Economics Bulletin

Volume 29, Issue 3

A note on welfare and the economic shocks

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Abstract

The behaviour of the permanent and transitory economic shocks for different levels of household's welfare is studied using both consumption and income measures. After testing for heteroskedasticity of the economic shocks, we use local polynomial regression models to estimate the variance of the shocks conditional on welfare level. Italian data covering the period 1980-2004 show evidence of heteroskedasticity of both the transitory and the permanent economic shocks, with the poor experiencing higher variances. The permanent shocks seem to have a more uniform effect at all welfare levels.

This paper benefited from useful discussion with Montezuma Dumangane, Ian Preston, João Santos Silva, and from comments by audiences at ESEM04 and UCP. Thanks also go to the Bank of Italy for availability of data. This study was supported in part by the Fundação para Ciência e a Tecnologia, program POCTI, partially funded by FEDER. The usual disclaimer applies.
Citation: Nicoletta Rosati, (2009) "A note on welfare and the economic shocks", *Economics Bulletin*, Vol. 29 no.3 pp. 1621-1630.
Submitted: Jun 03 2008. **Published:** July 07, 2009.

1 Introduction

An assumption that is fairly common in the literature is that the economic shocks are homoskedastic, at least within certain homogeneous groups. This is usually a quite mild assumption, since heteroskedasticity-robust inference can be done for most standard econometric techniques. However, a non-constant variance of the economic shocks is not only a statistical issue but also an interesting aspect of the economic study of welfare. Therefore, in the present study, rather than assuming homoskedasticity, the behaviour of the variances of the economic shocks is investigated, to see whether they vary along the population.

The study of welfare needs the careful distinction of its temporary and permanent aspects. Given the objective of this study, we wish to be able to distinguish the permanent economic shocks from their transitory counterpart, and study separately their effects along the welfare distribution. Studies by Deaton and Paxson (1994) and Blundell and Preston (1998), combine a specification of the permanent income process with an intertemporal model of optimization over the life cycle. In particular, the last paper highlights the value of the joint use of income and consumption measures in the identification of the temporary and permanent components of *inequality*. Following this line, the present study investigates further the joint role of income and consumption in the identification of temporary and permanent economic shocks.

The paper is organised as follows. Section 2 recalls a widely used intertemporal model of consumer's behaviour, and identifies the economic shocks. Section 3 presents the testing and estimating procedures, while section 4 reports the results of an application to Italian data. Section 5 concludes.

2 An economic model for income and consumption

This section recalls briefly the main features of the economic model of consumer's behaviour based on the joint use of income and consumption, as in Blundell and Preston (1998). In order to catch any generation effect, the population is split into birth cohorts. The model combines an income process with a life-cycle model for consumption, and can be summarised by the following three equations (for further details see the original paper):

$$y_{it} = y^p_{it} + u_{it} \quad (1)$$

$$y^p_{it} = y^p_{it-1} + v_{it} \quad (2)$$

$$c_{it} = c_{it-1} + v_{it} \quad (3)$$

where y is income, y^p is the permanent component of income, and c is consumption; u and v are the transitory and permanent shocks, respectively; index i represents the individual and t time. Assume that y^p_{it} and u_{it} are uncorrelated, and that v_{it} is uncorrelated with y^p_{it-1}, c_{it} and orthogonal to u_{it}. Both u_{it} and v_{it} have zero mean and are independent over time; let also $\mathrm{Cov}_j(u_{it}, y_{it-l}) = \mathrm{Cov}_j(v_{it}, y_{it-l}) = 0$ for all $l \geq 1$.

