VOL. 6 NUM. 1 FIRST SEMESTER 2010

Well-being and Social Policy

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Well-being and Social Policy VOL. 6 NUM. 1 FIRST SEMESTER 2010

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WELL-BEING AND SOCIAL POLICY
VOL 6, NUM. 1, pp. 95-129

DO SHOCKS AFFECT POVERTY PERSISTENCE? EVIDENCE USING WELFARE TRAJECTORIES FROM NICARAGUA

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Abstract

Shocks are often primarily associated with downward mobility or short-term movements in and out of poverty. However, households at the bottom of the welfare distribution are likely to face the most constraints to access insurance mechanisms. In this paper, we consider whether shocks directly affect poverty persistence. In order to analyze the impact of shocks on households' welfare path over time, we define trajectories as the sequence of households' position along the welfare distribution as time unfolds. Trajectories provide a consistent representation of households' mobility when the first-order Markov assumption is violated. In a three-round Nicaraguan panel, we assess the role of shocks in driving two specific mobility patterns. We confirm that shocks contribute to downward mobility, but find novel and robust evidence that shocks trigger poverty persistence, preventing upward movement from the bottom of the distribution. This result points to large potential gains from social risk management policies targeting not only the vulnerable non-poor, but also and in priority the poor.

Keywords: Economic mobility, poverty persistence, shocks, Nicaragua.
JEL classification: I32, O10, D30.

* This paper builds on material prepared for the research study "Strategies to Address Extreme Poverty in Low Income Countries: Balancing Prevention and Protection", funded by the Human Development Network, Social Protection Group, World Bank. The findings, interpretations, and conclusions expressed in this paper are entirely ours. They do not represent the views of the International Bank for Reconstruction and Development/ World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.
We are grateful to Stefan Dercon, Steve Bond, Chris Elbers, Valerie Kozel, Gaston Yalonetzky, Catherine Porter, Ximena del Carpio, and two anonymous referees for comments and suggestions. We are solely responsible for all remaining errors.

Introduction

Developing countries form environments prone to multiple risks, such as price volatility, natural disasters, climatic instability or illness. The very presence of ex ante risk affects households' welfare and directly contributes to poverty persistence through costly risk-management strategies (Fafchamps, 2003; Elbers et al., 2007). In the absence of complete insurance markets, households typically skew their income portfolio towards low-risk low-return assets or activities (Deaton, 1991; Rosenzweig and Binswanger, 1993; Morduch, 1995; Dercon, 1998).

Households' welfare still exhibits significant variations over time (Baulch and Hoddinott, 2000). Shocks—the realization of risk—have been singled out as a key determinant of welfare dynamics. Shocks can have heterogeneous dynamic impacts depending on the specification (and interplay) of the underlying welfare generating process and households' access to insurance mechanisms.

Shocks are often primarily seen as leading to households' mobility in the short-term. Movements in and out of poverty are captured by the concept of "transient poverty" (Jalan and Ravallion, 2000). The contribution of shocks to "transient poverty" highlights their impact on driving temporary downward mobility for the vulnerable non-poor. Such short-lived impacts rely on a welfare-generating process supporting relatively fast recovery from adverse events or households' access to non-costly insurance mechanisms.

A growing literature has suggested that shocks can have deeper and more long-lasting impacts, however. Shocks can generate welfare descent by directly depleting assets (Carter et al., 2004; McPeak, 2004) or triggering coping mechanisms involving decapitalization of productive assets (Rosenzweig and Wolpin, 1993; Zimmerman and Carter, 2003) or human capital (Jacoby and Skoufias, 1997; Dercon and Hoddinot, 2004). Depending on how the welfare-generating process is modeled, shocks can lead to slow recovery or even poverty traps (Barrett and Carter, 2006). Recent empirical studies have highlighted that shocks can impact on welfare dynamics beyond the short-term (Dercon, 2004; Jalan and Ravallion. 2004; Lokshin and Ravallion, 2004).

Much of the work on the long-term impact of shocks has focused on downward mobility of the vulnerable non-poor, which is perhaps best illustrated by research on poverty traps (Barrett, 2005; Barrett and Carter, 2006). This attention is legitimate given shocks can lead the vulnerable non-poor into permanent poverty in the presence multiple equilibria or non-convexities in the underlying welfare process.

Still, the consumption smoothing literature suggests that it is households at the very bottom of the welfare distribution who are likely to face the most constraints to access formal and informal insurance mechanisms. "Moral hazard and enforcement problems may be more likely to hurt poorer households" (Morduch, 1995, p.112). The poor are also more often credit-constrained or excluded from informal arrangements based on reciprocation.[1] Even if shocks are partially insured, non-poor

[1] Jalan and Ravallion (1999) indeed find that the poor are less well insured. Here, we focus on the dynamic link between shocks and poverty persistence.

households might still have access to less costly coping mechanisms. In addition, the horizon at which the impact of shocks unfolds can vary between the poor and the non-poor: shocks impacting on welfare can have more temporary effects on better-off households than on the poor.

This paper tackles the crucial but often overshadowed role of shocks as a direct cause of poverty persistence.[2] While we do consider whether shocks affect downward mobility of the vulnerable non-poor, the main contribution of this paper is to fill a gap in the literature by formally testing for the possibility that shocks trigger poverty persistence. In doing so, we bridge the consumption smoothing literature—which suggests the poor are less well insured—and the literature on poverty dynamics—which primarily associates shocks with short-run movements in and out of poverty or downward mobility of the vulnerable non-poor.

By analyzing the differentiated impacts of shocks on poverty persistence and downward mobility, we take a distributional perspective.[3] Heterogeneous effects along the welfare distribution are unveiled through a mobility approach, although at the cost of a discretization of the welfare space (Atkinson et al., 1992). For instance, poverty transition profiles consider whether factors associated with upward and downward mobility mirror each other (Jalan and Ravallion, 2000; Sen, 2003; Krishna, 2006). While standard profiles are often deterministic, we focus on the distributional impacts of shocks. As we will discuss, shocks can better lend themselves to causal interpretation. The impact of shocks on mobility depends on the effectiveness of insurance mechanisms to which households have access to. Full insurance contributes to immobility in the welfare distribution (Fafchamps, 2003), so that regions of the distribution where shocks explain mobility indicate where insurance mechanisms are most limited.

In order to explore these issues, we use a unique three-round panel from Nicaragua spanning 1998-2005, a setting marked by substantial exogenous climatic and economic shocks. We define three-period trajectories {ijk} as the sequence of households' position along the welfare distribution (by tercile, i.e. i,j,k=1,2,3)[4] over time. Trajectories are appealing for two key reasons. First, they provide the most general description of mobility in a three-round panel. Second, three-period trajectories do not rely on the first-order Markov assumption and as such yield a consistent representation of households' mobility. Indeed, while round-to-round transition matrices constitute the standard tool to study mobility and poverty dynamics in developing countries, they are only an appropriate representation of the underlying welfare process under a first-order Markov assumption. In our data, we explicitly test for the order of the underlying Markov chain, rejecting first-order against second-order.

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[2] We prefer using the term poverty persistence since "chronic poverty" has come to encompass broader definitions (Hulme, 2003; Hulme and Shepherd, 2003).

[3] Indeed, the typical approach in the literature has been to estimate growth regressions, which by design assume full symmetry in the direction of the change. Our approach accounts for changes in both levels and direction.

[4] As we will discuss, the sample is split in terciles in the first round, and the same absolute cut-offs used in the last two rounds. In practice, since the distribution is very stable over the three rounds, this is similar to a relative distributional analysis.

Our empirical analysis focuses on the role of shocks as triggers of two specific mobility patterns in the trajectory universe: downward mobility ({ijk}, with i>k)[5] and, centrally, poverty persistence ({111}).[6] We therefore evaluate the impact of shocks on the probability that a household exhibits a specific trajectory. In order to explore causality, we adapt matching techniques in our framework to isolate the potential impact of shocks. This ensures that households affected by shocks are strictly compared to non-affected households with similar pre-shock characteristics. Under the assumption that there is no selection on unobservables, the approach can consistently estimate the causal effect of shocks on trajectory patterns (Imbens, 2004).

Our results confirm that shocks drive downward mobility, but, most importantly, suggest a large impact of shocks on poverty persistence. This finding is consistent with increasing access to insurance mechanisms along the welfare distribution. It is also in the spirit of Jalan and Ravallion (2004), who conclude that "the speed of recovery from an income shock is lower for the poor" (p.1). Yet our results are the first we know that explicitly link shocks with poverty persistence. These results therefore suggest large potential gains from social risk management interventions targeting not only the vulnerable non-poor, but also and in priority the poor.

