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Making Inferences About the Vulnerable: A Study Using the British Household Panel Survey

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Making Inferences About the Vulnerable: A Study Using the British Household Panel Survey.

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Abstract

In this paper I examine the concept of "vulnerability" within the context of income mobility of the poor. While the concept of poverty is well developed, the concept of vulnerability is less established in the economic literature. I test for the dynamics of vulnerable households in the UK using Waves 1 - 12 of the British Household Panel Study 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. Vulnerability is found to be particularly significant in relation to changes in transitory income. I observe the vulnerability dynamics in light of smoothing mechanisms undertaken by vulnerable households to smooth consumption and find that savings and earnings from a second job are not significantly associated with smoothing consumption. The results strongly suggest that traditional poverty alleviating policies are not likely to assist the vulnerable.

JEL codes: D1, D31, I32

keywords : income variability, vulnerability, insurances.

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1 Introduction

In recent policy discussions, the importance of identifying the vulnerable has risen considerably. While newspapers and policy reports clearly distinguish between those who are "poor" and "vulnerable", these entities are not fully separate in their treatment in the economic literature. In the aftermath of the recent riots in England, discussions in journalistic literatures have frequently focussed on the uncertainties of those who are poor and "near-poor", and that policy measures ought to be implemented to prevent the near-poor from succumbing to the effects of the untoward economic scenario. While a well defined poverty line exists by which researchers and policy makers alike can count the number of the poor, there is no agreed definition on how to count the "vulnerable" or the "near-poor" in the economic literature. In this paper I will highlight who are UK's "vulnerable" and distinguish them from the "poor" as traditionally defined using static measures, using the British Household Panel Survey.

Income volatility and its effect on individual welfare has been at the forefront of economic and social policy for several decades. Such volatility is attributed to risks which originate both in the household and the economy. The dynamic nature of such risks however escape the purview of traditional poverty measures, which are designed only to capture static welfare levels. This has led to an increasing interest in the dynamic nature of poverty, focusing on those who are subject to risks and are unable to smooth their consumption in the face of shocks to their income stream. The "vulnerable" are a dynamic quantile of the population who are likely to become poor in the event of such shocks lowering their levels of well-being. In this paper I am interested in identifying the vulnerable in the UK using the British Household Panel Survey, using a panel regression approach, with a particular interest in observing the effects of smoothing mechanisms that may be at their disposal.

To identify those who are most susceptible to shocks and their responses to insurances, I focus on the dynamics of specific quantile groups in the distribution. In that respect, the work is close in spirit to that of income mobility. However, while the mobility literature focuses on the mechanisms that drives households both up and down along the income distribution, in our case I are more interested in those who are downwardly mobile. Another important point of departure from the mobility literature is that it rests on theories of risk and uncertainty - who the vulnerable are is determined on the basis of the risks they are exposed to. Vulnerability is, therefore, a more informed concept of poverty in that it is defined as conditional upon the economic circumstances they are exposed to. In this respect, this paper is very close in its motivation to the empirical studies on vulnerability in the

Development Economics literature (Amin et al. (2003), Dercon and Krishnan (2002)).

A large part of the literature devotes itself to identifying the nature of the shocks which affect the households the consumption stream and welfare - this is particularly studied with reference to Asia and Africa, using household level datasets. 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). Such shocks, while particularly characteristic of the developing world are not far from the kind of shocks households are subject to in the developed world.

The effect of income shocks on the consumption stream has received substantial econometric treatment, particularly under a macro-econometric framework. These are based on inter-temporal choice models based on some variant of the permanent income hypothesis that investigate the presence of consumption smoothing, or not. 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). The methods that I 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. This work, however, comes closer to the approach taken in the Development Economics literature, in that I am interested in identifying what kind of smoothing mechanisms may assist households from slipping into poverty.

The empirical investigation in this paper uses the British Household Panel Survey (BHPS) to identify prominent risks affecting household consumption at a number of quantiles across the income distribution. A panel regression approach is adopted similar to that used in Amin et al. (2003) and Dercon and Krishnan (2002). I do not propose new empirical approaches but identify location-specific dynamics of vulnerability and their responses to the smoothing mechanisms that are available to them. I use several concepts of income, gross and net, monthly and annual which reveal different vulnerability dynamics, particularly close to the poverty line. I test for several smoothing mechanisms, for example having savings, and having a second job, in abating the lack of consumption smoothing. The significance of the smoothing mechanisms are observed to be different at different parts of the income distribution and over different time-horizons. To further explore the temporal nature of vulnerability, income is then decomposed into its permanent and transitory components and the vulnerability dynamics are then tested with the transitory component of income. There is clear evidence of vulnerability being associated with the transitory component of income. All in all, the vulnerability dynamics revealed are not quite the same as one would obtain when performing similar analyses for a "determinants of poverty" paper. This suggests that the policy package to be devised by the policy maker to assist the vulnerable are likely to be different than that for simply poverty alleviation.

The paper is set out as follows. Section 2 sets up 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, Section 7 discusses the results and Section 8 concludes.

2 Background: Who are the vulnerable?

While there are several approaches to measuring vulnerability, how it is best measured and implemented is not fully agreed upon by researchers. There are several empirical approaches that have been undertaken to activate the idea of vulnerability. Much of its recent application, particularly in developing countries, stems from Townsend's (1994) framework. The paper addresses the efficacy of risk-sharing mechanisms in a full insurance framework. Townsend (1994) and several other empirical papers (Mace (1991), Cochrane (1991) were all based on a complete market structure as in the Arrow-Debreu model (1959, 64), much of which reject the complete market hypothesis. Mace (1991) studies inidividual consumption in the US and finds that growth and changes in the level of consumption is determined by the average consumption. Both Mace (1991) and Cochrane (1991) test for possible idiosyncratic, uninsured components that may impact upon levels or growth in consumption. In both cases, household incomes matter. Cochrane (1991) reveals that food consumption growth rates are lower for households that have experienced illness and job layoffs. In the developing country literature, Dercon and Krishnan (2002) also test the perfect risk-sharing model for Ethiopian households, and investigate public transfers via food-aid as risk-sharing arrangements. Here too the authors investigate idiosyncratic income shocks to test for testing risk-sharing where food aid to the village individuals functions as a "positive" income shock. They too find little evidence of perfect risk-sharing.