Notice that the transitory and permanent shocks are assumed to be uncorrelated with permanent income or consumption, but for the purpose of our study their variance is left unspecified. How can the variance of the shocks be studied, distinguishing between permanent and transitory? The basic idea is to start from equations (1) and (3) to obtain the two errors, and then use them to study the behaviour of their variance. For this reason, the functions of interest are the two conditional variances $\text{Var}(u_{it}|y_{it}^p)$ and $\text{Var}(v_{it}|c_{it-1})$. For this last case (permanent shocks), v_{it} can be simply obtained as $v_{it} = c_{it} - c_{it-1}$, and then its conditional variance can be studied. To study the transitory shocks, notice that the combination of (1)–(3) gives $y_{it} - c_{it} = u_{it} + y_{it-1}^p - c_{it-1}$; due to independence of u_{it} from both y_{it-1}^p and c_{it-1}, this in turn implies that $\text{Var}(sav_{it}) = \text{Var}(u_{it}) + \text{Var}(y_{it-1}^p - c_{it-1})$, where $sav_{it} = y_{it} - c_{it}$ represents savings. Therefore we can start from the simplest case where $y_t^p \approx c_t$, and study the regression of the squared savings on consumption, which gives an approximation of the conditional variance of the transitory shocks, given consumption, $\text{Var}(u_{it}|c_{it})$.

3 Testing and estimation

To study the conditional variances $\text{Var}(u_{it}|c_{it})$ and $\text{Var}(v_{it}|c_{it-1})$ consider the following additive models[1]:

$$\begin{aligned} u_{it}^2 &= m(c_{it}) + \varepsilon_{it} \qquad (4) \\ v_{it}^2 &= g(c_{it-1}) + \eta_{it} \qquad (5) \end{aligned}$$

where the regression functions m and g are assumed to be general functions of c_t and c_{t-1}. Consider first equation (4), as analogous reasoning can be followed for the case of permanent shocks. For a fixed time period t (we can drop the time index to simplify notation), the error ε is uncorrelated with c, and $E(\varepsilon) = 0$. Let us start from the standard case where $\text{Var}(\varepsilon) = \sigma_\varepsilon^2$ is a constant; this point will be relaxed later.

In order to test for heteroskedasticity of the shocks, an F-ratio type test can be derived to test the null hypothesis of no effect, i.e.

$$\begin{aligned} H_0 &: E(u_i^2) = \theta \\ H_1 &: E(u_i^2) = m(c_i) \end{aligned}$$

Let $RSS_0 = \sum_{i=1}^n \{u_i^2 - k\}^2$ be the residual sum of squares under the null, where k is the sample average of the u_i^2; let also $RSS_1 = \sum_{i=1}^n \{u_i^2 - \hat{m}(c_i)\}^2$ be the residual sum of squares under the alternative, where $\hat{m}(c)$ varies with the estimating procedures specified below. Then we can define the following F-statistic

$$F = \frac{(RSS_0 - RSS_1)/(df_0 - df_1)}{RSS_1/df_1} \qquad (6)$$

[1] See, for instance, Hastie and Tibshirani (1990).

where $df_0 = \text{tr}(I - L)$ and $df_1 = \text{tr}(I - S)$ denote the degrees of freedom for error under each hypothesis; here I is the identity matrix of order n, L is an $n \times n$ matrix filled with the value $1/n$, and S is the matrix such that $\hat{m} = Su_i^2$. S is analogous to the projection matrix $H = X(X'X)^{-1}X'$ in a standard linear model of the form $y = X\beta + \nu$. Due to the ratio form, the test statistic is independent of the unknown error variance σ_ε^2.

The simplest way to perform such test is to use the Ordinary Least Squares (OLS) procedure, wich allows us to test H_0 using heteroskedasticity-robust standard errors. Under the alternative hypothesis the regression function is specified as $m(c_i) = \beta_0 + \beta_1 c_i + \beta_2 c_i^2$, since we can reasonably expect an U-shaped $m(.)$ function. The F test of zero slopes associated to this OLS regression is equivalent to (6), and can be performed using heteroskedasticity-robust standard errors.