The structure of the paper is as follows. Section 1 defines and motivates our concept of welfare trajectories. Section 2 presents the estimation strategy to analyze the impact of shocks on welfare trajectories. Section 3 introduces the Nicaraguan panel and describes the frequency distribution of three-period trajectories. Section 4 contains the empirical analysis of the role of shocks as determinants of downward mobility and poverty persistence. Section 5 concludes. Tables are presented in the Annex.

1. Defining Poverty Persistence through Welfare Trajectories

When it comes to analyzing poverty dynamics, stochastic time-series and duration (or spell) approaches are usually applied based on long panels from developed countries. In the stochastic time-series approach, "given heterogeneity and serial correlation, knowledge of an individual's poverty history is very useful in predicting his poverty status in a given year" (Lillard and Willis, 1978, p.1002). Similarly, Stevens (1999) findings can be seen as typical from the spell approach: "the probability of exiting poverty declines as time in the poverty spell increases" (p.9). The most important feature of hazard models is to point to the existence of duration dependent exit probabilities. Non-permanent shocks can lead to such duration dependent exit probabilities (Bane and Ellwood, 1986).[7]

[5] The analysis of mobility triggers contrasts with the measurement of aggregate mobility, often the principal focus of the mobility literature (Fields and Ok, 2001).

[6] Section 1.2 shows that the consumption distribution remains very stable and thus that flat trajectories at the bottom of the distribution can characterise "absolute" poverty in our data.

[7] The empirical literature on poverty and risk suggests that shocks from the past can indeed have persistent impacts (Dercon, 2004). Our results will provide another example.

In the absence of long term panel data (which is commonly true in developing country settings), a Markovian framework provides an alternative to study welfare dynamics. Specifically, we define "welfare trajectories" as the sequence of households' position along the welfare distribution as time unfolds. With three rounds of data (t=3), trajectories take the form {ijk}, where i,j,k correspond to each household's position along the welfare distribution in period 1 (i), period 2 (j) and period 3 (k). Households who exhibit similar trajectories thus share the same position in a 3-dimensional transition cube.

A few studies have offered typological classifications of households' trajectories. In the context of developed countries, Jarvis and Jenkins (1997), Gardiner and Hills (1999) or Rigg and Sefton (2006) present a characterization of trajectories but their analysis of trigger events is limited to demographic changes. Life history studies take a similar approach based on qualitative data (Davis, 2009; Narayan et al., 2009).

There are many reasons why our definition of "welfare trajectories" is useful. First, from a descriptive standpoint, trajectories constitute the most comprehensive presentation of households' mobility patterns in a three-round panel. The universe of welfare trajectories traces all possible mobility outcomes. The related frequency distribution displays all the information contained in the data. Any analysis based on a subsequence of the general trajectories relies on specific restrictions. Such restrictions can be made on practical, normative or structural grounds.

Second, on practical grounds, some empirical mobility analyses consider trajectories spanning large time-windows in order to characterize longer-term welfare trends. In fact, Baulch and Hoddinott (2000) suggest using the word "trajectories" to analyze mobility over long time periods. This could be seen as considering a subsequence {ik} ($\forall$j) of the general trajectory universe {ijk}.

The entire path of households' welfare might be of interest in its own right. This is illustrated by recent work expanding poverty measurement over multiple periods (Calvo and Dercon, 2009; Foster, 2009), which use normative criteria in order to collapse "trajectories of the standard of living in one single index of intertemporal poverty" (Calvo and Dercon, 2009). The derived cardinal value of intertemporal welfare provides an appealing summary measure ex post. The approach amounts to weighting the diversity of information contained in the trajectory universe based on normative criteria.

Finally, the underlying structure of the welfare process can also justify simplifications of the general trajectory universe. Round-to-round transition matrices can be seen as particular cases of the general trajectory definition. Under a first-order Markov assumption, the monadic round-to-round matrices {ij} and {jk} suffice to yield an appropriate representation of the underlying welfare process. By contrast, deviations from the first-order Markov assumption provide a structural reason for the consideration of welfare trajectories. This more general motivation is fundamental for the consideration of trajectories.

In fact, the first-order Markov assumption is often taken for granted in empirical mobility analysis. Traditional round-by-round transition matrices constitute a particular form of trajectory: {ij} between the first two rounds, {jk} between the last two rounds and {ik} between the first and last rounds. The omission of information for one round is not innocuous: traditional round-to-round transition matrices only consistently model the underlying welfare process if a first-order

Markov assumption is satisfied: "…individuals in income class j at time t have the same transition probabilities regardless of their past history" (Shorrocks, 1976, p.567). The Markov assumption implies that the best possible future prediction for an outcome variable at time t+1 does not contain information prior to time t. While this assumption is often implicitly made when transition matrices are used, it might clearly not hold in practice.[8] As such, the type of dynamics supported by first-order Markovian models is restricted to state dependence, "the extent to which the experience of low income one year raises the risk of having low income in the following year" (Capellari and Jenkins, 2002, p.C60). State dependence relates to a first-order autoregressive model and is clearly very different from persistence:[9] "It should be noted that the transition probabilities in our model are not Markovian because the individual's probability of poverty in period r is affected not only by his poverty state in period t but also by his entire history of poverty states prior to t" (Lillard and Willis 1978, p.999). However, absence of persistence is not a "Markovian" property stricto sensu, but rather a limitation in the widespread use of first-order chains. The lack of sensitivity of first-order models to persistence can be relaxed by considering higher-order Markov models.

In this paper, we consider "welfare trajectories" {ijk} over the three rounds of our data. We focus on the role of shocks as mobility triggers, exploring how shocks affect two specific patterns from the trajectory universe: poverty persistence ({111}) and downward mobility ({ijk}, with i>k). We turn to this in the next section.

2. Estimation Strategy

We denote T a binary variable indicating whether a household exhibits each of the two trajectories of interest. In analyzing poverty persistence, T=1 for households with trajectories {111}, and T=0 for households exhibiting trajectories $\{1jk\},\forall(j,k)\neq(1,1)$. When tackling downward mobility, T=1 for households with trajectories {ijk} $(i>k, i=2,3,\forall j)$, and T=0 for households exhibiting trajectories $\{ijk\},(i\leq k, i=2,3,\forall j)$. For example, a household with trajectory {331} indicates a household that belonged in the highest welfare tercile for the first 2 periods and at the lowest in the third.

In general, the impact of shocks on trajectories can be analyzed in a probit model, based on the following specification for the latent variable equation:[10]

$$T^*_{i,t} = \alpha X_{i,t-2} + \beta S_{i,t-2} + \gamma S_{i,t-1} + \delta S_{i,t} + \varepsilon_{i,t} \qquad (1)$$

[8] As we show below, when applying Anderson and Goodman's (1957) test that a Markov chain is first-order over second-order using our data, we reject the null hypothesis of a first-order Markov chain (Section 4.1).
[9] Stevens (1999) stress the link between the Markov and duration approach: "A two-state first order Markov transition model (…) can be interpreted as discrete-time hazard rate regression model in which, crucially, it is assumed that there is no duration dependence in either the exit of entry transition rate" (p.557).
[10] *i* denotes a household subscript. $X_{i,t-2}$ includes a constant.

X_{t-2} denotes the vector of baseline characteristics, S_{t-2} shocks at or before the baseline, S_{t-1} shocks between the first two rounds of the data, and S_t shocks between the last two rounds. A given trajectory is observed when the latent variable is positive:

$$T_{i,t} = \begin{cases} 1 & \text{if} \quad T^*_{i,t} > 0 \\ 0 & \text{otherwise.} \end{cases} \qquad (2)$$

Unbiased estimates for the role of shocks on trajectories also assume:

$$\varepsilon_{i,t} \,|(X_{i,t-2}, S_{i,t-2}, S_{i,t-1}, S_{i,t}) \sim N(0,1) \qquad (3)$$

Given that assumption (3) is unlikely to hold (at minimum due to the discussion above), our preferred empirical approach uses matching methods based adapted from the program evaluation literature. Conceptually, in order to identify the effect of shocks on trajectories, one needs to estimate what would have happened to a particular household if - all else equal - an event happened compared to the case where the event did not happen. The matching approach attempts to replicate this counterfactual analysis. Households that are observationally similar at the beginning of the panel but who do not suffer from the same incidence of shocks are compared. If they indeed share the same counterfactual welfare path, the procedure identifies the causal effect of the treatment (a shock in our analysis).

