Short-Lived Shocks with Long-Lived Impacts?
Household Income Dynamics in a Transition Economy

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Abstract: It is possible in theory that the persistent poverty that has emerged in many transition economies is due to underlying nonconvexities in the dynamics of household incomes, such that a vulnerable household will never recover from a sufficiently large but short-lived shock to its income. To test the theory we estimate a dynamic panel data model of household incomes with nonlinear dynamics and endogenous attrition. Our estimates on data for Hungary in the 1990s exhibit nonlinearity in the income dynamics. But we do not find evidence of nonconvexities. In general, households bounce back from transient shocks though the process is not rapid.

Keywords: Income dynamics, poverty, multiple equilibria, Hungary

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1. Introduction

Consider a household that suffers a transient income shock, by which we mean an unexpected but short-lived drop in income. With limited access to credit, or other forms of (formal or informal) insurance, such a shock will cause a spell of hardship. For example, a family that was not poor before suddenly finds that it cannot secure its basic consumption needs. But could such a shock also cause a previously non-poor family to become poor, and stay poor, indefinitely? Or could it cause a moderately poor family to fall into persistent destitution?

If the answer is "yes" to these questions then there will be large long-term benefits from institutions and policies that effectively protect people from transient shocks. If the answer is "no" then the (still potentially important) gains from such social protection will also be transient; lack of a safety net may well cause hardship, but it would not be a cause of persistent poverty.

The answer depends on properties of the dynamic process determining incomes at household level. And they are properties of income dynamics about which we currently know very little. If the process by which household incomes evolve over time can be represented well by the simplest type of linear (first-order) autoregression then a household that experiences a transient shock will still see its income bounce back in due course. The family may well stay poor for a longer period than the duration of the shock. This can happen because incomes do not adjust instantaneously but do have some serial dependence; low current income may reduce future income such as by eroding a family's physical and human asset base. But the household will recover from just one draw from a distribution of serially independent income shocks. (The same is true of a broad class of commonly assumed stationary linear autoregressive and moving average dynamic processes.)

However, there is no obvious *a priori* reason why incomes would behave this way. It has been argued that economies as a whole have a "corridor of instability," meaning that they are stable with respect to small shocks but not large ones (Leijonhufvud, 1973). Nonlinear dynamic models with multiple equilibria have been widely used in explaining why seemingly similar aggregate shocks can have dissimilar outcomes. In macroeconomics, examples can be found in models of the business cycle (Chang and Smyth, 1971; Varian, 1979) and certain growth models (Day, 1992; Azariades, 1996). Similar ideas have been employed in modeling micro poverty traps (Dasgupta and

Ray, 1986; Banerjee and Newman, 1994; Dasgupta, 1997) and in understanding famines (Carraro, 1996; Ravallion, 1997).

It is not difficult to construct theoretical models that generate a type of nonlinear dynamics at individual level whereby short-lived shocks have long-lived effects. We give examples later. However, while it is theoretically possible that transient shocks have persistent effects, whether they do or not remains an empirical question. And it is a difficult question. We clearly need to observe incomes of the same households over time; panel data appear to be essential. Even so, there is a concern about whether we will be able to observe an unstable equilibrium. This will depend on the speed of adjustment relative to the survey data frequency and whether shocked households stay in the panel. Possibly the households who receive large negative shocks will drop out of the survey. For example, sufficiently large shocks may entail breakup of the family, un-planned migration and/or homelessness, and (hence) a high probability of dropping out of the panel survey. One clearly needs to allow for endogenous attrition. There are also econometric issues about estimated dynamic effects in panels of relatively short duration. Tests exist in the literature for determining whether a time series with white-noise properties is stochastic (i.i.d.) or deterministic (chaotic) (Brock and Potter, 1993; Liu, Granger and Heller, 1992). However, these call for large samples over time; 600 would be considered adequate, but not six! Furthermore, the question of interest here is not so much whether the economic dynamics is complex, but rather whether it exhibits low-income nonconvexities.

This paper tests whether persistent poverty can arise from sufficiently large but short-lived income shocks at the household level. We first look at the income dynamics using simple but flexible non-parametric methods. We then estimate a parametric model of income determination, incorporating nonlinear dynamics and endogeneous attrition arising from a nonzero correlation between the error term of the equation for incomes and an equation for the probability of staying in the panel. We also test for nonlinearity in the way initial incomes influence panel attrition.

Our choice of setting was dictated in part by the fact that we require household panel data. Of course, this would be of little use for our purpose if there had not been (unfortunately) large income shocks at household level. We chose a six-year household-level panel data set for Hungary. The data are close to ideal for our purposes, since the panel was designed for studying income

dynamics. And the setting is of substantive interest in this context. The collapse of central planning and transition to a market economy in the 1990s entailed sizable income shocks to Hungarian households. The shocks clearly hurt; for example, there was a rapid increase in the incidence of poverty. A crucial question for policy in this setting is whether these income shocks had long-lasting consequences. A further reason for choosing Hungary is that there exists a sizable safety net; we will test how much impact this might have had on the income dynamics.