Ligon et al (2004) propose a different approach to measuring vulnerability which allows them to quantify the welfare loss associated with poverty as well as the loss associated with different sources of uncertainty, applied to

Bulgarian panel data. Their measure can be decomposed into into distinct measures of poverty, aggregate risk, and idiosyncratic risk. With this approach they decompose the effects of each of these factors on levels of welfare - elimination of risks would only reduce welfare by 3%, whereas elimination of poverty would improve welfare by 14%. The effect observed via elimination of idiosyncratic shocks is insignificant compared to the size of the effect in reducing poverty and aggregate risk. Chaudhuri et al. 2002 and Pritchett et al (2001) use a measure of household vulnerability measured by the expected head count measure of poverty. Vulnerability as uninsured exposure to risk provides an alternative ex post assessment of welfare loss arising from the onset of an economic shock ((Glewwe and Hall 1998) , (Maloney and Bosch 2004) and (Lokshin and M.Ravallion 2000) all use this approach).

The approach used in this paper is in the spirit of macro models that incorporate the impact of risks on consumption (Cochrane 1991, Mace 1991 Meghir and Pistaferri 2004, Japelli and Pistaferri 2006, Blundell and Preston 1998). The Townsend (1994) approach, which uses constant absolute risk aversion preferences 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). The empirical model estimated in this paper 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).

2.1 The empirical strategy for measuring vulnerability.

The empirical approach in this paper is to use a panel regression based on the approach used in Dercon and Krishnan (2002) and in spirit to that of Cochrane 1991 and Mace 1991 to identify the impact of risks and "insurances" that are available to households. I will identify the shocks which characterise income risks, by inclusion of a number of household characteristics and year-specific dummies which will capture idiosyncratic and economy-wide shocks. To identify location-specific dynamics of the vulnerable in the income distribution, not revealed in a cross-section regression towards the mean, I will break up the income distribution into a number of quantiles, on the basis of a number of definitions on the same lines as introduced in Bandyopadhyay and Cowell (2007). Focusing on quantile specific dynamics will reveal particularly vulnerable households near the poverty line. Finally, I will include a number of "smoothing mechanisms", which I loosely call "insurances", to observe their effects on the vulnerability dynamics. All the variables that are used in the analysis are discussed in the following data section.

3 The British Household Panel Survey

The BHPS extends for 19 waves and follows the same representative sample of individuals over a period of 19 years from 1991 to 2008. Each annual interview round is called a wave: in our study I use 12 waves of data, and each wave is principally household-based, interviewing every adult member of sampled households. I work with 12 waves to maximise the complete availability of all the income (gross and net) and socio-economic variables that are used in the paper. 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.
- Savings of household, monthly
- Earnings from a second job, monthly
- Tenured job, or not.

Expenditure on durables is only available for one wave, hence cannot be included in the analysis. The dataset has a complete panel with 1,608 individuals per wave.

	FULL SAMPLE $N = 16590$				TRUNCATED SAMPLE $N = 14786$			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
xp	8.953	4.159	0	45.37	9.23	4.155	0	45.37
y_gross	566.9	457.3	0	2236	585.80	469.11	0	22365
y_net	157.81	183.5	-13.0	5204.9	163.05	189.09	-13.0	5204.93
y_net_an	8047.1	8958.4	0	287593	8312.6	9238.2	0	287593
dlxp	-0.137	0.601	-3.58	2.8594	0.0299	0.234	-0.980	0.944
dly_gross	0.0487	0.366	-7.02	3.944	0.0505	0.367	-7.022	3.944
dly_net	0.0399	1.012	-9.62	9.93	0.0399	1.029	-9.62	9.938
dly_net_an	0.926	0.0754	0.817	1.031	0.9386	0.0695	0.817	1.031
hhsize	2.657	1.4415	1	10	2.656	1.446	1	10
nkids	0.750	1.1045	0	7	0.7502	1.105	0	7
nwage	1.1425	1.1757	0	7	1.133	1.182	0	7

Table 1: Summary statistics

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 I 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 the results later.

Table 1 presents the summary statistics for the variables I will be using for the estimation of vulnerability dynamics, estimated at 2000 prices. What is interesting to observe is that the dynamics of level values of consumption and income vary significantly from the inter-temporal changes of the same variable. The main aim of the empirical analysis will be to identify the associations of the changes in consumption in response to changes in 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 - I 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 dlxp, the variable used to condition the truncation.

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 I am also avoiding possible problems with economies of scale with large households. This however is dealt with when using equivalised quantities (results are available with author and not presented in paper for reasons of brevity).

4 Vulnerability - initial glimpses

Our first set of estimates involve estimating the following model:

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \varepsilon_{it} \tag{1}$$

where $c_t := C_t/n$, denotes individual consumption (per-capita consumption of the household) in wave t, y_{it} is individual income (household income per capita) in 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 $t = 1$, and wave 12 corresponds to $t = 11$.

In addition to the wave dummies which capture year-specific aggregate shocks, I include household characteristics which may be significant determinants of household vulnerability dynamics. Variations in household size and composition may be seen as idiosyncratic shocks which have a direct impact upon the welfare of households. So I augment (1) as follows:

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \mathbf{X}_{it}\gamma + \varepsilon_{it} \tag{2}$$

where $\mathbf{X}_{it}$ is a vector of characteristics for individual i in wave t. 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.