In order to implement this, we use Abadie and Imbens (2006) nearest-neighbor covariate matching estimator.[11] Each treated unit is matched to a fixed number of untreated units with similar values for the baseline variables.[12] "The average effect of the treatment is then estimated by averaging within-match differences in the outcome variable between the treated and the untreated units" (Abadie and Imbens, 2006, p.236). The covariate matching method ensures homogeneity in initial conditions and yields estimates for the impact of subsequent shocks. The approach aims at

[11] Imbens (2004) and Zhao (2004) discuss various matching estimators, stressing the choice between them remains an issue far from settled in the literature. Abadie and Imbens' (2006) estimator has relatively transparent theoretical foundations. In covariate matching, households are matched directly based on a set of covariates. This contrasts with propensity-score matching where households would be matched based on how the covariates predict shocks' incidence. Propensity score matching estimators tackle the curse of dimensionality by summarizing multivariate initial conditions into a scalar (Rosenbaum and Rubin, 1983). Yet the approach remains unsatisfactory when the propensity score is unknown (Imbens, 2004). In particular, estimation of the propensity score is highly sensitive to the choice of the covariate set (Heckman and Navarro-Lozano, 2004). When participation to a social program constitutes the treatment, propensity scores are typically estimated based on the targeting criteria for the program under study (Angrist, 2006). Estimation of the propensity score is more problematic in absence of clear practical or theoretical guidance as to which covariates to consider. In addition, Zhao (2004) suggests that covariate matching is more robust than propensity score matching when the correlation between the covariates and treatment indicator is low (in presence of multiple covariates).
[12] The distance metric is computed from the diagonal matrix of the inverse of the covariate variances.

isolating the effect of shocks beyond households' baseline characteristics on which the matching is performed.[13]

The probit regression and matching methods share the same underlying assumption: selection only occurs on observable characteristics and no unobservable characteristics determine whether an individual suffer from a shock or not. It remains that matching has noteworthy advantages over a regression approach.[14] The regression framework assumes linearity, which constraints the treatment effect to be constant across households with different characteristics (as in Equation (1)). As a result, regression estimates can be inaccurate if treatment and comparison groups are dissimilar (Dehejia and Wahba, 1999; Imbens, 2004). This is important for two reasons. First, we take seriously the possibility that shocks' incidence is not necessarily fully random. In this sense, relaxing the assumption of linearity means that matching goes a step further than the regression approach in allowing the identified impacts to be interpreted as causal. Second (and related), matching relaxes the dependence of the estimated effects on the functional form of the model (Ho et al., 2007). This is particularly important given the empirical nature of Equation (1) and the degree of model uncertainty associated with it. For all these reasons, matching estimates constitute our preferred results and offer the best scope for interpretation of estimated effects as causal.

We focus on two binary outcomes: poverty persistence and downward mobility. The effect of each element of a set of shocks on the probability of exhibiting the trajectory of interest is estimated by comparing the average realization of the outcome between treated (affected by a shock) and comparison (non-affected by a shock) households. This impact can be considered as causal in absence of unobserved heterogeneity correlated with shocks, an issue that will be further discussed below. The matching procedure is implemented for the same control characteristics[15] as in probit estimates based on Equation (1), and estimates are obtained successively for each shock variable.[16]

In testing whether shocks are positively associated with poverty persistence and downward trajectories, their timing is important for interpretation. Trajectories are defined over three rounds of data (t-2, t-1 and t). While shocks between t-2 and t constitute within-sample shocks, shocks at (or prior to) t-2 represent pre-sample shocks and can also affect initial conditions. Table 1 summarizes the expected impacts that can be identified depending on the timing of each shock and its persistence. Pre-sample shocks embodied in S_{t-2} can generate a temporary shortfall limited to initial conditions, which could then diminish the probability of a household remaining in poverty or exhibiting a downward trajectory ($\beta \leq 0$). Alternatively, shocks prior to the baseline can have a persistent impact in driving "adverse" trajectories over the next two-rounds ($\beta > 0$). By contrast, the impacts of within-sample shocks on poverty persistence or downward trajectories are expected

[13] Mobility studies often test whether mobility regimes differ between population subgroups (e.g. gender or ethnicity). In the analysis of trigger events, matching estimators can be used in order to condition on a broader set of initial conditions, as such ensuring "population homogeneity".
[14] See Imbens (2004) for a general overview of the regression and matching approaches.
[15] This includes other shocks given observed shocks are not orthogonal to each others.
[16] Matching is performed on 4 nearest-neighbors, the case used by Abadie et al. (2004). Given Abadie and Imbens (2006) estimator can be biased in presence of continuous control variables, the bias-adjustment method they advocate is implemented.

to be non-negative. Within-sample shocks in the second data round (S_{t-1}) can either have a temporary short-term impact in round 2 (which would be consistent with γ=0) or a lasting impact until round 3 (γ>0). Finally, if a positive impact is expected for shocks observed in the last round of data (δ>0). The identification of a positive coefficient cannot inform whether the effect is persistent or transitory, however.[17] Below, we test for the impact of a set of shocks and consider the persistence consistent with the observed coefficient, both for downward mobility and poverty persistence.

3. Data

3.1 Three-period trajectories in Nicaragua

The empirical analysis of shocks' impact on welfare trajectories is based on three rounds of Nicaraguan Living Standards Measurement Surveys (LSMS) collected in 1998, 2001 and 2005. The first two waves of the panel were implemented in the summers of 1998 and 2001, the last one during the late summer of 2005.[18] 2485 panel households have complete consumption data in all years. Since the main focus is to study welfare mobility, the analysis is limited to households that remain in the panel.[19]

The Nicaraguan economy has been significantly shaped by risk and offers a natural context to analyze the impact of shocks on households' mobility. The panel is of particular interest since it spans a period characterized by large shocks which had heterogeneous impacts: droughts due to El Niño, Hurricane Mitch, as well as the collapse of international coffee prices. Measures for these shocks will be presented in section 3.2.

Traditional descriptive statistics for aggregate welfare changes over the survey period are presented in Table 2. The consumption aggregate used as welfare indicator contains both food and non-food consumption.[20] The consumption distribution remains very stable over the three

[17] Note that the lasting effect of unobserved shocks prior to the survey might die out over the panel period and as such explain lower occurrence of adverse trajectories. Such unobserved prior shocks will not bias the estimated impact of observed shocks as long as the two sets are orthogonal.
[18] Most data collection for the 1998 and 2001 surveys happened between May and July, but the 2005 survey was delayed to the July-October period. We do not explore seasonal effects here, but World Bank (2008) suggest they are minimal.
[19] Attrition is discussed in Section 4.4.3.
[20] The construction of the consumption aggregate is detailed in Castro-Leal and Sobrado (2001) and Sobrado (2001, 2003). The food component aggregates the value of food purchased at home and outside of home, as well as non-purchased food obtained from own production or gifts. The non-food component covers housing costs (proxied by a self-reported or estimated monthly rent), expenditures on health, education, consumer goods and household services (water, garbage collection, electricity, cooking fuel, non-electric lighting, and telephone), as well as the annual use value of durable goods (The use value of durable goods is estimated by dividing the current value of a durable good by its remaining useful lifetime (twice the estimated average age for each good under study (Sobrado, 2001)). The consumption aggregate is expressed per capita in 1998 prices and corrected for geographical price variations.

rounds of the data. Average annualized consumption growth amounts to 1.5% between 1998 and 2001 but -0.8% between 2001 and 2005.

Aggregate patterns for the consumption distribution translate into changes in poverty profiles (Table 3).[21] Poverty decreases between 1998 and 2005, mainly driven by the 1998-2001 spell. While there is some upward mobility out of extreme poverty, most of it is driven by mobility from extreme poverty to moderate poverty in 1998-2001.

In order to operationalize the trajectory concept introduced in section 1, we use tercile cut-offs from the baseline distribution of consumption expenditures (i,j,k=1,2,3). Since the complete trajectory universe can be traced, tercile division constitutes a compromise between the necessity and shortcomings of collapsing the diversity of trajectory patterns. The sample is split into terciles in round 1 and the same real absolute cut-offs are used to divide the sample in rounds 2 and 3. By focusing on absolute mobility, households in the lowest tercile can be interpreted as poor in an absolute sense: the bottom cut-off falls between the extreme poverty line and the general poverty line.[22] For the purpose of this paper, we therefore use a definition of poverty that is a bit more conservative than the official definition, but the subdivision by tercile has the advantage of maintaining the symmetry of the trajectory universe. Since the aggregate consumption distribution remains very stable over the three-rounds, absolute mobility patterns can also be interpreted as relative distributional changes. Robustness checks considering alternative cut-offs are presented in section 4.4.2.