As in micro studies for other settings, past work for Hungary has shown that differences in the long-term characteristics of households (such as asset holdings and human capital) and certain events interpretable as shocks (such as unemployment and illness) increase the risk of poverty. (We review this literature later.) While agreeing to the importance of such factors in determining current household incomes, in this paper we focus on the different question of whether transient income shocks might cause persistent poverty. Do households bounce back from such shocks? What are the reasons for differences in household income dynamics? Are there any household characteristics that contribute to the vulnerability of the family to income shocks? Why does it take much longer for some households to recover from a transient shock? These questions require a rather different approach to that found in the literature on poverty and income dynamics.

The following section gives examples of models that can yield the type of nonlinear income dynamics whereby short-lived shocks can have permanent consequences. Section 3 then discusses the literature on income dynamics in Hungary and elsewhere. Our data are described in section 4. We then present our econometric model in section 5. Section 6 presents our results, and our conclusions are summarized in Section 7.

2. Nonlinear dynamics in household incomes

Probably the simplest model that can generate the type of nonlinear income dynamics we are interested in testing for assumes that a family cannot borrow or save and derives income solely from labor earnings, but with a nonconvexity at low earnings. We can suppose that the worker's expected productivity and (hence) wage rate depends on consumption, as in the classic Efficiency Wage Hypothesis (Mirrlees, 1975; Stiglitz, 1976). This assumes that labor productivity and earnings are

zero at a low but positive level of consumption; only if consumption rises above some critical level, $Y^{min}>0$, will the worker be productive. In the efficiency wage literature, Y^{min} is usually interpreted as the nutritional requirements for basal metabolism, which represent two-thirds or more of normal nutritional requirements (Dasgupta, 1993). There are other interpretations. One can assume that a minimum expenditure level is necessary to participate in society, including getting a job. The expenditure is required for housing (or at least an address) and adequate clothing. Thus one can say that consuming below this point creates "social exclusion." Higher consumption permits social inclusion, but there are presumably diminishing income returns to this effect. For example, earnings rise but at a declining rate until after some point the productivity effect of consumption vanishes. Nonlinear dynamics can be introduced into this model by simply assuming that the wage rate in any period is contracted at the beginning of the period. Finally we assume that this dynamic process of income determination has at least one date for which incomes have risen.

Combining these assumptions, the process generating current income (Y_t) can be written as the nonlinear difference equation: $Y_t=f(Y_{t-1})$, where the function f is continuous with $f(Y)=0$ for $Y<Y^{min}$ and the function is increasing and concave for all $Y>Y^{min}$. An equilibrium of this model is a steady-state solution such that $Y=f(Y)$. It is evident that the model must have at least one such equilibrium, and if there are two, the one with lower income will be unstable[2].

Alternatively, we can think of a liquidity constrained household that faces the choice of investing in (physical or human) capital accumulation or consuming all income in a given period. Suppose that the household is only willing to forgo current consumption in order to invest if its income exceeds a critical level Y^{min}. The investment yields an income at time t of $f(Y_{t-1})$ where this function has the same properties as above.

The recursion diagram in Figure 1 illustrates the case of two equilibria. The equilibrium at Y^{**} ($>Y^{min}$) is stable, but Y^{*} is not. Consider a household at Y^{**}. With any shock exceeding $Y^{**}-Y^{*}$, the household will be driven beyond the unstable equilibrium, and will then see its income decline steadily (even precipitously). Persistent poverty will be the inevitable result.

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[2] Note that the assumption that $Y_t>Y_{t-1}$ for some t assures that there is at least one unstable equilibrium (by the intermediate value theorem, given continuity of f and the assumption that $Y^{min}>0$).

One can propose more complicated models than this one. For example, on can allow for some positive lower bound to incomes. Assuming that this lower bound is below Y^{**} in Figure 1 there will now be three equilibria, with the extra (stable) equilibrium at the lower bound. Again, with a sufficient negative income shock, a household at its high (stable) income will see its income then decline until it reaches the lower bound.

This type of model has a powerful policy implication. A transfer payment $T \geq Y^{**}$ will eliminate the low-income unstable equilibrium. The family will be fully protected from the possibility of a transient shock having an adverse long-term effect. The transfer will not only help protect current living standards, but will also generate a stream of future income gains. The safety net could be a long-term investment, and with a high return.[3]

Later we will see whether the empirical dynamics of household incomes in Hungary looks like Figure 1, such that sufficiently large short-lived shocks can have long-lived impacts.

3. The setting and literature

The last decade has seen a sharp decline in Hungary's GNP (by nearly a fifth of its 1989 value in the first four years of transition), large scale unemployment, declining real wages and household incomes, and a sharp increase in income poverty. Between 1990 and 1994 the number of employed people decreased by 1.4 million, and by 1995 formal employment had dropped by more than a quarter of its pre-transitional level. Unemployment increased by approximately 500 thousand people for that period (Galasi, 1998; Forster and Toth, 1998). The proportion of the population living below the subsistence minimum was about 50 percent higher in 1996 than in 1992 (Speder, 1998).

Under these conditions maintaining a social safety net has become an important concern of the Hungarian government. Both Hungarian and international scholars have been involved in the debate about the reforms of the social support system to avoid the emergence of massive poverty and to make the current system of social protection fiscally sustainable.

[3] A similar point is made by Keyzer (1995) in his analysis of a generalized version of the Dasgupta and Ray (1986) model.