A more flexible alternative to OLS is local polynomial regression[2]. If $m(c_i)$ is specified locally as a polynomial of order p in c, local polynomial regression procedures can be used to perform the test. In this case, the test statistic (6) turns out to be a pseudo-likelihood ratio, and therefore shall be referred to as the PLRT (pseudo-likelihood ratio test). The degrees of freedom are approximate, and the distribution of the test statistic can be obtained using results on quadratic forms in Normal variables, as illustrated in Azzalini and Bowman (1997). Standard procedures within this framework assume that $\text{Var}(\varepsilon) = \sigma_\varepsilon^2$ is constant. This would be equivalent to testing for $m(c_{it})$ constant, given $\text{Var}(\varepsilon) = \sigma_\varepsilon^2$. In this case, the stronger hypothesis of u_{it} independent of c_{it} can be tested, which implies both $m(c_{it})$ constant and $\text{Var}(\varepsilon) = \sigma_\varepsilon^2$. Under the null, the standard model can be used to test directly for constancy of $m(c_{it})$.

Once verified that the $m(.)$ function is not constant, estimation can be performed. Local polynomial regression models are a semi-parametric framework that is embedded in the classical weighted least squares problem, providing a full set of inferential tools, and therefore are an ideal setting for our analysis. This framework assumes that the regression functions m and g are (locally) polynomials of order p in c, and estimates them using a smooth function. For example, for a given c, solving the least squares problem

$$\min_{\alpha_c, \beta_c} \sum_{i=1}^{n} \{u_i^2 - \alpha_c - \beta_c(c_i - c)\}^2 w(c_i - c; h) \tag{7}$$

and taking as the estimate at c the value of $\hat{\alpha}_c$ gives a local linear regression, while in the quadratic case the term $\gamma_c(c_i - c)^2$ is added to the regression, and so on. The subscript c in the parameters is to stress the local nature of the minimisation problem, i.e. the dependence of the parameters on c. The smoother $w(.)$ is here chosen to be the standard normal density $\phi(\frac{c_i - c}{h})$; in this case h is the standard deviation of the normal kernel.

This approach can be viewed as a generalisation of the usual linear regression model. As the smoothing parameter h becomes very large, the curve estimate approaches the fitted least squares regression line. The minimum h that grants equivalence between local linear regression and ordinary least squares is $h \approx 40$ range(c). It follows that, for

[2]See, for instance, Fan and Gijbels (1996).

instance, the OLS-based test and the PLRT obtained with such h coincide. As usual, the bias of the estimator $\hat{m}(c)$ increases with large h, while the variance increases with small h. An optimal choice of the smoothing parameter h is obtained via cross-validation.

Local linear and quadratic estimation has been performed, and variability bands have been computed as

$$\hat{m}(c) \pm 2 \times \sqrt{\hat{v}(c)}$$

i.e. pointwise confidence intervals for $E[\hat{m}(c)]$ rather than $m(c)$. Such bands indicate the level of variability involved in the regression estimator, without attempting to adjust for the presence of bias, and are a widely accepted alternative to confidence intervals.

4 An empirical illustration

To investigate the behaviour of the economic shocks along the welfare distribution, the model presented above is now applied to Italian data covering the period 1980-2004 from the Survey on Household Income and Wealth (SHIW) of the Bank of Italy.

Income and consumption from the SHIW are available from 1980 to 2004, cross-sections of data being collected annually from 1980 to 1987 except in 1985, then every second year from 1989 to 1995, and again biannually from 1998 to 2004. From 1989 a panel data set has been collected on a restricted number of households, in the same years as the cross-sectional survey.

The sizes of the selected cross-sectional annual samples vary between around 2300 to 6000 households, giving a total of 69873 households in 1980-2004. The two-wave panel samples have between 1500 and 2500 observations, with a total of 14418 households in 1989-2004. Analyses have also been conducted within six ten-year birth cohorts, corresponding to heads of the family born in the 1920s through to the 1970s. In the cohort analysis, some groups were excluded due to small sample size (less than 99 observations) in the cross-sectional and/or in the panel data.