The sample frequency distribution from the trajectory universe is described in Table 4. Unconditional absolute and relative frequencies are displayed for each consumption trajectory. Flat trajectories at the top, bottom and middle of the distribution are the most frequent ({333}, {111}, {222}). Trajectories exhibiting one-tercile improvements ({233}, {223}, {122}, {112}) or one-tercile drop ({332}, {322}, {221}, {211}) are relatively frequent. Some "broken" trajectories are also common ({232}, {212}, {323}, {121}), but generally rarer, together with steady paths upward or downward.[23] The main trajectory patterns are summarized in Table 5. 16.9% of panel households are persistently poor ({111}) while 19.8% exhibit downward mobility.[24]

[21] Consumption-based poverty lines are computed from the household survey (Castro-Leal and Sobrado, 2001; Sobrado, 2003). The extreme poverty line (2489 cordobas in 1998 prices) represents the cost of the minimum caloric requirement recommended for Nicaragua using the observed consumption food basket and prices in the survey. The general poverty line (4223 cordobas in 1998 prices) adds an allowance for the consumption of nonfood goods and services.

[22] To repeat, the extreme and general poverty lines amount to 2489C$ and 4233C$ in 1998. The bottom tercile cut-offs are the following: 3384.53C$ for 1998, 3677.15C$ for 2001 and 3425.70C$ for 2005 (all figures in real 1998 cordobas, average cordoba-dollar exchange rate in 1998: 10.58C$).

[23] Since the trajectory universe is symmetric, a formal test of trajectory symmetry could provide another way to characterise the observed trajectory frequency distribution. This test could extend the traditional X^2 test of mobility symmetry in transition matrices (Atkinson et al., 1992).

[24] Downward mobility captures trajectories where the last (third) spell is lower than the first ({ijk}, with i>k: {321}, {322}, {311}, {211}, {332}, {331}, {221}, {231}, {312}).

3.2 Shocks and control characteristics

We consider three types of major exogenous shocks affecting panel households over the study period: rainfall shortages, a coffee-price crisis and hurricane Mitch. These shocks are covariate by nature, but their effects are identified based on substantial spatial variation in the sample. In addition, we also analyze two idiosyncratic shocks with high occurrence in the data: self-reported drought and child sickness. Descriptive statistics for shock measures are presented in Table 6. The incidence of shocks (particularly self-reported) diminishes along the welfare distribution, an issue to which we will return later but that does not affect the analysis to the extent that initial conditions are held constant. In section 4.3 and 4.4, we analyze the relative impact of each shock, focusing on their distributional effects and modeling shocks as time unfolds in order to assess the timing with which they impact on welfare trajectories.

Nicaragua suffers from recurrent droughts caused by El Niño phenomenon (INETER, 2002). Although there have been other episodes of drought during the period, we assess the impact of severe rainfall shortage during the main agricultural season the year prior to each survey, best captured by July rainfall (Rojas et al, 2000). Rainfall measures are obtained from NASA TRMM satellite and interpolated at the municipal level (Premand, 2010). Since TRMM data is only available from 1998 onwards, we use less extensive gauge data from *INETER* to interpolate municipal rainfall in 1997. Rainfall shortage is taken as the percentage deviation from the mean of the TRMM series for each municipality. In order to make probit and matching estimates directly comparable, dummies are built to capture rainfall shortages larger than 50%.[25] 33% of the sample suffered from severe drought in July 1997, 35% in July 2000 but no severe drought is observed in July 2004.[26]

Hurricane Mitch struck Nicaragua in October 1998, providing a second source of exogenous weather variation. A dummy is used to characterize communities affected by hurricane Mitch, according to which 15% of the sample suffered from the storm. Detailed evidence on the direct consumption impact of hurricane Mitch on Nicaraguan agricultural households is discussed in Premand (2010). The analysis in this paper is complementary by considering an additional round of data as well as distributional effects.

The 61% drop of international coffee prices between 1998 and 2001 constitutes a third exogenous covariate shock. Vakis et al. (2004) detail how the coffee crisis affected the local economy. A municipal measure of the intensity of coffee production is built from a 2001 agricultural census. A dummy is used to capture high-intensity coffee municipalities, defined as municipalities where more than 10.8% of farmland is dedicated to coffee production (Vakis et al., 2004). 16% of households in the sample were directly exposed to the coffee crisis based on this measure.

[25] Probit estimates presented below remain consistent if continuous measures are used instead.
[26] While some regions of the country suffered from rainfall shortages in July 2004, there is insufficient geographical variation in the occurrence of drought in the LSMS panel for that variable to be used in the analysis.

In addition to these three covariate events, two types of idiosyncratic self-reported shocks with sufficient variation in the data are considered: drought and child sickness. 33% of households report having suffered from a drought in 1998 and 29% in 2001.[27] While in the aggregate self-reported drought occurrence is in line with rainfall measures, self-reported drought is substantially higher for the lowest tercile. These differences reflect the fact that the two shocks cover different reference periods, but do suggest that poor households report higher occurrence of shocks. Between 42% and 44% of households reveal some child illness over the last year. Here again, poor households report higher incidence.

Descriptive statistics for control characteristics are presented in Table 7. Household-level controls cover education, demographics (number of children and adults in household, household head's age and sex), private assets (number of household durable goods, land, livestock) and income composition (share of agricultural income, dummy for remittance recipients, Herfindahl income diversification index). Control characteristics from the first round of the panel are complemented by municipal averages of public assets measured from a 1995 census. The percentage of households connected to the sewage system and electricity networks proxy local infrastructure. Households' access to the sewage and electricity network is also directly measured.

4. Analysis

4.1 Testing for Markov – first versus higher-order

As discussed in section 1, a key rationale for the consideration of welfare trajectories is that transition matrices only constitute a consistent representation of the underlying welfare process under a first-order Markov assumption. This might not be the case in practice, as we illustrate here with the existing data.

Table 8 contains period-per-period transition matrices between consumption terciles.[28] Unsurprisingly, observed patterns reflect stability for households initially in the first and top terciles, with more mobility in the middle of the distribution. There is slightly more upward mobility than downward mobility between 1998 and 2001, but the reverse occurs between 2001 and 2005. No clear overall trend appears between 1998 and 2005. Note that these descriptive patterns do not indicate whether households moving upward between 1998 and 2001 enjoyed persistent gains, or whether those moving upward between 1998 and 2001 are also move downward between 2001 and 2005. Such path dependence can be analyzed based on three-period trajectories, however.

[27] The 2005 questionnaire does not contain a question on self-reported droughts, reflecting the fact that no major drought occurred that year.
[28] Again, first-period cut-offs are used throughout. This is consistent with Shorrocks' (1976) treatment.

Violation of the first-order Markov assumption can be illustrated as follows. Denote the 1998-2001 transition matrix M_1, the 2001-2005 matrix M_2 and the 1998-2005 matrix M_3. Shorrocks (1976, p.569) stresses that the first-order Markov assumption is at best suspicious if $M_1*M_2 \neq M_3$. Table 9 shows that the diagonal elements of the M_1*M_2 matrix are substantially smaller than their counterparts in the M_3 matrix. This makes the first-order Markov chain "at least suspect" as a representation of the underlying welfare process (Shorrocks, 1976, p.569). Shorrocks (1976) concludes: "Given that the Markov assumption is to be abandoned, the simplest modification is to allow transition rates to depend on both current income and immediate past history" (p.570).

Anderson and Goodman (1957) present a formal test that a Markov chain is first-order over second-order. Consider a household in state i at t-2 and in j at t-1, and denote by p_{ijk} (i,j,k=1,...,3) the probability of being in state k at time 3.[29] n_{ijk} is the number of households whose trajectory is {i,j,k}. In this context, "a first-order stationary chain is a special second-order chain, one for which p_{ijk} does not depend on i" (Anderson and Goodman, 1957, p. 99).

The null hypothesis that the chain is first-order can be tested against the alternative that it is second-order. Under the null hypothesis, $p_{1jk} = p_{2jk} = p_{3jk} = p_{ijk}$, for $j,k = 1,...,3$. The likelihood ratio criterion for testing this hypothesis is:

$$\lambda = \prod_{i,j,k=1}^{3} (\hat{p}_{jk} / \hat{p}_{ijk})^{n_{ijk}}$$

-2log(λ) follows a χ^2-distribution with 12 degrees of freedom. The maximum likelihood estimators of $\hat{p}_{ijk}$ and $\hat{p}_{jk}$ are, respectively:

$$\hat{p}_{ijk} = \frac{n_{ijk}}{\sum_{l=1}^{m} n_{ijl}}$$

$$\hat{p}_{jk} = \frac{\sum_{i=1}^{3} n_{ijk}}{\sum_{i=1}^{3}\sum_{l=1}^{3} n_{ijl}}$$

[29] Stationarity is assumed throughout.