The dynamics of poverty and the performance of the safety net in Hungary have been a them of past research.[4] Dynamic aspects of poverty in Hungary were studied by Ravallion et al. (1995) based on two rounds of data from the Household Budget Survey conducted by the Central Statistical Office for 1987 and 1989. They constructed the joint distribution of household welfare over time, in which the panel structure was exploited to show how households moved between welfare groups. The results showed considerable transient poverty over the period of the survey. The safety net did help protect vulnerable households from falling into poverty.

Further research on poverty dynamics has been facilitated by the Hungarian Household Panel Survey (HHPS). This was conducted by Hungary's Social Research Informatics Center (Tarki) and began in 1991, with the purpose of providing researchers with data for further investigating household income dynamics.[5] Several recent papers have used the HHPS to analyze the dynamic aspects of poverty in Hungary (Galasi 1998; Speder 1998; Forster and Toth 1998). Using income transition matrices, Galasi (1998) studied the dynamics of poverty incidence, the chances of escaping from and reentering poverty, and the characteristics that distinguish households who stay in poverty from those who escape. The results suggest considerable income mobility from one year to the next. Most of the initially poor escaped poverty within two years, but a high proportion of the households who escaped poverty were found to be poor again withing three years. However, the majority of households move to neighboring quintiles, and households in the middle of the income distribution experience the most income mobility. The income level of households in the top and bottom quintiles tends to be more stable.

Applying a similar method, Speder (1998) examined the effects of certain life cycle events on the long-term income status of Hungarian households. Changes in household composition and size were found to have an impact on household incomes. Childbirth, dissolution of the household (divorce and widowhood) as well as changes in economic-activity status were found to increase the

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[4] While there is a large and recent literature on poverty in Hungary, here we focus on panel data studies. The composition of absolute poverty was examined by Kolosi et al., (1995). Relative poverty was studied by Andorka (1992) and Andorka and Speder (1993a, b). Work by Toth et al., (1994) and Andorka et al., (1995) looked at the composition of poverty using various measures.

[5] Information on the sample design, sample weights and representability can be found in Toth (1994) and Sik and Toth (1993, 1996, 1997).

risk of being poor. Analysis of household income components indicated that wages and joint incomes of the household members were mainly responsible for the dynamics of poverty in Hungary.

Forster and Toth (1998) found that the durations of poverty spells in Hungary depended on characteristics of the individual and the household. Persons with lower education were less likely to escape poverty than persons with higher levels of education. Persistent poverty is rare among persons with a university diploma. Children and the elderly have fewer chances of escaping poverty.

None of this past work has tested whether the dynamic process determining incomes is such that transient income shocks can create persistent, long-term, poverty. Indeed, we know of no tests for any other setting. Although much has been learnt about the processes determining poverty in the present setting, past work cannot answer the question in our title. The following sections propose and implement a method of testing for nonlinearity in the income dynamics consistent with the existence of multiple equilibria.

4. Data and descriptive results

We use six waves (1992-1997) of the HHPS. The first wave of the survey was designed to include a nationally representative sample of Hungarian households. The aim was for all persons living in households selected for the first wave to be re-interviewed at one-year intervals. Originally (in 1992) the panel included 2668 households. The household response has been around 85 percent at each round of the survey, so that by the sixth wave (1997) only 52 percent (1385) of the initially selected households remained in the sample. Attrition is clearly a concern with this survey.

The questionnaire includes detailed questions about the incomes of every adult member of the household. Income components that cannot be directly allocated to any individual household member are registered separately in the questionnaire. Total household income is calculated as a sum of wages and salaries of individual members of the household, social security transfers, private transfers, in-kind income, and income from home production, with imputed values when necessary.

Table 1 provides some descriptive results on household recovery times following a negative income shock. We selected all households who experienced a decline in their real total income between 1992 and 1993 and categorized these households according to the time it took them to get

back to at least 98% of their income in 1992. More than one third (37.5 percent) of households that had a negative income shock recovered their income loss within one year. However, 47 percent of Hungarian households had not recovered within five years after a shock.

The time it takes for a household to recover after a decline in income clearly depends on the size of the shock. Among households that experienced a decline in real income of less than 10% between 1992 and 1993, 47% recovered within the first year after the shock. Among the households that lost more than 30% of their income between 1992-93, only 15% recovered in the first year and 73% had not recovered after five years.

These calculations might be interpreted as indicating that two types of income dynamics exist amongst Hungarian families. For the first type, an initial income shock leads to only a temporary drop in household income. However, it seems that for almost half of the households in Hungary, the income shock was more devastating, and appears to have put them on a declining income path leading to chronic poverty.

That interpretation is questionable however. There are other ways one might explain Table 1. Possibly the households that had not recovered within five years experienced other shocks in the intervening period. Or possibly the first shock was not transient, and lasted for many years. Or the shock may have been transient, but the recursion process is linear with a slow speed of adjustment due to sizable lagged effects of past incomes on current incomes. One cannot conclude from Table 1 that short-lived shocks have long-lived impacts.

Quite generally we can postulate that a household has its own stable equilibrium income Y^* which is a function of the household's characteristics. The time it takes for the household to reach its equilibrium state depends on the size of the income shock, the level of pre-shock income, and the characteristics of the household. However, conditional on household characteristics there may well be more than one steady state.