Finally to take into account the effects of possible insurances that may be at the behest of the households, I include a number of insurance variables. These are considered as variables that are likely to "condition" the relationship between $\Delta \ln c_{it}$ and $\Delta \ln y_{it}$.

$$\Delta \ln c_{it} = \nu \Delta \ln y_{it} + \phi_t W_t + \gamma X_{it} + \mathbf{G}_{it}\beta + \varepsilon_{it} \tag{3}$$

where $\mathbf{G}_{it}$ is the vector of insurances for individual i in wave t. These variables are savings, (lagged by one period, and by two periods to avoid effects of endogeneity), earnings from a second job, whether the household has access to credit, whether it already has a loan (indicative of its ability to have access to credit from banks), whether the individual has a mortgage, value of property owned, and whether the person owns credit cards.

I assume the error term to be uncorrelated with the RHS variables and to have zero mean. Let us also assume the following dynamic structure:

$$\begin{aligned} \operatorname{var}(\varepsilon_{it}) &= \sigma_i^2 \\ \operatorname{cov}(\varepsilon_{it}, \varepsilon_{jt}) &= 0 \\ \operatorname{cov}(\varepsilon_{it}, \varepsilon_{it'}) &= 0 \end{aligned} \tag{4}$$

The error term can be expected to vary across individuals, 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 (3) taking into account the heteroscedastic nature of the error term using standard Feasible Generalised Least Squares (FGLS), σ_i^2 in equation 4 is given as:

$$\sigma_i^2 = \exp\left(\sum_j \beta_j z_{ij}\right) \tag{5a}$$

where the z_{ij} are observables such as household size, number of children.

Several 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 I use FGLS 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.[1] The GLS method used takes into account any residual correlation across panels that may still remain after the first-differencing. Equation (3) is estimated both under FGLS and the standard panel regression techniques.

I have run the above models using both FGLS, and standard fixed and random effects panel regressions with all these insurance variables. Barring savings and earnings from second job, none of the other insurance variables are significant in the estimated models. I therefore only present results from the regressions including these two insurance variables.

4.1 Insurance variables and endogeneity.

To observe the effect of the insurances that are available to households, I may encounter some endogeneity due to the close relationship between age, education, income and saving. Including these variables separately as explanatory variables in equation 3 increases the possibility of further endogeneity due to the strong correlations between these variables. I first, therefore, take into account the effects of age and education on the levels (and variation) of income. For this, I will model what are known commonly in the literature as Mincer regressions[2], and extract the effect of age and education on income, and use the residuals from these regressions as an instrument for income.

This method has two benefits. One, is to be able to extract the effects of age and education on income and use that component of income that is free from the effects of age and education. Second, on further including the insurance variables, such as savings, or access to credit, a further source of endogeneity is also dealt with here.

I run the following Mincer regression model to account for the variation in income that is governed by factors other than age and education:

$$s = \alpha_1 + \alpha_2 age + \alpha_3 age^2 + \alpha_3 age * school + \alpha_4 school + e_{it} \tag{6}$$

[1] 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 statistic.

[2] I thank Frank Cowell for this suggestion.

where, I estimate school as

$$school = 3 * \text{highest qualification achieved} + 5 \tag{7}$$

where highest qualification achieved is the scaling I propose based on the following:

- 5 Higher degree
- 4 Degree
- 3 A level/HND, HNC
- 2 CSE/O level
- 1 No academic qualifications.

e_{it} is assumed to be an error term normally distributed, $N(0, \sigma_e^2)$.I now instrument income with the residuals from the regression 6 for the estimation of equation 3. To avoid similar issues of endogeneity again, I lag the variables savings [3]. Earnings from second job is documented in the BHPS questionnaire as earnings in the week prior to the current week, therefore not requiring any further lagging. I observe that of all the "insurances" that have been included as regressors, only lagged savings is robustly associated with changes in consumption. To account for the length of the memory of income, I have also run a few specifications to observe the effect of lagged income differences, for which I have obtained the same dynamics as current income first differences. For each of the models that I have estimated, the Durbin-Wu-Hausman statistic does not suggest in any of the models that the use of standard panel methods would have been inconsistent (the F statistic is not significant in any of the models estimated). Likewise the Anderson LM test and Sargan tests for over-identification also do not result in a significant test statistic to suggest over-identification in any of the models estimated.

In the following section I will focus on the vulnerability dynamics specific to the location of households in the income distribution in light of these insurance variables.

[3] I was also motivated to use lagged values because of obtaining insignificant results with the current time period's savings as a regressor. It is clearly suggestive that last period's savings are more influential in deciding the current period's expenditures.

5 Locating the vulnerable in the income distribution

I am particularly interested in the location of the vulnerability dynamics in the income distribution. This is important as not all cases where an individual's or household's current consumption is responsive to current income should be characterised as vulnerability. Richer agents respond to surprise positive income shocks by boosting their consumption, this is not to be characterised as "vulnerability". Likewise, the poor already under the poverty line are also not "vulnerable" in the sense we wish to define here, even though one may obtain a strong association between volatile incomes and volatile consumption for these households/quantiles. In other words, one can be both poor and "vulnerable" by the empirical definition set out earlier, but we are more interested in those who are not in poverty now but likely to slip into it.

To identify the dynamics in the neighbourhood of the poverty line and to compare dynamics in specific parts of the distribution I adopt the following procedure[4]. 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 (3) 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. Tables 2 to 3 presents results of the first method for fixed quantile groups throughout the income distribution; Table 4 and 5 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.

I first observe the distribution specific dynamics by observing the vulnerability dynamics at different parts of the income distribution. For this, I take 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 2 to 3 present results across the different quantile groups using the FGLS specification using three different income definitions: gross monthly, net monthly and net annual income. Two important observations

[4]This method is also used in Bandyopadhyay and Cowell (2007)

are clear: first, that the vulnerability dynamics are clearly quantile-specific. The vulnerability dynamics differ across the income distribution. Second, the vulnerability dynamics are also sensitive to the definition of income. While there is some significant vulnerability for the gross income definitions for a number of quantiles (namely 50-60th and 60-70th), these are not so apparent in the net income definitions. For the net monthly income model, I obtain significant vulnerability only for the 30-40th percentile, while for net annual, there are none.