Here, -2*log(λ)= 280.1. The null hypothesis that the chain is first-order can be rejected unambiguously (p-value=0) and a second-order chain is preferred. Violations of the first-order Markov assumption are visible in the frequency distributions of trajectories (Table 4). For instance, 25 households follow trajectory {123}, 103 trajectory {223} and 72 trajectory {323}. Households starting in the second tercile are more likely to move from the 2nd to the 3rd tercile between the last two rounds. As such, the trajectory construct presented in this paper is useful in pointing to deviations from the first-order Markov assumption. Shorrocks (1976) and Yalonetzky (2008) tackle the methodological implications of higher-order Markov representations as concerns the measurement of mobility and modeling of the underlying welfare process. These contributions are important and their practical implications would warrant further considerations once longer panel datasets become available in the context of developing countries. In the rest of this paper, we focus on empirical analysis of trigger events for a specific sub-set of the trajectory universe.

4.2 Shocks and downward mobility

We now turn to the analysis of mobility triggers for two specific patterns: this section considers the impact of shocks on downward mobility ({ijk}, with i>k),[30] section 4.3 studies their impact on poverty persistence ({111}). In both cases, we consider how shocks affect welfare trajectories beyond initial conditions.

19.8% of households in the sample exhibit downward trajectories. Table 10 displays results regarding the effect of shocks on downward mobility. Column (I) through (III) present marginal effects from probit estimation for the probability of a household exhibiting downward mobility conditional on starting in tercile 2 or 3 (column (I)), tercile 2 (column (II)) or tercile 3 (column (III)).

As laid out in Equations (1) to (3), the benchmark probit specification is built as a function of shocks and control characteristics. Even though coefficients of control variables cannot be interpreted causally, probit profiles suggest the role of structural baseline variables in determining subsequent dynamics. The possibility to associate control characteristics with those dynamics comes at the cost of maintaining some heterogeneity in the subset of households compared to each other: probit estimates are derived by conditioning on households' initial tercile.

In terms of control characteristics, low levels of education and physical assets (durable goods and livestock, but not land) are correlated with larger downward mobility from the top two terciles. Larger households tend to exhibit more downward mobility (particularly from the top tercile) as do households from the middle tercile with a higher share of agricultural activities.

[30] Because the available panel is short and most observed shocks happen between the first and second round, the data does not allow a full empirical treatment of path dependence. The focus is on the empirical identification of the impact of shocks on specific trajectories.

Finally, lack of access to public infrastructure is associated with higher downward mobility from the second and third tercile, but significant infrastructure externalities only appear for households in the top terciles. These probit estimates highlight the potential role of baseline structural variables in determining downward trajectories beyond initial conditions: for instance, households with lower education are more likely to suffer from downward trajectories from the top tercile, even though at the baseline households in the top tercile have higher education than households in the other two terciles.

Probit results show evidence supporting shock-driven downward mobility. Column (I) characterizes downward mobility jointly for households in terciles 2 and 3 at the baseline. While no shock prior to 2001 is significant and positive, the occurrence of a severe rainfall shortage in 2001 increases the probability of downward mobility by 10% and self-reported drought in 2001 by 8%. These marginal effects are large, and suggest that drought shocks have lasting impacts in our sample. Idiosyncratic illness shocks in the last round also increase the probability of downward mobility by 11%. Interestingly, the coefficient of the Mitch hurricane dummy indicates that households in communities affected by the hurricane are less likely to exhibit downward trajectories, echoing the limited persistence in the hurricane's welfare effects discussed in Premand (2010).

The contrast between columns (II) and (III) provides suggestive evidence that shocks better explain downward mobility from the middle tercile compared to the top tercile. The significance of severe rainfall shortage and hurricane Mitch is confined to tercile 2. In addition, the negative coefficient of child sickness in 1998 is consistent with a temporary effect of that shock. However, child sickness is the only significant shock in explaining downward mobility from the top tercile. Such results are also suggestive of the idea that vulnerable non-poor households (but closer to the poverty line) are more vulnerable to uninsured risks.

Still, as we argued earlier, matching methods offer more flexible specification than probit regressions. We now turn to matching estimates. Columns (IV) to (VI) in Table 10 display matching estimates for the probability to exhibit downward mobility from tercile 2 or 3 (column (IV)), 2 (column (V)) and 3 (column (VI)) respectively. By contrast to the probit specification, the matching approach considers homogenous comparison groups with identical values of baselines covariates, better isolating the impact of shocks on welfare trajectories since it bypasses the linear functional form imposed by probit regressions.

Overall, matching estimates confirm that shocks substantially increase the probability that households suffer from downward trajectories. When downward mobility is analyzed jointly for terciles 2 and 3 (column (II)), severe drought in July 2000 (8%), self-reported drought in 2000-1 (14%) and child sickness in 2004-5 (10%) all have a significant positive impact in driving downward mobility.

For the second tercile, the effects of rainfall shortage (2001), self-reported drought (2001) and child sickness (2004-5) are still positive and significant. In addition, child sickness and drought in 1997-1998 take a negative sign (marginally insignificant in the later case), consistent with a temporary impact of these out-of-sample shocks at the baseline. Results for the third tercile (column (VI)) somewhat nuance the decreasing impact of shocks along the welfare distribution: drought in 2000-1 and child-sickness in 2004-5 have large coefficients in determining downward mobility over the panel period.

Overall, the evidence confirms that shocks have substantial effects in driving downward mobility. These findings arise from both probit and matching methods, highlighting their robustness.

4.3 Shocks and poverty persistence

Table 11 contains results regarding the effect of shocks on poverty persistence. As noted above, 16.9% of households in the sample remain persistently poor. Column (I) presents estimates for the probability of a household remaining poor conditional on starting in the lowest tercile (based on Equations (1) to (3)). The specification of control variables and shocks is as discussed above.

A limited number of control characteristics are significantly associated with poverty persistence. Low levels of education and physical assets (durable goods and livestock, but not land) are correlated with lower upward mobility from the bottom tercile. Larger households are also more likely to remain at the bottom of the distribution. However, no association appears between public assets or the composition of income portfolios and poverty persistence.

By contrast with the limited significance of control characteristics, probit estimates (column (I)) reveal that shocks have substantial power in explaining poverty persistence. All shocks have positive effects, and statistically significant coefficients are of large magnitude. Households initially in the first tercile are more likely to remain poor if they suffer from a shock: a severe rainfall shortage in July 1997 increases the probability of remaining poor by 10%, a self-reported drought in 1997-1998 by 13%, the coffee-crisis proxy by 16%. Importantly, the significance and magnitude of shocks prior to 2001 suggest that their effects are lasting. Child sickness in 2005 is also associated with a 9% increase of poverty persistence, consistently with a limited short-term impact. Throughout, results show that shocks significantly hinder upward mobility from the bottom tercile.

Matching estimates (column (II)) further highlight the important role of shocks in driving poverty persistence. All significant estimated treatment effects have positive signs: drought in 1997-1998 increases the probability of observationally similar households to remain at the bottom of the distribution by 10%, hurricane Mitch by 7%, the coffee-crisis by 8%, rainfall shortage in July 2000 by 10% and child sickness in 2004-5 by 6%.[31] Results confirm that shocks have strong and consistent impacts on poverty persistence. Some long-term effects of shocks in the first two rounds of the data are again identified. Compared to probit results, the matching approach reinforces the significance of shock variables, even though estimated coefficients are of smaller magnitude.

4.4 Robustness checks

Our results indicate that shocks not only affect downward mobility, but also trigger poverty persistence. In this section we explore the robustness of these results.

[31] The evidence on hurricane Mitch is not robust in the estimated specification (as illustrated by probit results).

4.4.1 Robustness checks

The first issue is whether shocks can be considered exogenous in the analysis. Table 6 illustrates that there is some variation in the incidence of shocks between terciles. However, most of these differences are insignificant if the list of control characteristics used in section 4.2 and 4.3 are also accounted for. A higher incidence of hurricane Mitch, self-reported drought in 1998 and 2001 in the lowest tercile of the consumption distribution is the only significant difference.

In any case, a variation in the incidence of shocks between tercile does not constitute a problem for the analysis presented above. Indeed, the analysis always conditions on baseline welfare. For instance, the analysis of poverty persistence conditions on households starting in the first tercile of the welfare distribution. By doing so, variations in the incidence of shocks between terciles does not affect the internal validity of the findings for the first, second or third tercile.

A more important consideration is whether shocks are exogenous within each tercile. There are two aspects to this issue: within-tercile correlation between shocks and baseline control characteristics and within-tercile correlation between shocks and unobserved heterogeneity.