It is instructive to first examine some graphs of the relationship between income changes and initial incomes to see if there is any sign of multiple equilibria. Figure 2 shows a smoothed plot (a Lowess running-line smoother) based on the pooled sample of observations for all six years of the survey. On the vertical axis we graph the difference between current and last-year's income. The horizontal axis gives last-year's income. The intersections with the horizontal axis represent

equilibria at mean values of all other factors influencing incomes. There is only one stable equilibrium Y^* in the positive quadrant. For all households that had last-year's income less than Y^* the difference $Y_{(t)}$ -$Y_{(t\text{-}1)}$ is positive. Over time, the income of such households will increase until it reaches Y^*. Households with income in the previous year greater than Y^* will experience a decline in income over time, and their income will stabilize at Y^*.

It can be seen from Figure 2 that the relationship is quite flat in a neighborhood of the equilibrium. Consider the interval between the median and $2Y^*$ minus the median (i.e., a symmetric interval around Y^*). On the lower side of Y^* (with rising incomes), the slope is about -0.15, equivalent to an autoregression coefficient of 0.85. The slope is about twice as high on the side with falling incomes, implying an autoregression coefficient of 0.70. The slope tends to rise at low incomes, implying lower serial correlation.

Figure 2 suggests considerable stickiness (high serial correlation) in household incomes in a neighborhood of the steady state equilibrium. Modest transient shocks from equilibrium could thus entail quite long-lasting effects, given this pattern in the income dynamics. This does not arise from multiple equilibria, but rather serial dependence of incomes in a region of the equilibrium. Consider a one-year only income loss at year 1 for a household at the steady state value indicated in Figure 2. With an autoregression coefficient of 0.7, about half this shock will still be evident in year 3 and one quarter in year 5.

The pattern in Figure 2 was also found when we stratified the sample into various household types. Figure 3 shows a non-parametric estimation of income dynamics for male and female headed households. While income trajectories for these two types of households look similar, the point of a stable equilibrium for the households headed by females is associated with the lower level of household income.

Figure 4 gives the results stratified by the educational level of the household head. Again, there is only one point of stable equilibrium in the positive quadrant of ($Y_{(t)}$, $Y_{(t\text{-}1)}$) space for each type of household. The equilibrium level of income almost coincides with the median income for households whose head has a high-school-only level of education. For such households one would expect to observe both downward and upward income mobility. For households with higher levels of education, the equilibrium levels of income exceed the median incomes, and this difference is

larger for the households where the head holds a university degree. More than half of these households experience upward income mobility in the absence of income shocks.

5. Econometric model

To further investigate household income trajectories with a broader set of controls, and to allow for attrition, we need an econometric model. Total household income $Y_{(t)}$ at time t is assumed to be a smooth non-linear function $f(Y_{(t-1)}, X_t)$ of income $Y_{(t-1)}$ at time t-1 and the set of household characteristics (X_t), both permanent and time-variant, at period t. The simplest form of the non-linear relationship between $Y_{(t)}$ and $Y_{(t-1)}$ that can allow two equilibria in a positive quadrant as a general case is a third degree polynomial. That is what we assume.

Numerous consistent estimators for dynamic panel data models have been proposed in the literature, including IV type estimators (Balestra and Nerlove, 1966; Sevestre and Trognon, 1992; Anderson and Hsiao, 1982), FIML estimators (Bhargava and Sargan, 1983) and GMM estimators (Arellano and Bond, 1991; Arellano and Bover, 1995). However, none of these methods controls for panel attrition, which is clearly an important feature of the data, and may well be endogenous to the shocks and household characteristics. We estimate a dynamic panel data model of income dynamics with a control for panel attrition bias, treating lagged income as endogenous.

The system of equations for the six-year (1992-1997) panel of Hungarian data consists of five simultaneous equations of income dynamics for the years after the first, namely:

$$Y_{i(t)} = \gamma_0 + \sum_{m=1}^{3} \alpha_m Y_{i(t-1)}^m + X_{i(t)}\beta + \varepsilon_{i(t)} \quad (t = 1,\ldots,5) \tag{1}$$

where Y_{it} is the total income of household i in year t, $Y_{i(t-1)}$ is total income of household i in year t-1, X_t is a vector of exogenous variables, and the α's and β's are unknown parameters. The error terms are allowed to be serially dependent and correlated with lagged incomes. Following Bhargava and Sargan (1983), we also have an instrumenting equation that determines initial income (1992) as a function of the exogenous variables for all six years of the survey:

$$Y_{i0} = \xi_0 + \sum_{k=0}^{6} X_{k(i)} b_k + \varepsilon_{i0}, \tag{2}$$

where the b_k's are the vectors of coefficients on all exogenous variables.

To control for attrition bias, we estimate equations (1-2) simultaneously with the equation that determines whether the households that were selected in the sample in the first wave of the survey stayed in the panel until the end. The equation that controls for attrition has the form:

$$Z_i = X_{1i}\pi + \vartheta_i \qquad D_i = 1 \; if \; Z_i > 0$$
$$D_i = 0 \; otherwise$$
$$\Pr(D_i = 1) = \Pr(\vartheta_i > -X_{1i}\pi) = \Psi(X_{1i}\pi) \qquad (3)$$

where Z_i is a continuous latent variable that determines whether the household was in the sample in rounds 1 through 6 and D_i is an indicator variable that has value 1 if the household stayed in the sample all six years and has the value 0 otherwise, X_{1i} is the vector of explanatory variables from the first wave of the data and Ψ is the cumulative normal distribution function.