In short, that the net income definitions yield no significant vulnerability are suggestive that net incomes (which are incomes net of the transfers and benefits for this sample) are successful in smoothing consumption. This highlights the importance of benefits and transfers for the vulnerable.

Of the two insurance variables, I do not observe a great deal of significant association of these with changes in consumption. Lagged savings is only significant for the monthly gross income definition - earnings from second job does not appear to be significant in any of the specifications. Of the household characteristics, I observe the number of children and number of wage employable members in the family to be significantly associated with changes in consumption. To summarise, vulnerability is particularly specific to the location in the income distribution, and is also sensitive to the income definition.

It is also important to observe the temporal nature of vulnerability. For both monthly (gross and net) income definitions, I observe some significant vulnerability. However, for net annual income, I do not observe any significant vulnerability for any of the quantiles. This suggests that vulnerability is likely a short-term phenomenon.

5.1 Dynamics around the poverty line

I now focus on the vulnerability dynamics in the immediate neighbourhood of the poverty line. To identify these dynamics I need to define 1) a poverty line, 2) what defines proximity to the poverty line and 3) a criterion on the basis of which I define whether the household is "close" to the poverty line.[5] I treat each in turn.

- *Poverty line*: The poverty line is defined to be at 60% of the median income. This is the standard approach adopted with reference to the UK.

[5] This approach is also undertaken in Bandyopadhyay and Cowell (2007).

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**	**80-100%**
drygross	0.015	0.001	$0.057^{\dagger}$	$0.057^{\dagger}$	-0.002	-0.002
dwave2	0.075^{*}	0.134^{*}	$0.088^{\dagger}$	0.097^{*}	0.099^{*}	0.099^{*}
dwave3	0.043	0.002	0.013	$0.069^{\dagger}$	$0.052^{\dagger}$	$0.052^{\dagger}$
dwave4	$0.049^{\ddagger}$	0.010	0.048	$0.060^{\ddagger}$	0.024	0.024
dwave5	0.045	0.016	0.024	0.041	0.010	0.010
dwave6	$0.056^{\dagger}$	0.021	-0.010	0.044	$0.042^{\ddagger}$	$0.042^{\ddagger}$
dwave7	0.000	$0.075^{\dagger}$	$0.083^{\dagger}$	$0.070^{\dagger}$	0.024	0.024
dwave8	$0.065^{\dagger}$	0.052	0.122^{*}	0.10^{*}	0.093^{*}	0.093^{*}
dwave9	0.009	-0.005	-0.044	0.045	-0.002	-0.002
dwave10	0.033	0.029	0.039	0.023	-0.023	-0.023
dwave11	$0.067^{\dagger}$	0.007	0.010	0.046	$0.056^{\dagger}$	$0.056^{\dagger}$
nkids	0.006	0.005	0.001	0.002	0.003	0.003
nwage	-0.002	-0.003	0.001	-0.003	-0.006	-0.006
tenured	-0.011	0.002	0.011	0.008	-0.012	-0.012
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000^{*}	$0.000^{\ddagger}$	$0.000^{\ddagger}$
cons	0.003	0.014	0.000	-0.015	0.026	0.026
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.871	0.783	0.634	0.657	0.711	0.976
Notes	$*$: Significant at the 1% level					
	†: Significant at the 5% level					
	‡: Significant at the 10% level					

Table 2: Vulnerability dynamics, selected quantiles for monthly gross per capita income

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**	**80-100%**
drincome	0.003	0.002	-0.008	-0.012‡	-0.001	0.001
dwave2	0.093*	0.104*	0.097†	0.082†	0.106*	0.107*
dwave3	0.045*	0.004	0.051	0.073†	0.079†	0.055*
dwave4	0.032†	0.038	0.042	0.013	0.072‡	0.033
dwave5	0.043*	0.033	0.030	0.059‡	0.065‡	0.024
dwave6	0.030†	0.023	0.079†	0.022	0.065‡	0.019
dwave7	0.035*	0.009	0.010	0.031	0.065‡	0.067†
dwave8	0.088*	0.066†	0.062	0.104*	0.126*	0.110*
dwave9	0.009	-0.003	0.045	0.031	0.045	-0.042
dwave10	0.015	0.045‡	0.007	0.008	0.024	0.022
dwave11	0.039*	0.010	0.051	0.030	0.068‡	0.042
nkids	0.002	-0.001	0.006	0.000	0.009	-0.008
nwage	-0.003	-0.004	-0.013‡	-0.001	-0.002	-0.001
tenured	-0.001	0.004	0.007	0.009	0.000	-0.008
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000	0.000	0.000
cons	0.009	0.022	0.006	-0.007	-0.029	0.008
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.654	0.327	0.276	0.164	0.659	0.793
Notes	$*$: Significant at the 1% level					
	$\dagger$: Significant at the 5% level					
	$\ddagger$: Significant at the 10% level					

Table 3: Vulnerability dynamics, selected quantiles for annual net per capita income

- *The poverty zone*: I define a 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^*. Since any particular specification of the poverty zone would be an arbirtrary choice, I take two separate 20% neighbourhoods of this value,

$$I^*_{\text{sym}} = [q^* - 0.1, q^* + 0.1) \tag{8}$$

and

$$I^*_{\text{asym}} = [q^* - 0.15, q^* + 0.05). \tag{9}$$

- *Being at the threshold*: For each version of the poverty zone I^* I estimate the model for both "starts in poverty zone" case (*sipz*), where the household was in I^*at the beginning of the panel, and for "ever in poverty zone" (*eipz*) case, where the household is in I^* for at least one year covered by the panel. The *eipz* case is clearly one where there will be a much larger number of households.