It can be shown that in the Nicaraguan panel shocks are not orthogonal to control characteristics.[32] Probit and matching estimates rely on different functional forms to account for pre-treatment observed characteristics. As discussed in section 2, probit estimates may be inaccurate if treatment and comparison groups are dissimilar, but matching estimates corrects for potential biases due to a correlation between shocks and control characteristics. The fact that the core results in sections 4.2 and 4.3 are robust to estimation by both methods is also reassuring. This suggests that the evidence is not driven by linearity in the latent variable equation behind the probit model and by the correlation between shocks incidence and observed characteristics between treated and non-treated households. As such, results are also robust to model uncertainty.

The second issue links to the identifying assumption common to the probit and matching models: if shock incidence is correlated with unobserved heterogeneity, estimated coefficients would be inconsistent. This could arise if self-reported shocks in the lowest tercile are correlated with unobservable attributes of the persistently poor. It is important to mention this potential limitation as selection on unobservables cannot be formally tested and a longer time-series would be required to show that realization of shocks is uncorrelated with the previous welfare path.

4.4.2 Alternative specifications

The results above are robust to alternative definitions and specifications. For example, the results are similar irrespective of the use of discrete versus continuous rainfall shock variables, or the number of matches and modifications to the covariate set. Table 12 shows that the results are

[32] Results are not presented here since they reveals few consistent patterns.

robust to estimation on the rural subsample only, which is important as many of the shocks we explore are arguably more likely to affect farm households. Finally, Table 13 explores alternative trajectories definitions using other cut-offs along the consumption welfare space (quintiles and septiles).[33] Again, the nature of the results remains unchanged.

4.4.3 Attrition

A final issue we explore is that of attrition. The Nicaraguan LSMS panel suffers from a high attrition rate. 38.4% from baseline households were not tracked over the three data rounds. Even if attrition rate is not statistically significant between the three terciles,[34] it remains important to consider the sensitivity of our results to potential attrition bias. Rosenzweig (2003) stresses that unobserved heterogeneity can bias mobility studies based on panel suffering from attrition, even though the direction of the bias is unclear a priori. Beegle et al. (2009) use a tracking survey to show that geographic mobility is associated with substantial welfare gains: in Tanzania, if permanent migrants had not been properly tracked, economic mobility would be substantially underestimated.

In the context of our study, the potential correlation between attrition and shocks is of particular interest. In Nicaragua, seasonal migration constitutes an important risk-coping mechanism (Macours and Vakis, 2010). Permanent migration has been much less studied. If shocks also drive permanent migration (as suggested by Rosenzweig and Stark, 1999), the evidence presented above might overstate the degree to which shocks trigger adverse trajectories. Other mechanisms could lead to bias if attrition is correlated with initial welfare, for instance if migration is systematically higher for the poorer households and generates a change in the composition the sample, or if the possibility to cope with the shock by migrating varies along the welfare distribution.

To explore this further, Table 14 presents a simple model of attrition as a function of baseline welfare and shocks. Table 14 first shows that shocks are consistently negatively associated with attrition. Attritors live in regions less affected by shocks in 1998, and are also less likely to suffer from shocks between 1998 and 2001. The pattern holds for the entire sample (column I), but is particularly strong for households in the bottom tercile (column II). These results suggest that shocks are associated with lower migration. If migration is itself associated with higher economic mobility (as in Beegle et al., 2009), these results suggest the above may be seen as lower bounds for the impact of shocks on poverty persistence and downward trajectories.

In parallel, Table 14 shows that there is no overall correlation between attrition and baseline welfare in the entire sample (column I). In particular, there is no correlation between attrition and baseline welfare in the bottom tercile (column II), so that attrition bias is not likely to affect the main

[33] Matching results are also robust to the inclusion of initial consumption in the set of matching variables. Unsurprisingly, the repetition of shocks also has strong effects on poverty persistence and downward mobility.
[34] Attrition amounts to 38.4% in bottom tercile, 35.8 in middle sample and 40.9% in top tercile.

results of the paper on the effect of shocks on poverty persistence can still be considered a lower bound. The same holds for results on downward mobility from the second tercile since there is no correlation between attrition and baseline welfare in the middle tercile (column III). However, there is a positive correlation between attrition and baseline welfare in the top tercile (column IV). An upward attrition bias cannot be ruled out for the analysis on downward mobility from the top tercile, the region for which we already discussed results on shock-driven mobility appeared the weakest since those households may be best able to cope with shocks.

5. Conclusions

This paper uses welfare trajectories to analyze the role of shocks as triggers for downward mobility and poverty persistence based on a unique three-round Nicaraguan panel spanning 1998-2005, a period marked by substantial exogenous climatic and economic shocks. While this paper primarily focuses on unveiling mobility triggers, it suggests methodological extensions for empirical mobility analysis by introducing mobility patterns based on "welfare trajectories", a representation consistent with higher-order Markov processes. Using matching estimators, we isolate the impact of shocks as trigger of trajectories. We find that shocks have large impacts on downward mobility, particularly from the middle of the welfare distribution. Most importantly, we find strong impacts of shocks on poverty persistence. A shock at the beginning of the panel has long-term effects on poverty persistence more than 7 years later. Those findings are robust to a series of alternative specifications and seem mostly robust to attrition bias, but rely on the identifying assumption of selection on observables.

To our knowledge, these are the first results that empirically link poverty persistence to shocks and they complement existing evidence that risk leads to poverty persistence ex ante (Fafchamps, 2003), as well as theoretical contributions on the relative role of ex ante and ex post risk in welfare dynamics (Elbers et al., 2007). While overall results are consistent with increasing access to insurance along the welfare distribution, in this paper were not able to directly analyze the specific strategies used by households to cope with shocks as the data contains little information to identify such mechanisms, which are typically endogenous.

The fact that causes of poverty persistence (the lack of upward mobility) and downward mobility can differ means that each may require distinct sets of policy options (Gardiner and Hills, 1999; de Janvry et al., 2006). Jalan and Ravallion (2000, p.83) state that "insurance and income-stabilization schemes which protect households against idiosyncratic economic shocks would appear to be more important when poverty is transient". In highlighting the often overshadowed role of shocks on poverty persistence, this paper suggests large potential gains from social risk management policies targeting not only the vulnerable non-poor, but crucially and in priority the poor. As such, this paper makes an efficiency case for targeting safety nets and improving risk management capacities towards the very bottom of the welfare distribution.

Annex

Table 1
Expected Effects of Shocks on Three-Round Trajectories, by Type of Shock

	Shocks prior to t-2	Shocks between t-2 and t-1	Shocks between t-1 and t
Temporary impact	- / 0	0	+
Impact one-round ahead	- / 0	+	+
Impact two-round ahead	+	+	+

Note: Expected impact on downward trajectory and poverty persistence per type of shock.

Table 2
Descriptive Statistics: Consumption and Consumption Growth

	Year	Median	Mean	Sd
Consumption	1998	4633.64	6434.82	6876.00
	2001	4862.35	6531.49	5936.06
	2005	4579.69	6288.52	5815.40
Log consumption	1998	8.44	8.46	0.75
	2001	8.49	8.51	0.73
	2005	8.43	8.48	0.70
Consumption growth	98-01	0.012	0.015	0.179
	01-05	-0.008	-0.008	0.127
	98-05	0.002	0.002	0.083

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; all values in 1998 real cordobas; average cordoba-dollar exchange rate in 1998: 10.58; annualised growth rates.

Table 3
Descriptive Statistics: Poverty Trends
(percentages)

	Extreme poverty	General poverty	Out of poverty
1998	19.5	24.3	56.2
2001	13.1	27.2	59.6
2005	11.6	28.6	59.8

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; extreme and general poverty lines amount to 2489C$ and 4233C$ in 1998.

Table 4
Frequency Distribution for Three-Round Trajectories

Sequence {ijk}	Trajectory type	n_{ijk}	n_{ijk}/N (%)	n_{ijk}/N_i (%)
{333}	Other	465	18.7	56.2
{332}	Downward	122	4.9	14.7
{331}	Downward	9	0.4	1.1
{323}	Other	72	2.9	8.7
{322}	Downward	97	3.9	11.7
{321}	Downward	30	1.2	3.6
{313}	Other	3	0.1	0.4
{312}	Downward	19	0.8	2.3
{311}	Downward	11	0.4	1.3
{233}	Upward	115	4.6	13.9
{232}	Other	100	4.0	12.1
{231}	Downward	23	0.9	2.8
{223}	Upward	103	4.1	12.4
{222}	Other	208	8.4	25.1
{221}	Downward	95	3.8	11.5
{213}	Upward	13	0.5	1.6
{212}	Other	85	3.4	10.3
{211}	Downward	86	3.5	10.4
{133}	Upward	24	1.0	2.9
{132}	Upward	23	0.9	2.8
{131}	Other	10	0.4	1.2
{123}	Upward	25	1.0	3.0
{122}	Upward	102	4.1	12.3
{121}	Other	123	4.9	14.8
{113}	Upward	14	0.6	1.7
{112}	Upward	89	3.6	10.7
{111}	Poverty persistence	419	16.9	50.5

Notes: Trajectories are defined as the sequence of households' position along the welfare distribution as time unfolds; trajectories take the form {ijk}, where i,j,k=1,2,3 correspond to each household's position along the welfare distribution in period 1 (i), period 2 (j) and period 3 (k); N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; last column gives frequency per tercile.