As regards the variables used in the analysis, note that income is average monthly family disposable income, and the consumption measure is average monthly total expenditure, where the average is computed over the year of observation. Both income and consumption are equivalised, and the analyses are run in the logarithmic scale.

Brandolini *et al.* (2001) report several inequality and poverty indices for Italy based on income measures, such as the Gini index, the 90-10 decile ratio, the share of low-paid workers and the head count poverty ratio. All indices show a decrease starting from 1987 for a few years, going back to the 1987 values only in 1995. Other factors that characterised the Italian economy in this period are the wage-setting mechanism "Scala Mobile" (literally "escalator"), which had a strong equalising effect on wages until 1992, when it was abolished. Moreover, in the early 1990s Italy experienced the deepest economic recession since the Second World War, which probably put all families in difficult economic situation, with an equalising effect. Brandolini *et al.* (2004) report steady growth of housing prices in Italy from 1987 to 1993, and a decline of wealth inequality from 1989 to 1991, with a following rise in the rest of the decade "driven by large gains at the very top of the distribution". Bertola and Ichino (1995) show decreasing GDP rates in the period 1987-1994, and decreasing unemployment growth rate from 1989 to 1993. Real wage growth also decreased in the period 1989-1993, as the country transitioned from rigid to flexible employment.

The empirical results obtained in the present study not only confirm the presence of heteroskedasticity, but also show patterns in line with the picture of the Italian economy just given.

For the transitory shocks, both the PLR test and the OLS-based test were performed, and gave very similar results. The p-values of the nonparametric test are always smaller than 0.05, in most cases equal to zero, for any values of the smoothing parameter within a reasonable range. Likewise, the OLS-based test presents all zero p-values. Analogous results were obtained in the analysis by cohort; for instance, the OLS test rejects the hypothesis of constancy of the variance in 82% of the cases. To estimate now the actual regression function, the standard local linear regression approach is used[3]. For simplicity, the annual results jointly for all cohorts are shown. Figure 1 reports the estimates of the local linear regression, together with the variability bands, and the logarithm of the poverty line. The optimal values for the smoothing parameter obtained by cross-validation are also shown. A local quadratic regression was also estimated and is superimposed in Figure 1; the curve is almost overlapping with the local linear estimate, and always lying within the variability bands. For this reason, we analyse here the results from the local linear model.

Most heteroskedasticity is concentrated at the bottom of the consumption distribution, in most cases a cut-off point being values around the logarithm of the poverty line, showing that the families that suffer a more volatile effect of the transitory economic shocks are those at the bottom of the consumption distribution. In the central years of observation, in particular from 1987 to 1995, the shocks show a more homoskedastic behaviour, and then go back to higher variances at the low consumption levels after 1995. The more equal behaviour between 1987 and 1995 can be due to several factors that affected the Italian economy in those years. In particular, since the transitory shocks are part of the income process, their more equal behaviour can be a reflection of the reduction in income inequality and poverty observed in this period in Brandolini *et al.* (2001).

The analysis of the permanent shocks requires the use of panel information. Due to biannual observations, equation (5) is modified as $v_{it}^2 = g(c_{it-2}) + \xi_{it}$. The form of function g shows whether the impact of the permanent shocks is uniform along the distribution of consumption. Both in the OLS-based and in the nonparametric test, the hypothesis of constancy of the variance function is always rejected. The results of estimation are reported in Figure 2.

Higher levels of variance are observed in the bottom part of the distribution of consumption, i.e. the families with lower levels of consumption experience stronger

[3] In fact, the assumption of $\text{Var}(\varepsilon) = \sigma_\varepsilon^2$ only affects the variability (hence the results of the test), but not the estimates.

impact of the economic shocks, but an overall more equal effect along the consumption distribution is evident, if compared to the transitory shocks. In particular, the variance levels at the top and bottom of the distribution are very similar, which did not happen for the transitory shocks where variances for the poor were around 1.5 to 2 times the variances of the rich. The behaviour of the shocks does not show large differences across time, levels being slightly flat only in the first wave (1989-1991), and then settling around a U-shaped pattern from 1993 onwards. The local quadratic regression yields results almost identical to the local linear case, as is evident from Figure 2. The analysis by cohort gave the same indication as in the annual case, both in the tests and the estimates.