I estimate our vulnerability model for each of the two interpretations of the poverty zone (sipz and eipz cases) using all three income definitions, and using the two interpretations of each poverty zone (symmetric and asymmetric poverty zones, I^*_{sym} and I^*_{asym}). In Table 4 I present the results of the *sipz* sub-sample. Significant vulnerability is now evident, particularly for symmetric subsamples around the poverty line. Here I obtain significant vulnerability for all three income definitions. Of the insurance variables, lagged savings is strongly significant for the net annual income definition. This result also holds for the *eipz* sample. This may be interpreted as savings having assisted as an insurance over the longer term, as opposed to the short-to-medium term. In Table 5, I observe the vulnerability dynamics of the *eipz* sample. Here there is significant vulnerability for only the gross income variable. The number of children and number of wage employable members in household are not significant again, though one of the the insurance variables, *tenured,* is significant for only one of the specifications estimated. For both *sipz* and *eipz* cases it is clear that none of the "insurances" have any association with changes in consumption.

To summarise our findings:

	y_net		y_net		y_net_ann	
	Sym	Asym	Sym	Asym	Sym	Asym
drincome	0.041*	0.050*	-0.004*	-0.004‡	0.010‡	0.004
dwave2	0.013	0.041	0.027	0.048	0.033	0.054‡
dwave3	0.032	0.039	0.039	0.047	0.043	0.050
dwave4	0.004	-0.018	0.011	-0.009	0.018	-0.005
dwave5	0.052*	0.084*	0.056‡	0.089*	0.062†	0.094*
dwave6	0.003	-0.013	0.010	-0.009	0.014	-0.005
dwave7	0.005	0.034	0.009	0.036	0.015	0.043
dwave8	0.073*	0.085*	0.078†	0.090*	0.084*	0.095*
dwave9	-0.021	0.014	-0.016	0.020	-0.008	0.026
dwave10	0.037	0.023	0.044	0.028	0.041	0.026
dwave11	0.007	-0.008	0.013	-0.005	0.020	0.002
nkids	0.002	0.000	0.003	0.001	0.002	0.001
nwage	-0.005	-0.007	-0.006	-0.008	-0.005	-0.008
tenured	-0.003	0.004	0.000	0.008	-0.001	0.007
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000	0.000	0.000
cons	0.030	0.032	0.023	0.028	0.019	0.024
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.451	0.922	0.138	0.383	0.845	0.641

∗: Significant at the 1% level
†: Significant at the 5% level
‡: Significant at the 10% level

Table 4: Vulnerability model for SIPZ case, symmetric and asymmetric samples

	y_net		y_net		y_net_ann	
	Sym	Asym	Sym	Asym	Sym	Asym
drincome	0.069*	0.055*	-0.004	-0.007	-0.008	0.002
dwave2	0.012	0.033	0.093*	0.069*	0.111*	0.070*
dwave3	0.054†	0.030	0.029	0.007	0.049‡	0.036
dwave4	0.019	0.007	0.017	-0.007	0.047‡	0.023
dwave5	0.061†	0.057†	0.046‡	0.035	0.056†	0.052†
dwave6	0.027	0.013	0.050‡	0.031	0.020	0.025
dwave7	0.012	0.013	0.077‡	0.045	0.052	0.063
dwave8	0.064†	0.038	0.066†	0.042	0.074*	0.087*
dwave9	-0.007	0.010	0.023	0.013	0.033	0.025
dwave10	0.046‡	0.031	0.034	-0.013	0.009	-0.001
dwave11	0.009	-0.004	0.036	0.013	0.008	0.003
nkids	0.000	-0.006	-0.007	-0.002	0.001	0.004
nwage	-0.004	0.000	-0.006	-0.007	0.005	-0.001
tenured	-0.011	-0.011	-0.021	-0.030†	-0.017	-0.014
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000	0.000	0.000
cons	0.029	0.043‡	0.026	0.046‡	0.009	0.027
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.543	0.023	0.356	0.834	0.964	0.872

∗: Significant at the 1% level
†: Significant at the 5% level
‡: Significant at the 10% level

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

- Vulnerability is more evident in the case of the *(sipz)* model, compared to the *(eipz)* model. For the former, there is significant vulnerability for all three income definitions.

- Of the insurance variables, none of them have been significantly associated with changes in consumption, except for that of *tenured* under (*eipz)* model. It is therefore clear that while there may be a weak significant relationship between whether one's job is tenured or not, the other "liquid assets" have not proven to be significantly associated with changes in consumption. It is therefore not clear whether any of these assets have any "insurance" properties.

- There continues to be wave-specific shocks impinging upon the income stream which are driving the vulnerability dynamics. In both cases, there is no clear pattern for which subsample, or income definition they are significant for. However, for both cases Waves 5 and 8 are significant, thereby indicating economy-wide shocks having had a significant impact in those specific years.

What is interesting is that the vulnerability dynamics observed are quite robust to the choice of the poverty zone definition. It does not matter much whether the poverty zone was symmetric or asymmetric; the vulnerability dynamics are pretty much the same. Likewise, results are similar for both *sipz* and *eipz* subsamples. It is not surprising that with a more stricter definition of vulnerability with the case *sipz* case, that significant vulnerability is more evident. What is, however, clear is that there are different vulnerability outcomes depending upon the income definition. The income definition therefore matters.