To estimate the system of simultaneous equations (1)-(3) we use a Semi-Parametric Full Information Maximum Likelihood method (Heckman and Singer, 1984; Mroz and Guilkey, 1992; Mroz, 1999). A five-factor specification is used to approximate an unrestricted error structure for equations (1)-(3). The Appendix describes our estimation method in detail.

The set of exogenous variables includes: household size, number of children under 7 years of age, number of children 7-16 years, number of elderly people, type of locality where the household resides, gender and educational level of the household head, and some household asset indicators. Endogenous variables consist of the polynomial of lagged income. Values of the exogenous and endogenous variables are normalized to be in the [0,1] range.

For comparison, we also estimate (1)-(2) without the correction for attrition. The econometric specification is then a simplification of the model described above (see Appendix).

6. Results

Table 2 gives our estimates of equation (1). Household composition, characteristics of the locality, and individual characteristics of the household members affect total income. The estimated parameters on the X variables have the signs one would expect. Larger families tend to have higher income, households with children are significantly poorer than households with no children,

households from Budapest are better off than households in other rural and urban areas of Hungary and in rural Hungary. Households for which the head has a university degree have higher income, families with access to land and households that own a car are better off. The presence of people aged 60-69 has a negative impact on the level of total household income.

Table 3 gives the equation for attrition. There some significant demographic, life-cycle and geographic effects. Households with a middle-aged head were less likely to drop out, as were smaller households, and those not living in Budapest. However, the most notable feature is that initial income is not a significant predictor of attrition. We also tried adding squared and cubed terms in initial income, but these were individually and jointly insignificant.

We also tested whether negative income shocks lead to households dropping out of the panel. To test this we used the second year as the base, namely 1993, and added a variable for the change in income between 1992 and 1993. The coefficient on this variable was allowed to vary according to whether income increased or decreased between 1992 and 1993. There was no significant effect of an income change in either direction on the probability of staying in the panel; for an income decline, the z-score was 0.27, while for an income increase it was 1.77 which is not significant at the 5% level (though it does make it at the 8% level).

To interpret the income dynamics implied by the parameters of our cubic specification, let $q = \frac{1}{3}\beta - \frac{1}{9}\alpha^2$; $r = \frac{1}{6}(\alpha\beta - 3\gamma) - \frac{1}{27}\alpha^2$ where $Z + \alpha Z^2 + \beta Z + \gamma = 0$. If $q^3+r^2>0$ there will be one real root and two complex conjugate roots, if $q^3+r^2>0$ all roots are equal and at least two will be equal, and $q^3+r^2<0$ the equation will have three real roots. Given the values of the estimated coefficients, the cubic polynomial equation has three real roots. However, we find that in the positive quadrant there is only one point of equilibrium when setting all exogenous variables at their mean points. This equilibrium is stable.

The income paths are different for households with different characteristics, though the property of a single stable equilibrium still holds. For example, Figure 5 presents the simulated income dynamics for the households categorized by educational level of the head interacted with

whether the household lives in Budapest or not.[6] For each household category there is only one point of stable equilibrium in the positive quadrant. (This was true for other combinations of characteristics.) The equilibrium level of income for the households where the head holds a university degree and lives in Budapest is the highest. It is almost five times higher than the income level of households for which the head has no more than a high school diploma and does not live in Budapest.

Would there have been a low level unstable equilibrium without the safety net? We repeated this set of calculations setting all government transfers to zero. This ignores behavioral responses to the safety net, though if anything one would expect that they would make it even less likely that there is a nonconvexity at low levels, because pre-intervention incomes will probably not be as low as simply subtracting transfers would suggest. Again only one root was found in the range of the data.

7. Conclusions

Economic theory offers little support for the common assumption of linear income dynamics, whereby households inevitably bounce back in time from a transient shock. Indeed, one can construct theoretical models that exhibit nonlinear income dynamics, with low-level nonconvexities, such that a short-lived uninsured shock can have permanent consequences. Whether this exists in reality, and so might explain the seemingly persistent poverty that has emerged in many transition economies, is an open empirical question.

We have offered what we believe to be the first test. This entails estimating a dynamic model of incomes, allowing current income to be a nonlinear function of lagged income with endogeneous attrition from the survey. On implementing the test on household panel data for Hungary in the 1990s, we find evidence of nonlinearity in the dynamics of household incomes. However, we find

[6] The variables are scaled to be between 0 and 1 to minimize the likelihood of overflow and underflow and to improve the convergence properties of the optimization algorithm (see for example Judd, 1998).

no evidence in these data of low-level non-convexities. The data are not consistent with the existence of an unstable equilibrium at low incomes.

Our results suggest that households in this setting tend to bounce back from transient shocks. The adjustment process is clearly not rapid. Transient shocks can have relatively long-lasting impacts due to the evident stickiness of incomes. However, it does not appear likely that a short-lived shock can create permanent destitution.