Putting together this last information with the results on transitory shocks, we can observe that the permanent shocks seem to be affecting all families more or less the same way, while the transitory shocks appear to have a more uneven effect along the distribution of consumption, with the families with lower consumption levels experiencing higher volatility. There might be many reasons for this behaviour. One possibility is, for instance, that the transitory shocks can be absorbed through access to financial and credit system (which is not available to the poorer families), while the permanent shocks are more difficult to compensate, and therefore affect everyone more uniformly. Further analyses can reveal more reasons for the observed behaviour of the shocks.

The more homoskedastic behaviour of transitory shocks in the central years could be interpreted as a signal of the more critical situation of the Italian economy during and after the recession of the early 1990s: even the richest families lost their ability to compensate for transitory shocks in the economy, so that such shocks affect all families similarly.

5 Conclusions

Starting from an economic model of intertemporal optimization, identification of permanent and transitory shocks of the economy is obtained through joint use of income and consumption measures.

In an application to Italian data, strong heteroskedasticity is detected for the transitory shocks, where higher variances are observed in the lower part of the distribution of consumption. Permanent shocks seem to be affecting all families more equally.

Although very preliminary, this study indicates that the common assumption of homoskedasticity of the shocks deserves some further attention, given the evidence encountered.

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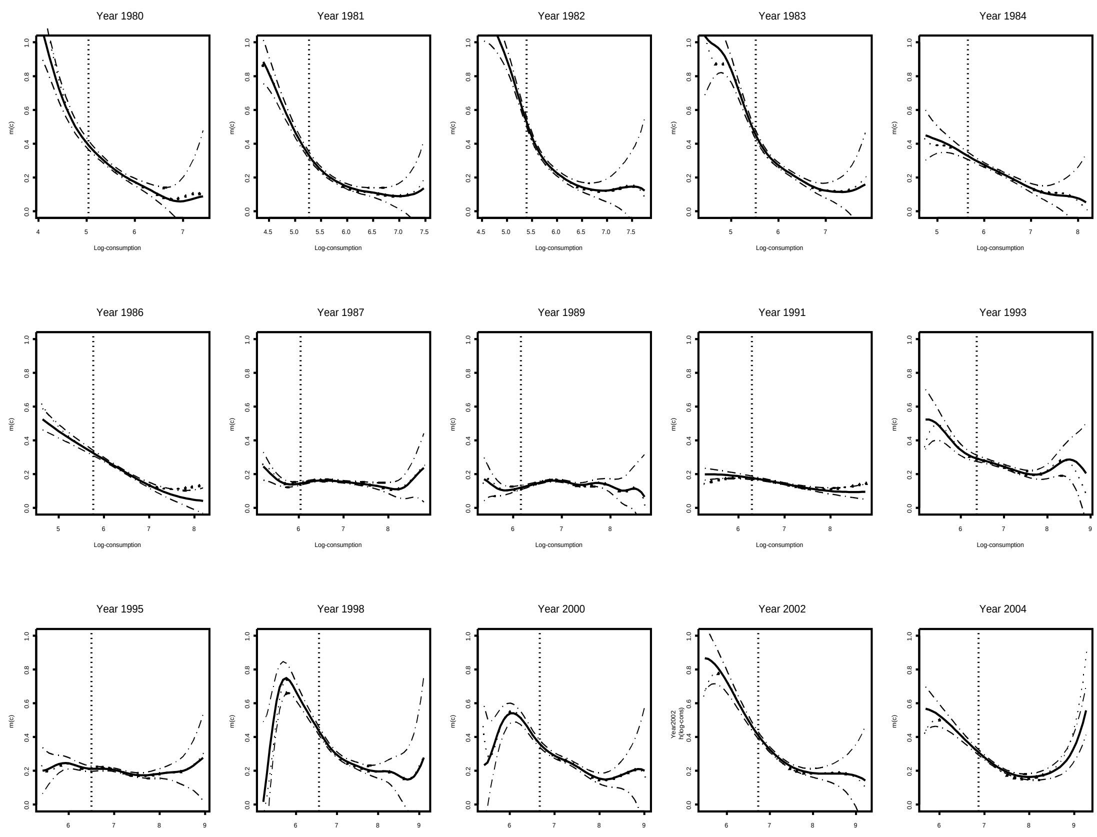