6 Transitory income volatility and vulnerability

Let us now focus closely on the sources of the temporal nature of vulnerability. Our initial empirics suggests that vulnerability is likely a short to medium term phenomenon. This is evinced by the fact that much of the vulnerability dynamics are revealed for the monthly income definitions and not the annual income definition. These results seem to suggest that while vulnerability is likely to show up in the short-to-medium term, individuals may be able to cushion the shock over a longer period of time. It is also widely recognised and documented in the poverty literature that poverty and deprivation has varying inter-temporal dynamics (Blundell and Preston 1998). This is usually tested in the macro and micro-econometric literature by identifying the sources of the shocks to the income stream (Blundell and Preston 1998, Pistaferri and Jappelli 2002), mostly by distinguishing between the individual effects of each of these shocks to the permanent and transitory components of the income stream. Such a decomposition is most appropriate for our purposes; identifying which component of income is the source of the shock will enable the policy maker to assist such vulnerable households in a more directed fashion. Specifically, a shock to the transitory income component is suggestive of policies such as providing greater incentives towards savings, via preferential interest rates or reward schemes, and providing short-to-medium term easy-access social security or credit schemes. Vulnerability arising from shocks to the permanent income stream are more suggestive of a different set of policies enabling households to achieve higher levels of permanent incomes, via education and permanent employment.

To take this idea further I now distinguish between the permanent and transitory components of income. There are several methods in the literature by which the permanent and transitory income components are estimated, and this literature is highly developed in terms of the econometric model that is used to estimate the two components of income. For our purposes to identify the relative effect of transitory incomes compared to the permanent income component, I select a popular method used by Gottschalk and Moffit (2004) and many similar empirical works (Dynarski and Gruber 2002) to estimate the transitory income component. A deviation of income from an individual's own permanent income is defined as transitory income. Therefore, income is therefore composed of permanent and transitory components, given by

$$y_{it} = y_{itT} + y_{itP} \tag{10}$$

where, y_{itP} is permanent income and y_{itT} is transitory income.

I define (as in Gottschalk and Moffit (2004)) permanent income as the average income of individual i over all waves, defined as $\bar{y}_{iP}$

$$\bar{y}_{iP} = \sum_{t=1}^{N} y_{it,} \text{ where, } N = \text{number of waves} \tag{11}$$

Deviations from this average is defined as the transitory income, given by

$$y_{itT} = y_{it} - \bar{y}_{iP} \tag{12}$$

I then estimate equation 3 replacing the income variable by its individual transitory component. The regressions are run using Feasible Generalised Least Squares, which takes into account heterogeneity across the households. I do not present the results with fixed or random effects (these results are available from the author on request).

I first observe the vulnerability dynamics in response to changes in transitory income at different parts of the income distribution. For this, I take the following fixed quantile groups as key "starter intervals": 20-40%, 40-50%, 50-60%, 60-70% and 70-80%. Tables 6 to 8 present results across the quantile groups for the FGLS specification using gross monthly, net monthly and net annual income definitions respectively, where for each income definition I use the residuals have been extracted from the Mincer regressions as described in Section 5. The most interesting result obtained is that there is significant vulnerability for all sub-groups under the monthly net income specification. This is however not the case for monthly gross income - in Table 6, I observe that the vulnerability co-efficient is significant only for the highest quantile, the 70-80th percentile, and the 50-60th percentile. Similarly for net annual income, I observe significant vulnerability for the percentile groups of 20-40% and 70-80% . Of the two "insurance" variables, lagged savings is not significant in any models estimated with all three income definitions, and the coefficient associated with it is also very small[6]. However, earnings from second job shows up as significant for gross monthly income and net annual income (but not for net monthly income).

To summarise the quantile-specific results:

- I obtain significant vulnerability with transitory gross income only at higher percentiles of the income distribution. Changes in transitory gross income is not found to result in significant vulnerability at the lower end of the income distribution. This result is suggestive that significant vulnerability at the lower quantiles of the distribution is more a consequence of a shock to the permanent income stream rather than a result of changes in transitory income.

- For net monthly income, however, I observe significant vulnerability on the lower end - the 20-40% quantile has strongly significant vulnerability. This is also observed for annual net incomes. This is indicative of two things - first, that transitory income, net of transfers, is still a source of vulnerability. This holds in spite of the fact that second job earnings are significantly associated with changes in consumption.

[6]The tenured variable has been dropped in these models as it was not found to be significant for any of the variants estimated.

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dry_gross	0.0141	0.0095	0.0266†	0.0120	0.0321*
dwave3	0.0162	0.0297†	-0.0008	0.0021	0.0213
dwave4	0.0262†	0.0043	0.0217	0.0271‡	0.0171
dwave5	0.0151	0.0275‡	0.0055	0.0077	0.0137
dwave6	0.0246‡	0.0143	-0.0215	0.0337†	0.0166
dwave8	0.0570*	0.0441*	0.0726*	0.0509*	0.0556*
dwave9	0.0078	0.0185	-0.0331†	0.0014	-0.0048
dwave10	0.0262†	0.0187	0.0112	-0.0067	0.0166
dwave11	0.0359*	0.0112	-0.0128	0.0003	0.0198
nkids	0.0010	-0.0047	-0.0012	0.0018	-0.0023
nwage	-0.0008	0.0100*	0.0035	0.0020	0.0013
lagsaved	0.0000	0.0000	0.0000	0.0000	0.0000
lagj2pay	0.0002†	0.0000	0.0000	0.0001*	0.0001
cons	0.0031	-0.0079	0.0199	0.0071	0.0022
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.456	0.411	0.786	0.976	0.345
	$*$: Significant at the 1% level				
	$\dagger$: Significant at the 5% level				
	$\ddagger$: Significant at the 10% level				

Table 6: Vulnerability model with transitory incomes, selected quantiles for monthly gross per capita income

- The overall empirical evidence above suggests that there is a significant association between changes in transitory income and changes in consumption, and that the significant vulnerability observed with gross and net incomes in Section 5 are therefore likely tied to changes in transitory incomes.
- It is also clear that earnings from second jobs and lagged savings are not strongly associated with changes in income as is clear by the quantile specific results and, therefore, are not able to assist these households to cushion income shocks.