Appendix: SPFIML estimation of equations (1)-(3)

Let the error terms of equations (1)-(3) have the form:

$$\varepsilon_{i(t)} = \mu_{i(t)} + \sum_{l=1}^{4} \rho_{(1t)} v^{l}_{(1i)} + \rho_{(2i)} v_{(2i)} \qquad (4.1)$$

$$\vartheta_i = \lambda_i + \rho_{(2i)} v_{(2i)} \qquad (4.2)$$

where $\mu_{i(t)}$ is a normal IID random variable, $v^{m}_{(1i)}$ are components (common factors) of the error term, which are uncorrelated with the observed exogenous variables of the model and uncorrelated with $\mu_{i(t)}$ but can be correlated with the lagged incomes in equations (1)-(2), and $v_{(2i)}$ is a common factor that is responsible for the correlation between the error terms arising from endogenous attrition. We introduce five-factor specification to be able to approximate an unrestricted error structure for equations (1)-(3).[7] Conditional on the value taken by the factors v_1 and v_2, the joint distribution of the error terms can be written as:

$$f(\varepsilon_{(0)},\ldots,\varepsilon_{(5)},\vartheta \mid v_1^1 \ldots v_1^4, v_2) = \Psi(\vartheta - \rho_2 v_2) \cdot \prod_{m=0}^{5} \frac{1}{\sigma_m} \varphi\left(\frac{\varepsilon_{(m)} - \sum_{k=1}^{K} \rho_1^k v_1^k - \rho_2 v_2}{\sigma_m} \right) \qquad (5)$$

where σ_m's are square roots of the variances of the error terms in equation (2), and $\boldsymbol{\varphi}$ is the probability density function of a standard normal distribution. If the cumulative distribution functions of v_1 is $F_1(v_1)$ and the cumulative distribution function of v_2 is $F_2(v_2)$, then the unconditional distribution of the errors is:

$$f(\varepsilon_{(0)},\ldots,\varepsilon_{(5)},\vartheta) = \int\int\int\int\int f(\varepsilon_{(0)},\ldots,\varepsilon_{(5)},\vartheta \mid v_1^1 \ldots v_1^4, v_2)\, dF_1^1(v_1^1) \ldots dF_1^4(v_1^4)\, dF_1(v_2) \qquad (6)$$

The cumulative distributions of the common factors v_1 and v_2 can be approximated by a step function. Suppose that the distributions of v_1 and v_2 are given by:

[7] For a discussion of the choice of the optimal number of factors, see Anderson and Rubin (1956).

$$\Pr(v_1^k = \eta_l) = p_l \geq 0;\ \sum_{l=1}^{L} p_l = 1 \quad (l = 1,\ldots,L;\ k = 1,\ldots 4) \qquad (7.1)$$

$$\Pr(v_2 = \gamma_l) = \pi_l \geq 0;\ \sum_{l=1}^{L} \pi_l = 1 \,(l = 1,\ldots,L) \qquad (7.2)$$

where η_k and γ_l are points of support of the approximated distributions, and k and l are the numbers of points of support. Then the unconditional distribution functions are:

$$f(\varepsilon_{(0)},\ldots,\varepsilon_{(5)},\vartheta) = \sum_{l=1}^{L}\pi_l \sum_{a=1}^{A} p_a \sum_{b=1}^{B} p_b \sum_{c=1}^{C} p_c \sum_{d=1}^{D} p_d \left[\frac{1}{\sigma_d}\psi\left(\frac{\vartheta-\rho_2\gamma_l}{\sigma_d}\right)\cdot\prod_{m=0}^{5}\frac{1}{\sigma_m}\varphi\left(\frac{\varepsilon_{(m)}-\rho_{1m}^1\eta_a-\rho_{1m}^2\eta_b-\rho_{1m}^3\eta_c-\rho_{1m}^4\eta_d-\rho_2\gamma_l}{\sigma_m}\right)\right] \quad (8)$$

and the corresponding log-likelihood function for the system of simultaneous equations is:

$$\Im = \sum_{i=1}^{N}\ln\left(\sum_{l=1}^{L}\pi_l \sum_{a=1}^{A} p_a \sum_{b=1}^{B} p_b \sum_{c=1}^{C} p_c \sum_{d=1}^{D} p_d \left[\frac{1}{\sigma_d}\psi\left(\frac{\vartheta-\rho_2\gamma_l}{\sigma_d}\right)\cdot\prod_{m=0}^{5}\frac{1}{\sigma_m}\varphi\left(\frac{\varepsilon_{(m)}-\rho_{1m}^1\eta_a-\rho_{1m}^2\eta_b-\rho_{1m}^3\eta_c-\rho_{1m}^4\eta_d-\rho_2\gamma_l}{\sigma_m}\right)\right]\right) \quad (9)$$

Choosing *a priori* a number of points of support, the log-likelihood is maximized w.r.t. the α's, β's, p's, ρ's, and v's. For identification, the two points of support of both factors are normalized to equal 0 and 1. The number of points of support is increased until the difference in the log-likelihoods after maximization satisfies the convergence criteria. Standard errors for the estimated coefficients can be calculated by inverting the Hessian of the second derivatives of the log-likelihood function $\Im$.

In estimating (1)-(2) without the correction for attrition (for comparison purposes), the econometric specification is a simplification of the model developed above such that only one common factor v_1 is used for the approximation of the joint distribution of $\epsilon_{(0)},\ldots,\epsilon_{(5)}$.

The following functional forms were assumed in estimating the probability weights and the points of support:

$$\pi_{mn} = \frac{\exp(b_{mn})}{1+\sum_{1}^{N-1}\exp(b_{mn})} \quad n = 1,\ldots,N-1;\ m = 1,2 \qquad \pi_{mN} = \frac{1}{1+\sum_{1}^{N-1}\exp(b_{mn})}$$

$$v_{mn} = \frac{\exp(a_{mn})}{1+\exp(a_{mn})} \quad n = 2,\ldots,N-1;\ m = 1,2 \qquad v_{m1} = 0;\ \ v_{mN} = 1$$

where a_{mn} and b_{mn} are the actual parameters estimates by the optimization routine.

