
dwave3	0.02582‡	0.02934	0.00112	0.00177	0.01935
dwave4	0.03479†	0.00638	0.03159	0.04091†	0.03751‡
dwave5	0.02935†	0.02488	0.00822	0.00555	0.02301
dwave6	0.03337†	0.02171	-0.01926	0.03224‡	0.02786
dwave8	0.07271*	0.05084*	0.08098*	0.05259*	0.06651*
dwave9	0.01707	0.01802	-0.03422‡	0.00148	0.00779
dwave10	0.03292†	0.02056	0.02079	0.00290	0.01267
dwave11	0.04022*	0.01945	-0.00899	0.00230	0.03547‡
nkids	-5.1E-05	-0.00893‡	-0.00597	-0.00318	-0.00309
nwage	-0.00533	0.00812‡	0.00032	-0.00292	-0.00384
cons	0.00075	-0.00326	0.02172	0.01045	0.00162
Notes	$*$: Significant at the 1% level				
	†: Significant at the 5% level				
	‡: Significant at the 10% level				

Table 10: Vulnerability model for selected quantiles- GLS estimates; monthly gross income only

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dlhhnetipc	0.00730*	0.00309	0.01057*	-0.00143	-0.00785
dwave2	-2.09513*	-2.0918*	-2.09919*	-2.07759*	-2.00372*
dwave3	0.03939*	0.01965	0.03727‡	0.05586*	0.07287*
dwave4	0.01902	0.05729*	0.03725‡	0.02331	0.06283*
dwave5	0.03216†	0.01501	0.03155	0.02813	0.08174*
dwave6	0.02847†	0.04749†	0.01499	0.02305	0.02916
dwave8	0.06868*	0.06040*	0.06929*	0.08271*	0.07015*
dwave9	0.02249	0.01606	0.04631†	-0.00956	0.04952†
dwave10	0.02801‡	0.03106	0.03112	0.04161†	0.04598‡
dwave11	0.02639‡	0.02543	0.03164	0.02715	0.07768*
nkids	-0.00298	-0.00188	-0.00468	-0.00303	-0.01243
nwage	-0.00158	-0.00347	0.00027	-0.00507	-0.00485
cons	0.00264	0.00798	-0.00287	-0.00184	-0.01990
Notes	$*$: Significant at the 1% level				
	†: Significant at the 5% level				
	‡: Significant at the 10% level				

Table 11: Vulnerability model for selected quantiles - GLS estimates; monthly net income only

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dlhhynetipc	0.00294	0.00362	0.01017†	0.00669‡	0.00974†
dwave2	-2.12169*	-2.04946*	-2.0297*	-2.06286*	-2.00813*
dwave3	0.00514	0.03881‡	0.02925	0.03744†	0.04072‡
dwave4	0.01799	0.03307	0.00814	0.03037‡	0.04497†
dwave5	0.01459	0.02186	0.02860	0.02291	0.05789*
dwave6	0.00813	0.06769*	0.02053	0.02276	0.04566†
dwave8	0.05751*	0.06334*	0.08444*	0.07686*	0.06936*
dwave9	-0.0105	0.03009	0.00863	0.01460	0.04324‡
dwave10	0.02084	0.03118	0.01583	0.01490	0.05380†
dwave11	0.00297	0.02518	0.01986	0.02704	0.04821†
nkids	-0.00552‡	-0.00207	-0.00922‡	0.01028‡	0.00463
nwage	-0.00444	-0.00832‡	-0.00128	-0.00387	-0.00315
cons	0.02936†	0.00615	0.01085	-0.01015	-0.02273
Notes	$*$: Significant at the 1% level				
	$\dagger$: Significant at the 5% level				
	$\ddagger$: Significant at the 10% level				

Table 12: Vulnerability model for selected quantiles: GLS estimates; annual net income only

C Robustness: Treatment of outliers

In case the results might be driven by influential outliers we perform truncations of households from the dataset on the basis of outliers for changes in expenditure - we truncate households for whom changes in log consumption (i.e. dlxpfoodmnpc) is greater than 1 or less than -1. The truncated subsample results are presented in Tables 13 to 15, where once again we use the standard fixed-effect panel regression method. The most notable result observed is that of the level of significance, and the size of the effect of the Wave 2 dummy, being pulled down significantly all across the models. Comparing the estimates by varying the equivalence parameter θ, we can see that the estimates of ν remains unchanged compared to the case for the untruncated estimates. For the monthly gross income (mninc) definition, we find that the significance of the ν coefficient first falls and then improves as we decrease the value of θ from 1 to 0; this is similar to the case observed without any truncations. Likewise, the effects of the wave dummies also remains unchanged – waves 2 and 8 (and for $\theta = 0.5$, often wave 11) are significant, as was in the case for the untruncated results. We also find that for the specifications with household characteristics included, the significance goes down from $\theta = 1$ to 0.5 and then rises again for $\theta = 0$. This is particularly pronounced for number of children in household, compared to number of employable age members in household, where the level of significance gradually drops as we proceed from models with $\theta = 1$ to 0. The effects on the other definitions of income are identical. This holds across all sets of symmetric and asymmetric subsamples of 20% of the households around the poverty line for all income definitions. Our main results therefore continue to hold.