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dry_net	0.0076*	0.0022	0.0105*	-0.0003	0.0004
dwave3	0.0392*	0.0140	0.0294‡	0.0613*	0.0556*
dwave4	0.0170	0.0367†	0.0196	0.0263	0.0407‡
dwave5	0.0270†	0.0072	0.0225	0.0311‡	0.0688*
dwave6	0.0230‡	0.0343‡	0.0116	0.0374†	0.0133
dwave8	0.0536*	0.0539*	0.0589*	0.0839*	0.0427†
dwave9	0.0186	0.0098	0.0335†	-0.0029	0.0289
dwave10	0.0239‡	0.0136	0.0234	0.0534*	0.0336
dwave11	0.0199	0.0100	0.0199	0.0268	0.0390‡
nkids	0.0017	0.0016	-0.0030	-0.0017	-0.0088
nwage	0.0006	-0.0020	0.0031	-0.0040	-0.0002
lagsaved	0.0000	-0.0001	-0.0001	0.0000	0.0000
lagj2pay	0.0000	0.0001	0.0001	0.0000	0.0001
cons	-0.0024	0.0152	0.0037	-0.0088	-0.0041
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.974	0.459	0.786	0.785	0.878

$*$: Significant at the 1% level
†: Significant at the 5% level
‡: Significant at the 10% level

Table 7: Vulnerability model with transitory incomes, selected quantiles for monthly net per capita income

I_j :	**20-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**
dry_net_ann	0.0093*	-0.0024	-0.0012	0.0005	0.0136*
dwave3	0.0030	0.0356†	0.0496*	0.0373†	0.0412†
dwave4	0.0158	0.0298‡	0.0016	0.0268‡	0.0371†
dwave5	0.0161	0.0282	0.0332‡	0.0210	0.0361‡
dwave6	0.0096	0.0634*	0.0233	0.0133	0.0385†
dwave8	0.0479*	0.0660*	0.0668*	0.0671*	0.0496*
dwave9	-0.0082	0.0261	0.0147	0.0154	0.0235
dwave10	0.0181	0.0260	0.0138	0.0097	0.0307
dwave11	0.0042	0.0342‡	0.0168	0.0211	0.0381†
nkids	-0.0024	-0.0015	-0.0068‡	0.0090	0.0066
nwage	-0.0029	-0.0015	0.0042	0.0006	-0.0022
lagsaved	0.0000	0.0000	0.0000	0.0000	0.0000
lagj2pay	0.0001*	0.0001*	0.0000	0.0000	0.0000
cons	0.0220†	-0.0005	0.0043	-0.0077	-0.0096
Anderson LM p-value	0.000	0.018	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.724	0.345	0.791	0.950	0.764

$*$: Significant at the 1% level
†: Significant at the 5% level
‡: Significant at the 10% level

Table 8: Vulnerability model with transitory incomes, selected quantiles for annual net per capita income

6.1 Location around the poverty line

I now turn to observe the dynamics at the poverty threshold. I again 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 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^* I estimate the model for both "starts in poverty zone" case (*sipz*), where each household was initially present 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.

Table 9 present the FGLS regressions of the symmetric and asymmetric subsamples around the poverty line, using the starter-intervals-in-poverty zone definition (*sipz).* The vulnerability coefficient is significant for all income specifications and for at least one of symmetric or asymmetric. This is again indicative that significant vulnerability is associated with transitory income dynamics. I also observe that of the two "insurance" variables, lagged savings and earnings from second job, are not significant for either the gross or net income variables.

In the following table, Table 10 presents the FGLS regressions for the ever-in-poverty-zone subsample. For both symmetric and asymmetric samples, there is no significant vulnerability observed for all income definitions - monthly gross, net monthly and net annual. Of the two insurance variables, lagged savings is only significant for the model using annual net income. Likewise, earnings from second job is only significant for net monthly income.The number of children in household and number of wage employable members in household remain significant for most of the models estimated. It is interesting to note the differences in results obtained using the SIPZ case and the EIPZ case. That there is no significant vulnerability obtained using the EIPZ sample (in comparison to the SIPZ sample, where there is significant vulnerability) is suggestive that the sample being larger than that of SIPZ has households which are successfully able to leave the poverty zone.

[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.

	y_gross		y_net		y_net_ann	
	Sym	Asym	Sym	Asym	Sym	Asym
drincome	0.051*	0.057*	0.015*	0.001	0.003	0.009†
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000	0.000	0.000
dwave3	0.033	0.039	0.065†	0.038	0.002	0.024
dwave4	0.005	-0.017	-0.014	0.023	0.037	0.030
dwave5	0.054‡	0.085*	0.048‡	0.013	0.031	0.051†
dwave6	0.004	-0.013	0.031	0.005	0.021	0.004
dwave7	0.006	0.035	0.019	0.033	0.008	0.026
dwave8	0.075*	0.085*	0.064†	0.075*	0.065†	0.072*
dwave9	-0.020	0.015	0.031	0.008	-0.004	0.019
dwave10	0.038	0.025	-0.011	-0.004	0.044‡	-0.006
dwave11	0.009	-0.006	0.035	0.033	0.009	0.033
nkids	0.003	0.002	0.005	-0.006	0.001	0.001
nwage	-0.004	-0.008	-0.008	0.005	-0.004	-0.004
cons	0.028	0.030	0.016	0.021	0.026	0.028
Anderson LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.587	0.776	0.384	0.384	0.920	0.878

∗: Significant at the 1% level
†: Significant at the 5% level
‡: Significant at the 10% level