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Table 1: Recovery times after a negative income shock

Recovery time	Any shock	Small shock[1]	Medium shock[2]	Large shock[3]
	Percentage of households			
1 year	37.8	46.6	37.0	16.7
2 years	8.5	10.2	5.5	5.1
3 years	3.3	3.6	3.5	1.9
4 years	3.1	4.1	3.5	3.2
Not recovered after 5 years	47.3	35.5	50.5	73.1
Total	100.0	100.0	100.0	100.0

[1] Small shock: 10 percent or lower decline in total household income
[2] Medium shock: 10-30 percent decline in total household income
[3] Large shock: 30 percent or larger decline in total household income

Table 2: SPFIML estimate of the household income equation

	Estimation without the correction for attrition bias		Estimation with the correction for attrition bias	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	0.015	*0.707*	0.052	*3.421*
Lagged income	0.569***	*0.041*	0.806***	*0.051*
Lagged income square	0.033*	*0.022*	0.234***	*0.019*
Lagged income cubed	-0.014***	*0.003*	-0.016***	*0.003*
Household size	0.963***	*0.061*	1.101	*0.082*
Number of males 60+	-0.045	*0.073*	-0.143*	*0.061*
Number of females 55+	-0.262*	*0.119*	-0.209*	*0.150*
Number of small children	-0.478***	*0.074*	-0.572***	*0.080*
Number of big children	-0.441***	*0.068*	-0.510***	*0.043*
Single parent household	0.009	*0.025*	0.017	*0.025*
Other types of households	*Reference*			
Type of locality				
Budapest	*Reference*			
Other urban	-0.087***	*0.012*	-0.102***	*0.008*
Rural	-0.102***	*0.013*	-0.243***	*0.010*
Education of household head				
Highschool	-0.096***	*0.015*	-0.095***	*0.022*
Technical/Vocational	-0.077***	*0.014*	-0.090***	*0.022*
University degree	*Reference*			
Gender of household head				
Male	0.001	*0.016*	-0.001	*0.022*
Female	*Reference*			
Age of household head				
Age	0.481**	*0.160*	0.232	*0.209*
Age squared	-0.451**	*0.151*	-0.201	*0.200*
Own land	0.042**	*0.013*	0.044***	*0.020*

Note: * is significant at 10% level; ** at 5% level; *** at 1% level.

Table 3: Probability of attrition

	Coefficient	Std. Error
Constant	-2.153***	0.333
Total household income in 1992	-0.018	0.022
Household size	-0.085**	0.033
Number of males 60+	0.124**	0.050
Number of females 55+	0.128	0.092
Number of small children	0.209***	0.044
Number of big children	0.021	0.038
Single parent household	0.178	0.148
Other types of households	*Reference*	
Type of locality		
Budapest	*Reference*	
Other urban	0.255***	0.066
Rural	0.299***	0.073
Education of household head		
Highschool	-0.081	0.071
Technical/Vocational	-0.080	0.072
University degree	*Reference*	
Gender of household head		
Male	0.100	0.100
Female	*Reference*	
Age of household head		
Age	0.07***	0.010
Age_2/100	-0.06***	0.01
Own land	0.15**	0.08

Number of observations = 2356 LR $\chi^2(15) = 88.75$ Prob > $\chi^2 = 0.0000$
Log likelihood = -1515.032 Pseudo $R^2 = 0.0285$

Note: * is significant at 10% level; ** at 5% level; *** at 1% level.