Table 5
Occurrence of Each Trajectory Type

	n	%
Poverty persistence	419	16.9
Downward	492	19.8
Upward	508	20.4
Others	1,066	42.9

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; poverty persistence: {111}; Downward mobility: {ijk}, with i>k; Upward mobility: {ijk}, with i<k.

Table 6
Descriptive Statistics: Shock Incidence Using Baseline Welfare Status
(percentages)

	All Mean	Tercile 1 Mean	Tercile 2 Mean	Tercile 3 Mean
Severe rainfall shortage (July 1997)	33	20	35	45
Drought (1997-1998)	33	53	29	16
Child sickness (1997-1998)	47	57	48	36
Mitch (October 1998)	15	22	14	10
Coffee-crisis proxy (1998-2001)	16	22	14	13
Severe rainfall shortage (July 2000)	35	38	33	33
Drought (2000-2001)	29	41	22	13
Child sickness (2000-2001)	42	49	37	27
Child sickness (2004-2005)	44	55	46	36

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; drought and child sickness self-reported from LSMS panel, 1997 rainfall from INETER data, 2000 rainfall data from NASA TRMM, coffee-crisis proxy from 2001 agricultural census, Mitch dummy from 1999 LSMS in communities affected by Mitch.

Table 7
Descriptive Statistics: Control Characteristics

	All		Tercile 1		Tercile 2		Tercile 3	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
% sewage connection (1995)	0.13	0.17	0.07	0.12	0.12	0.16	0.19	0.20
% electricity connection (1995)	0.58	0.27	0.44	0.24	0.60	0.26	0.69	0.23
hh with sewage connection	0.10	0.30	0.02	0.13	0.07	0.26	0.22	0.42
hh with electricity	0.64	0.48	0.33	0.47	0.71	0.45	0.88	0.32
Max education in hh	7.22	4.03	5.00	3.04	7.11	3.50	9.53	4.12
N kids in hh	2.50	2.01	3.71	2.11	2.39	1.79	1.40	1.32
N adults in hh	3.40	1.69	3.69	1.77	3.42	1.66	3.08	1.57
Male hh head	0.71	0.45	0.74	0.44	0.71	0.45	0.69	0.46
Hh's head age	46.99	15.07	46.49	14.70	47.24	15.43	47.25	15.06
Agricultural income share	0.26	0.34	0.43	0.36	0.24	0.33	0.11	0.24
Hh receives remittances	0.23	0.42	0.17	0.37	0.25	0.43	0.29	0.45
Income diversification	0.45	0.25	0.47	0.25	0.45	0.25	0.42	0.24
N hh durables	4.46	3.83	2.22	1.76	4.02	2.74	7.12	4.59
Land cultivated	0.37	0.99	0.49	1.06	0.36	1.02	0.25	0.87
N livestock	2.00	12.62	1.31	4.72	1.57	8.46	3.11	19.56

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; % sewage and electricity connection are municipal averages from 1995 national census; all other variables from 1998 LSMS panel.

Table 8
Consumption Tercile Transition Matrices
(percentages)

Transition between 1998 and 2001				
		2001		
	M_1	1	2	3
	1	63.0	30.2	6.9
1998	2	22.2	49.0	28.7
	3	4.0	24.0	72.0
Transition between 2001 and 2005				
		2005		
	M_2	1	2	3
	1	62.2	23.3	3.6
2001	2	30.0	49.2	24.2
	3	5.1	29.6	72.9
Transition between 1998 and 2005				
		2005		
	M_3	1	2	3
	1	66.6	25.8	7.6
1998	2	24.6	47.5	27.9
	3	6.0	28.7	65.2

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel.

Table 9
Comparison Between Observed 1998-2005 Transition Matrix and Prediction from First-Order Markov Chain
(percentages)

		2001		
	M_1*M_2	1	2	3
1998	1	48.6	31.5	14.6
	2	30.0	37.8	33.6
	3	13.3	34.0	58.5
		2005		
	M_3	1	2	3
1998	1	66.6	25.8	7.6
	2	24.6	47.5	27.9
	3	6.0	28.7	65.2

Note: N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel.

Table 10
Shocks and Downward Trajectories

	Probit estimates						Matching estimates					
	I Downward mobility Initial tercile: 2 or 3		II Downward mobility Initial tercile: 2		III Downward mobility Initial tercile: 3		IV Downward mobility Initial tercile: 2 or 3		V Downward mobility Initial tercile: 2		VI Downward mobility Initial tercile: 3	
	coef	sd	coef	sd	coef	sd	coef	sd	coef	sd	coef	sd
Control characteristics												
% sewage connection (1995)	-0.10	0.10	-0.25	0.15	-0.27*	0.15						
% electricity connection (1995)	-0.02	0.07	-0.08	0.08	0.11	0.11						
hh with sewage connection	-0.08**	0.04	-0.12*	0.06	-0.08*	0.05						
hh with electricity	-0.04	0.04	-0.04	0.04	-0.09	0.08						
Max education in hh	-0.02***	0.00	-0.02***	0.01	-0.02***	0.01						
N kids in hh	-0.01	0.01	0.01	0.01	0.04**	0.02						
N adults in hh	0.01	0.01	0.02**	0.01	0.04***	0.01						
Male hh head	0.03	0.03	-0.00	0.04	0.05	0.04						
Hh's head age	0.00	0.00	0.00	0.00	0.00	0.00						
Agricultural income share	0.06	0.05	0.10*	0.06	0.12	0.09						
Hh receives remittances	-0.03	0.03	-0.04	0.04	-0.03	0.04						
Income diversification	0.03	0.05	-0.01	0.06	0.11	0.07						
N hh durables	-0.01***	0.00	-0.02**	0.01	-0.03***	0.01						
Land cultivated	0.00	0.02	-0.01	0.02	-0.03	0.03						
N livestock	-0.00*	0.00	-0.01**	0.00	-0.00*	0.00						

Table 10 (continued)

	Probit estimates						Matching estimates					
	I Downward mobility Initial tercile: 2 or 3		II Downward mobility Initial tercile: 2		III Downward mobility Initial tercile: 3		IV Downward mobility Initial tercile: 2 or 3		V Downward mobility Initial tercile: 2		VI Downward mobility Initial tercile: 3	
	coef	sd	coef	sd	coef	sd	coef	sd	coef	sd	coef	sd
Shock variables												
Severe rainfall shortage in July 1997	-0.00	0.03	-0.01	0.04	0.05	0.05	-0.04	0.03	-0.01	0.04	-0.05	0.04
Drought (1997-1998)	-0.03	0.04	-0.00	0.04	-0.03	0.07	0.01	0.05	-0.08	0.05	0.11	0.09
Child sickness (1997-1998)	-0.03	0.03	-0.06*	0.03	-0.03	0.04	-0.03	0.02	-0.07***	0.03	-0.03	0.04
Community affected by Mitch (Oct 1998)	-0.06*	0.03	-0.07**	0.03	-0.02	0.06	-0.02	0.04	-0.07	0.05	0.08	0.07
Coffee-crisis proxy (1998-2001)	0.02	0.04	0.01	0.04	0.05	0.06	-0.02	0.04	-0.07	0.05	0.02	0.05
Severe rainfall shortage in July 2000	0.10***	0.03	0.13***	0.04	0.05	0.04	0.08***	0.03	0.13***	0.03	0.05	0.04
Drought (2000-2001)	0.08**	0.04	0.05	0.04	0.11	0.07	0.14***	0.06	0.10*	0.06	0.25***	0.09
Child sickness (2000-2001)	0.02	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.02	0.03	0.05	0.04
Child sickness (2004-2005)	0.11***	0.02	0.07**	0.03	0.17***	0.04	0.10***	0.02	0.06*	0.03	0.14***	0.04
Number of observations	1,655		828		827							
Pseudo R^2	0.109		0.170		0.204							

Notes: Significance at the level *** p<0.01, ** p<0.05, * p<0.1; N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel; downward mobility: {ijk}, with i>k. *Note for probit estimates*: (columns I, II and III): marginal effects indicate the change in the probability of a household exhibiting downward mobility when each shock occurs. *Note for matching estimates:* (colums IV, V and VI): bias-adjusted nearest-neighbor matching estimates (Abadie and Imbens, 2006); matching on 4 nearest-neighbors, coefficients are the average treatment effect, estimating the change in the probability of a household exhibiting downward mobility following the impact of a shock; matching performed on all control characteristics from probit estimates (including other shocks).