Table 9: Vulnerability Dynamics, SIPZ of transitory incomes

	y_gross		y_net		y_net_ann	
	Sym	Asym	Sym	Asym	Sym	Asym
drincome	0.054	0.045	-0.020	0.014	0.026	0.023
lagsaved	0.000	0.000	0.000	0.000	0.000	0.000
lagj2pay	0.000	0.000	0.000	0.000	0.000	0.000
dwave4	0.007	0.013	-0.042	0.012	-0.020	-0.010
dwave5	0.030	0.056	0.040	0.037	-0.047	0.032
dwave6	0.024	0.037	0.017	0.040	-0.019	0.039
dwave8	0.045	0.020	0.062	0.068	-0.002	0.046
dwave10	0.019	0.024	0.046	0.031	-0.041	-0.031
dwave11	-0.021	0.004	0.037	0.056	-0.036	0.020
nkids	-0.004	-0.017	-0.004	-0.021†	-0.015	-0.002
nwage	-0.008	-0.002	-0.034*	-0.024†	-0.022†	-0.003
tenured	-0.006	-0.017	-0.012	-0.032	-0.047‡	0.010
cons	0.029	0.040	0.083‡	0.068	0.138*	0.044
Anderson LM p-value	0.000	0.018	0.000	0.000	0.000	0.000
Sargan	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Wu-Hausman	0.767	0.544	0.791	0.980	0.938	0.660

$*$: Significant at the 1% level
$\dagger$: Significant at the 5% level
$\ddagger$: Significant at the 10% level

Table 10: Vulnerability Dynamics, EIPZ with transitory income

What is interesting to note in the results with the transitory income dynamics is that most of the income quantiles that were revealed to be vulnerable for the full income results in Section 5 are also those which have significant vulnerability with transitory income. In other words, the results suggest that the vulnerability dynamics could be driven by variations in the transitory incomes. Given that the size of the transitory income component (compared to permanent income) is expected to be smaller (this may not be the case for households around the poverty line), significant vulnerability obtained for several of the income quantiles above is suggestive that much of the vulnerability is triggered by short-term fluctuations in the income stream of the vulnerable.

7 Interpretation

I have now identified the several income quantiles percentiles that have revealed to have a significant vulnerability co-efficient using several income definitions and smoothing mechanisms. In addition, I find that vulnerability is a "transitory phenomenon" - one that is likely to significantly change over the short-to-medium term, a characteristic which is not typically associated with measuring poverty. For the policy maker, these empirics shed new light on how to provide assistance for the vulnerable. Traditional poverty alleviating tools used by the welfare policy maker suggest favourable credit schemes, incentives for saving and asset building. In the empirics above, these variables are not found to be associated with the vulnerable. However, the empirics do strongly suggest that transfers and benefits do assist the vulnerable. The policy package for the poor, and for the vulnerable, are therefore different.

Similarly for quantiles under the poverty line, (particularly relevant for developing countries where the number of the poor is large), the vulnerability revealed allows the policy maker to target specific quantiles who are more prone to risks and shocks to their incomes than others. For example, a quantile of the income distribution under the poverty line revealed to be vulnerable (note from our estimates above that all quantiles under the poverty line are not necessarily (significantly) vulnerable) may have specific socio-economic characteristics which render them particularly vulnerable to an income shock. These could be the lack of assets which could be used as a "rainy day fund", or the absence of another earning member in the family. Having information of who the identified vulnerable are, or at least having knowledge of the socio-economic characteristics of the different vulnerable quantiles, both below and just above the poverty line will allow the policy maker to make much more informed decisions on policies to assist the vulnerable, both above and below the poverty line.

8 Conclusion

In this paper I have modelled the vulnerability dynamics of UK households using the British Household Panel Survey. I was particularly interested in observing the effects of "insurances" that are available to households on their expenditure. Panel regression methods are used to identify the vulnerable for which volatile incomes translate into volatile consumption patterns, at different parts of the income distribution. I observe that vulnerability is significantly associated with economy-wide shocks, captured by year-specific dummies, household composition and also the nature of insurances that they may have access to. Most importantly, different income concepts have different stories to tell: expenditure changes significantly track income changes when “income” is monthly gross income; but the vulnerability relationship defined for net income is less clear.

That we do not observe significant vulnerability so clearly with the net income concept, implies that benefits and transfers serve to cushion income shocks, as also revealed in Bandyopadhyay and Cowell (2007). This is particularly the case when observing the effects of different kinds of consumption smoothing mechanisms - in particular for savings and earnings from second job. The results are suggestive that these smoothing devices (i.e., savings and earnings from second job) may not be sufficient to cushion the effect of an income shock for the vulnerable households.

Significant vulnerability is observed for most definitions of income when using the transitory income definition. The temporal nature of vulnerability - that it is likely a short term phenomenon - is clearly revealed.

While these empirics suggest that "the vulnerable" are different from "the poor" (though, one can be both poor and vulnerable), and that vulnerability is most likely limited to particular parts of the income distribution (i.e., around the poverty line) , I would not like to interpret vulnerability as simply a "locational device". Identifying the vulnerable is more than identifying their level of household income, however income may be defined; the vulnerable are characterised by the lack of the smoothing mechanisms at their behest in the face of an income shock. Thus a description of the "vulnerable household" is incomplete without a characterisation of their consumption smoothing story. Therefore, the definition of "the vulnerable" is subject to country specific conditions, and will vary across countries, particularly whether it is a developed or developing country. Identifying the vulnerable therefore is incomplete without identifying the source of the vulnerability.

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A Appendix

In this section I 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 by the following:

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, 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).

B Expenditure

Weekly expenditure on food is available in the BHPS as actual expenditure in £s for Wave 1, and from Wave 2 onwards is coded over intervals. I convert the coded weekly expenditure into actual weekly expenditure by using the mid-point of the interval used for the code. The code provided in the BHPS is given below:

Under £10: 1
£10-£19: 2
£20-£29: 3
£30-£39: 4
£40-£49: 5
£50-£59: 6
£60-£79: 7
£80-£99: 8
£100-£119: 9
£120-£139: 10
£140-£159: 11
£160 or over:12

C Insurance variables

Here I describe the insurance variables that have been used in the initial analysis to determine their individual effects on vulnerability.

- Savings, per week
- Loans: Dummy variable, whether the person has a loan or not
- Debts: Dummy variable, whether the person has debt
- Credit: Dummy variable, whether the person has credit cards, store cards.
- Mortgages: Two types of variables: Dummy variable, whether the person has a mortgage, another variable, value of old mortgage
- House Value: Value of property.