Figure 1: Income dynamics with a nonconvexity at low income

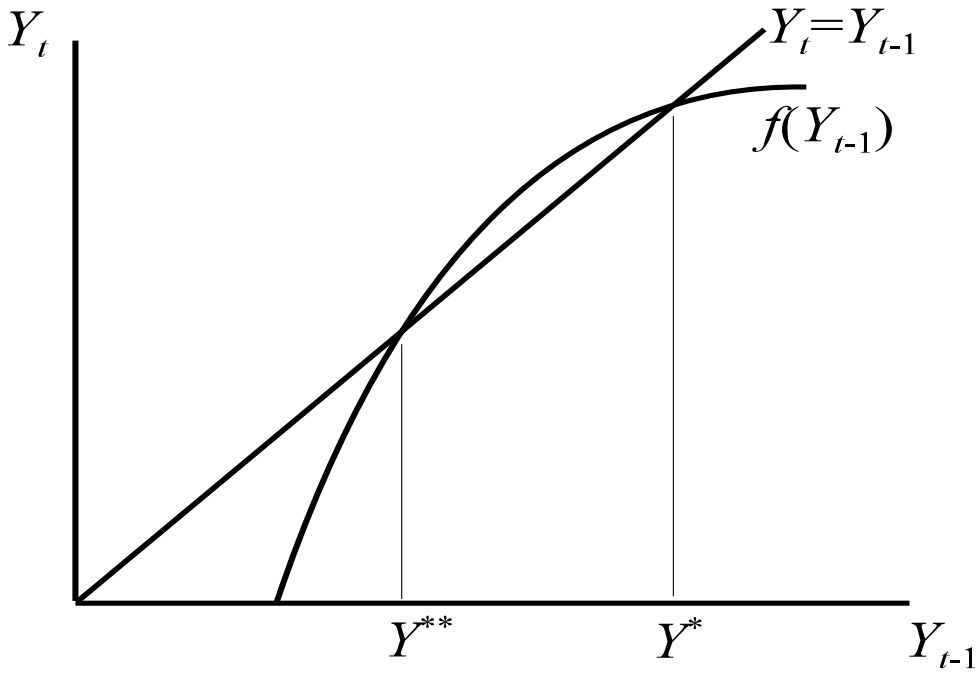

Figure 2: Non-parametric estimation of income dynamics in Hungary

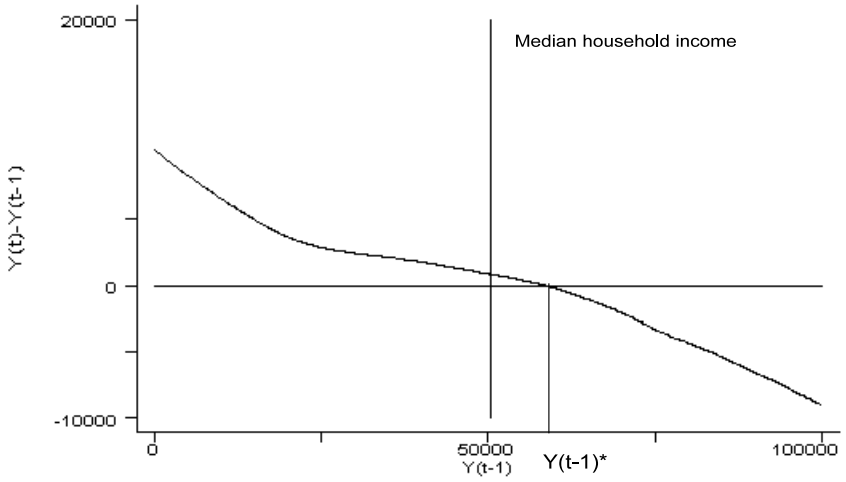

Figure 3: Non-parametric estimation of income dynamics by the gender of the household head

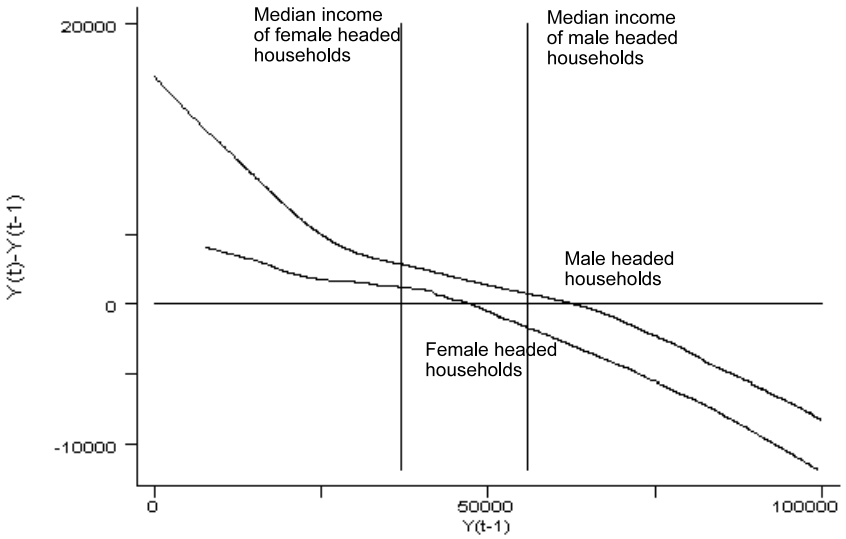

Figure 4: Non-parametric estimation of income dynamics by the education level of the household head

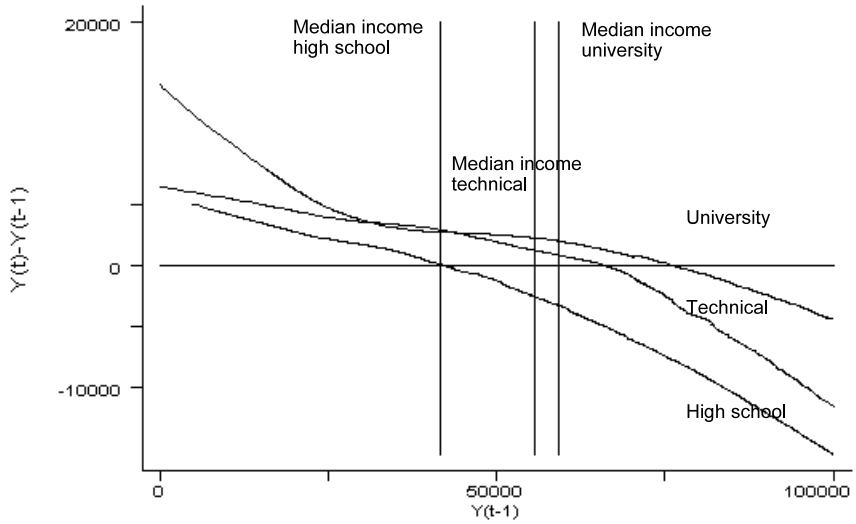

Figure 5: Simulated income dynamics from the econometric model for households with different levels of education and in Budapest versus other regions