Figure 1: Nonparametric estimates of the variance function for the transitory shocks, as function of log-consumption. Local linear regression (—), local quadratic regression $(\cdots)$, variability bands $(- \cdot - \cdot -)$. Log of poverty line superimposed (vertical dashed line). Optimal cross-validation smoothing parameter. SHIW data, 1980-2004.

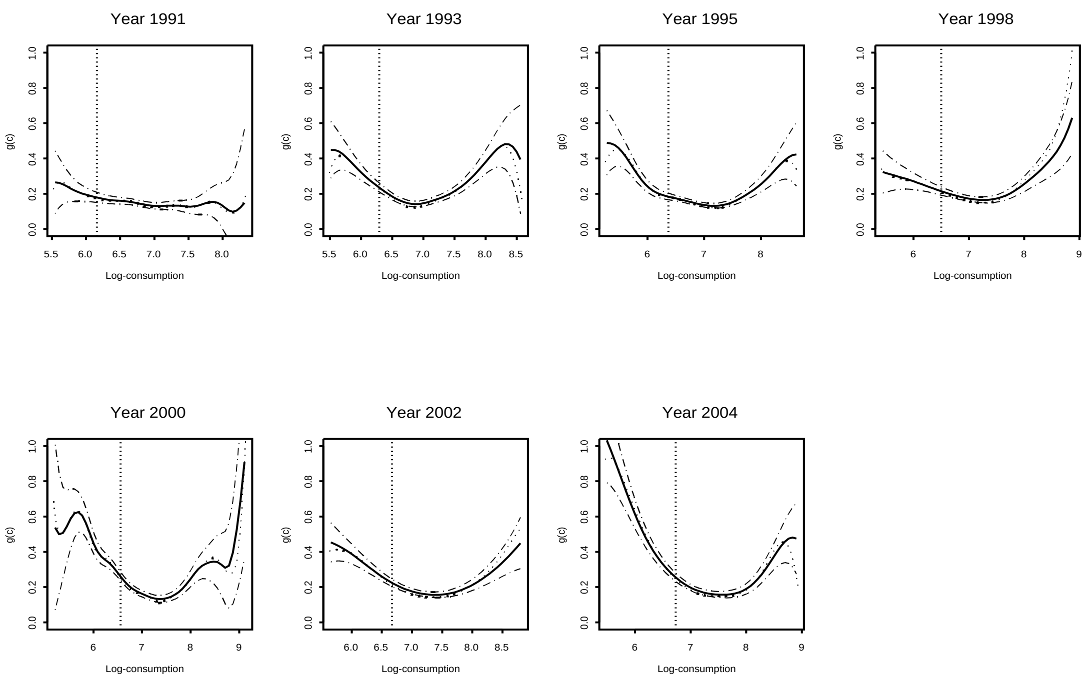

Figure 2: Nonparametric estimate of the variance function for the permanent shocks, as function of log-consumption. Local linear regression (—), local quadratic regression (· · ·), variability bands (− · − · −). Log of poverty line superimposed (vertical dashed line). Optimal cross-validation smoothing parameter. SHIW panel data, 1989-2004.