Table 11
Shocks and Poverty Persistence

	Probit estimates I		Matching estimates II	
	Initial tercile: 1		Initial tercile: 1	
	coef	sd	coef	sd
Control characteristics				
% sewage connection (1995)	-0.21	0.23		
% electricity connection (1995)	-0.11	0.12		
hh with sewage connection	0.04	0.16		
hh with electricity	-0.05	0.05		
Max education in hh	-0.03***	0.01		
N kids in hh	0.05***	0.01		
N adults in hh	-0.00	0.01		
Male hh head	-0.02	0.05		
Hh's head age	0.00	0.00		
Agricultural income share	0.07	0.06		
Hh receives remittances	-0.06	0.05		
Income diversification	-0.02	0.08		
N hh durables	-0.04***	0.01		
Land cultivated	0.00	0.02		
N livestock	-0.02***	0.01		
Shock variables				
Severe rainfall shortage in July 1997	0.10*	0.06	-0.02	0.05
Drought (1997-1998)	0.13***	0.05	0.10***	0.04
Child sickness (1997-1998)	0.03	0.04	0.03	0.04
Community affected by Mitch (Oct 1998)	0.08	0.05	0.07*	0.04

Table 11 (continued)

	Probit estimates I		Matching estimates II	
	Initial tercile: 1		Initial tercile: 1	
	coef	sd	coef	sd
Coffee-crisis proxy (1998-2001)	0.16***	0.05	0.08*	0.04
Severe rainfall shortage in July 2000	0.03	0.04	0.10***	0.04
Drought (2000-2001)	0.05	0.04	0.02	0.04
Child sickness (2000-2001)	0.02	0.04	0.04	0.03
Child sickness (2004-2005)	0.09**	0.04	0.06*	0.03
Number of observations	829.00***			
Pseudo R^2	0.160			

Note: Significance at the level *** p<0.01, ** p<0.05, * p<0.1; n=2485 households in 1998-2001-2005 Nicaraguan LSMS panel.
Note for probit estimates: (column I): marginal effects indicate the change in the probability of a household exhibiting poverty persistence {111} when each shock occurs, conditioning on being in bottom tercile at the baseline.
Note for matching estimates: (column II): bias-adjusted nearest-neighbor matching estimates (Abadie and Imbens, 2006); matching on 4 nearest-neighbors, coefficients represent average treatment effects, estimating the change in the probability that a household starting in the bottom tercile exhibits poverty persistence {111} following the impact of a shock; matching performed on all control characteristics from probit estimates (including other shocks).

Table 12
Shocks and Poverty Persistence in Rural Subsample

	Probit estimates		Matching estimates	
	I		II	
	Initial tercile: 1		Initial tercile: 1	
	coef	sd	coef	sd
Shock variables				
Severe rainfall shortage in July 1997	-0.05	0.09	0.02	0.09
Drought (1997-1998)	0.05	0.07	0.08	0.06
Child sickness (1997-1998)	-0.06	0.06	-0.05	0.05
Community affected by Mitch (Oct 1998)	0.16**	0.07	0.11**	0.06
Coffee-crisis proxy (1998-2001)	0.23***	0.07	0.10	0.06
Severe rainfall shortage in July 2000	0.16**	0.06	0.19***	0.06
Drought (2000-2001)	-0.00	0.06	-0.01	0.05
Child sickness (2000-2001)	0.01	0.06	0.02	0.05
Child sickness (2004-2005)	0.15***	0.06	0.13***	0.05
Number of observations	383			
Pseudo R^2	0.184			

Note: Significance at the level *** p<0.01, ** p<0.05, * p<0.1; N=1152 households in 1998-2001-2005 Nicaraguan LSMS panel, rural subsample.
Note for probit estimates: (column I): marginal effects indicate the change in the probability of a household exhibiting poverty persistence {111} when each shock occurs, conditioning on being in bottom tercile at the baseline. The same control characteristics as in Table 10 and 11 are included.
Note for matching estimates: (column II): bias-adjusted nearest-neighbor matching estimates (Abadie and Imbens, 2006); matching on 4 nearest-neighbors, coefficients represent average treatment effects, estimating the change in the probability that a household starting in the bottom tercile exhibits poverty persistence {111} following the impact of a shock; matching performed on all control characteristics from probit estimates (including other shocks).

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Table 13
Shocks and Poverty Persistence
(alternative definitions)

	I		II		III		IV	
	Probit estimates		Probit estimates		Matching estimates		Matching estimates	
	Initial quintile: 1		Initial septile 1		Initial quintile: 1		Initial septile 1	
	coef	sd	coef	sd	coef	sd	coef	sd
Shock variables								
Severe rainfall shortage in July 1997	-0.04	0.07	-0.07	0.08	-0.06	0.07	-0.14	0.08
Drought (1997-1998)	0.05	0.06	0.12**	0.06	0.01	0.05	0.03	0.06
Child sickness (1997-1998)	-0.04	0.05	-0.06	0.06	-0.00	0.05	-0.05	0.05
Community affected by Mitch (Oct 1998)	0.13**	0.06	0.07	0.07	0.09*	0.05	0.08	0.07
Coffee-crisis proxy (1998-2001)	0.22***	0.06	0.21***	0.07	0.08	0.05	0.15***	0.06
Severe rainfall shortage in July 2000	0.15***	0.05	0.17***	0.06	0.16***	0.05	0.18***	0.06
Drought (2000-2001)	-0.00	0.05	-0.03	0.06	0.00	0.04	0.01	0.05
Child sickness (2000-2001)	-0.04	0.05	0.04	0.05	-0.01	0.04	0.06	0.05
Child sickness (2004-2005)	0.16***	0.05	0.03	0.06	0.11***	0.04	0.05	0.05
Number of observations	491		352					
Pseudo R^2	0.213		0.188					

Note: Significance at the level *** p<0.01, ** p<0.05, * p<0.1; N=2485 households in 1998-2001-2005 Nicaraguan LSMS panel.
Note for probit estimates: (column I): marginal effects indicate the change in the probability of a household exhibiting poverty persistence {111} when each shock occurs, conditioning on being in bottom tercile at the baseline. The same control characteristics as in Table 10 and 11 are included.
Note for matching estimates: (column II): bias-adjusted nearest-neighbor matching estimates (Abadie and Imbens, 2006); matching on 4 nearest-neighbors, coefficients represent average treatment effects, estimating the change in the probability that a household starting in the bottom tercile exhibits poverty persistence {111} following the impact of a shock; matching performed on all control characteristics from probit estimates (including other shocks).

Table 14
Attrition, Baseline Welfare and Shocks

	I Probit estimates Attrition		II Probit estimates Attrition: tercile 1		III Probit estimates Attrition: tercile 2		IV Probit estimates Attrition: tercile 3	
	coef	sd	coef	sd	coef	sd	coef	sd
Consumption in 1998 (log)	0.01	0.01	-0.06	0.04	-0.05	0.08	0.12***	0.03
Severe rainfall shortage in July 1997	-0.03	0.02	-0.07*	0.04	-0.03	0.03	0.01	0.03
Drought (1997-1998)	-0.04**	0.02	-0.08***	0.03	-0.05*	0.03	-0.00	0.04
Child sickness (1997-1998)	-0.03**	0.02	-0.03	0.03	-0.02	0.03	-0.05	0.03
Community affected by Mitch (Oct 1998)	-0.05**	0.02	-0.07**	0.03	-0.03	0.04	-0.07	0.05
Coffee-crisis proxy (1998-2001)	-0.02	0.02	-0.06*	0.03	0.00	0.04	0.03	0.04
Severe rainfall shortage in July 2000	-0.03*	0.02	-0.06**	0.03	-0.01	0.03	-0.00	0.03
Number of observations	3,905		1,294		1,261		1,350	
Pseudo R^2	0.006		0.017		0.004		0.016	

Note: Significance at the level *** p<0.01, ** p<0.05, * p<0.1; N=3905 households in 1998 LSMS data; probit estimates for attrition; marginal effects; shock variables in chronological order; attrition from 1998 cross section: 38.4%; attrition from 1998 bottom tercile: 38.4%; attrition from 1998 middle tercile: 38.4%; attrition from 1998 top tercile in 1998: 40.1%; differences in attrition between terciles are not significant.

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