	symmetric			asymmetric		
θ :	**1.0**	**0.5**	**0.0**	**1.0**	**0.5**	**0.0**
dlmnincpc	0.03371*	0.02347‡	0.07153*	0.03283*	0.01625*	0.08175*
dwave2	-0.34843†	-0.62280†	-1.29644*	(dropped)	-0.77051*	-1.30615*
dwave3	0.02834	0.03858‡	0.01888	0.01769	0.04768†	0.04316‡
dwave4	0.00095	0.03838‡	-0.00064	0.00762	0.05003†	-0.01557
dwave5	0.04402†	0.03847‡	0.01612	0.05398†	0.04468	0.02451
dwave6	0.00767	0.00781	-0.03047	0.01209	0.02635	-0.02998
dwave8	0.06537*	0.08538*	0.04967†	0.06518	0.08804*	0.05861†
dwave9	-0.01546	0.00520	-0.02775	0.01682	0.01587	-0.03367
dwave10	0.02876	0.02653	-0.01553	0.02518	0.04535†	0.00638
dwave11	0.00123	0.04556†	0.00744	-0.00104	0.04994†	0.01153
nkids	-0.03314*	-0.00241	0.03934†	-0.03972*	-0.00709	0.05093*
nwage	-0.06154*	-0.03077†	0.00793	-0.07006*	-0.03166†	0.01587
cons	0.14005*	0.01862	-0.01194	0.18058*	0.01563	-0.01881
Notes.	$*$: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 13: Vulnerability model for equivalised incomes with truncations; monthly gross income only

	symmetric			asymmetric		
θ :	**1.0**	**0.5**	**0.0**	**1.0**	**0.5**	**0.0**
dlhhnetipc	0.01192*	0.00543	0.00397	0.01083†	0.00167	0.00056
dwave2	-0.97764*	(dropped)	(dropped)	-0.81992*	-0.68410†	-0.69181†
dwave3	0.03843‡	0.02481	0.00810	0.04042‡	0.05446†	0.02024
dwave4	-0.00240	0.01226	0.02072	0.00558	0.03790‡	0.01728
dwave5	0.02823	0.02184	0.00132	0.03733‡	0.04227‡	-0.00060
dwave6	0.02358	0.01409	-0.00438	0.02027	0.02419	-0.01189
dwave8	0.04642†	0.04876†	0.02671	0.04867†	0.05962*	0.02448
dwave9	0.01429	0.01104	-0.00688	0.02352	0.03321	0.00524
dwave10	-0.00775	-0.00627	-0.01460	-0.00029	0.03028	-0.01525
dwave11	0.01887	0.02825	0.00160	0.02272	0.04471†	0.01981
nkids	-0.05420*	-0.01278	0.02299	-0.04579*	-0.01575	0.04086*
nwage	-0.07447*	-0.02027‡	0.03657*	-0.06556*	-0.01599	0.04067*
cons	0.17746*	0.04579‡	-0.04393‡	0.16361*	0.02579	-0.05966†
Notes.	$*$: Significant at the 1% level					
	$\dagger$: Significant at the 5% level					
	$\ddagger$: Significant at the 10% level					

Table 14: Vulnerability model for equivalised incomes with truncations; household monthly net income only

	symmetric			asymmetric		
θ :	**1.0**	**0.5**	**0.0**	**1.0**	**0.5**	**0.0**
dlhhynetipc	0.00404	0.00474	0.00228	0.00065	0.00570	0.00354
dwave2	(dropped)	(dropped)	-0.92767*	0.03495	(dropped)	-0.91380*
dwave3	0.02691	0.02043	-0.01260	-0.01349	0.00382	0.00674
dwave4	0.03102	0.01555	0.01023	-0.01405	0.01262	0.02703
dwave5	0.00882	0.00915	-0.00224	-0.03258	-0.00450	-0.00146
dwave6	0.01389	0.02172	-0.00392	-0.02231	0.00010	0.00966
dwave8	0.05217†	0.03938‡	0.01337	0.00010	0.02450	0.02659
dwave9	-0.00445	-0.00229	-0.00970	-0.04660†	-0.02226	0.00232
dwave10	-0.00595	-0.00123	-0.02923	-0.04489†	-0.01481	-0.01901
dwave11	0.00264	0.00742	-0.00714	-0.05529*	-0.00118	0.00486
nkids	-0.04402*	-0.00246	0.04591*	-0.03323*	-0.01139	0.03531†
nwage	-0.05442*	-0.01153	0.03131†	-0.04918*	-0.0264†	0.01896
cons	0.14669*	0.03343	-0.03934	0.17431*	0.07123*	-0.03044
Notes.	$*$: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 15: Vulnerability model for equivalised incomes with truncations; household annual net income only