Workshop / *Atelier*

Wednesday-Thursday, June 24-25, 2015 / *Mercredi-Jeudi 24-25 Juin 2015*

Commodity market instability and asymmetries in developing countries:

Development impacts and policies

Les asymétries et l'instabilité du marché des matières premières dans les

pays en développement : politiques et impacts sur le développement

Food Price Shocks-induced Poverty Traps: Analysis Using a Panel Dataset From Uganda

By

Adamon N. Mukasa

FOOD PRICE SHOCKS-INDUCED POVERTY TRAPS: ANALYSIS USING A PANEL DATASET FROM UGANDA

Adamon N. Mukasa

Department of Economics and Management

Catholic University of Bukavu

2 Av. de la Mission

Bukavu, DR Congo

Tel.: (+243) 99 0185 523

adamon.mukasa@ucbukavu.ac.cd

Abstract

This paper tests the assumption that differential exposure to food price shocks leads to different welfare trajectories and to potentially increased risks of poverty traps. Using four waves of longitudinal data from Uganda, we find no evidence of any poverty trap induced by exposure to food price shocks. Instead, households are converging towards specific equilibria, depending on their demographic characteristics, vulnerability and exposure to food price shocks. Particularly, households highly exposed to price shocks were expected to move to consumption equilibrium levels located at 15.1% lower than those less exposed but only at 3.3% lower in terms of assets accumulation.

Key words: consumption, poverty traps, food price shocks, assets, welfare dynamics

1. INTRODUCTION

Eradicating poverty has always been one of key challenges for and earliest objectives of national policymakers and international agencies. Although at the global level, the Millennium Development Goal (MDG) of halving extreme poverty (proportion of people living with less than 1$ a day) has been achieved since 2010 (UN, 2014), some regions, particularly in Southern Asia and Sub-Saharan Africa (SSA), are still lagging behind and will not probably meet the target by 2015 (World Bank, 2013). More than in any other regions of the world, populations in SSA are not only among the most vulnerable to shocks and stressors (such as droughts, floods, or livestock and other asset losses) but also face multiple failures in land, credit, and insurance markets (Barrett and Carter, 2013) which make them largely dependent on donor and humanitarian assistance to make their ends meet. Recent research on poverty has thus advocated the need to study the underlying welfare dynamics so as to better understand the process through which some individuals or households may fall into or climb out of poverty (Naschold, 2005, 2013). Particularly, a bourgeoning empirical literature on the intertemporal dynamics of poverty focuses on the existence of poverty traps, broadly defined as "(…) any self-reinforcing mechanism which causes poverty to persist" (Azariadis and Stachurski, 2005: 326). At the core of the poverty trap's literature lie three interrelated concepts, namely the presence of *critical thresholds* preventing people to move from one welfare path onto another (Barrett and Carter, 2013), the occurrence of *shocks*, either permanent or temporary, likely to push people at a low-level stable equilibrium from which they cannot escape without an important positive shock to their welfare (van Campenhout and Dercon, 2012), and the existence of a *single or multiple equilibria* (Carter and Barrett, 2006).

The existence of these traps of poverty is an empirical matter. While some studies (Lybbert et al, 2004; Adato et al, 2006; Barrett et al, 2006; Amare and Waibel, 2013) find evidence in support for poverty traps, the results of others (Jalan and Ravallion 2002; Lokshin and Ravallion 2004; Antman and McKenzie 2005; Naschold, 2013, among others) suggest the absence of any poverty trap. If poverty traps do exist, then their identification and location become crucial for the implementation of appropriate policies likely to lift households from persistent poverty zones to desirably higher and self-sustained well-being equilibrium (Dutta, 2014). Accordingly, the paper examines households' welfare pathways to identify the links between shocks' occurrences and poverty traps. More precisely, it studies traps and identifies potential critical thresholds to determine whether households' welfare dynamics are characterized by a single or multiple equilibria.

The evidence shown in this study contributes to the existing literature on shocks, welfare dynamics, and poverty traps in two ways. First, I lay emphasis on and investigate the link between instabilities in commodities' prices and the existence of poverty traps. Indeed, in many SSA countries, the majority of the population earns their income from agricultural activities, intrinsically very sensitive to changes in crop market prices. While numerous studies have raised widespread concern that the recent global food price crisis might have pushed millions of population into poverty (Cudjoe et al, 2008; Headey and Fan, 2008; Ivanic and Martin, 2008; Boysen, 2009; Hella et al, 2011; Vu and Glewwe, 2011; Ferreira et al, 2011), they all fall short of evaluating the extent to which some households have fallen into chronic poverty or have been caught into poverty traps as a result of such price shocks. Built upon a modified standard optimal growth model (Geromini et al, 2006) allowing for reference-dependent preferences (Köszegi and Rabin, 2006) and a measure of household's exposure to food price instabilities (Collier and Dehn, 2001; Dehn, 2001; Combes et al, 2012), I show that food price shocks may lead to a lower equilibrium and therefore reinforce the persistence of poverty for those already thrust into a trap.

The Ugandan context is particularly germane for this empirical analysis for two main reasons. On the one hand, its poverty profiles are heterogeneous across regions and between rural and urban areas. In fact, although Uganda is generally praised for its economic performance characterized by a growth rate of Gross Domestic Product (GDP) well above that of the SSA, its economy has been accompanied by rising inequality between rural and urban areas and across different geographical regions. For instance, while the share of poor households living in rural areas increases from 26.7% in 2009/10 to 31.2% in 2010/11, the proportion of urban poor decreased from 11% to 7% during the same period (UBOS, 2013). Spatially, poverty rates were the highest in the Northern and Eastern regions with respectively 38.9 and 36.8% in 2010/11 against only 1% in Kampala (UBOS, 2013). On the other hand, the household panel dataset used in this study not only includes a large number of observations (around 2,200 households per survey), has detailed information on assets, income, or consumption expenditures, but also covers periods of stable and large food price changes, suitable for analyzing the impact of price instabilities.

Second, the paper uses a battery of econometric techniques to check whether the identified welfare pathways are genuine dynamics or instead an artifact of the specific estimation method used (Naschold, 2013). By means of parametric methods (System-GMM and cubic polynomial regression models), non-parametric methods (locally weighted scatterplot smoother (LOWESS) and local polynomial regression with Epanechnikov kernel weights), and semi-parametric methods (Ruppert et al.'s penalized splines estimators), I identify critical welfare thresholds, test for the presence of poverty traps in Uganda, and check for their robustness to model specifications.

This study is organized as follows. In the next section, a modified consumption growth model is presented and its theoretical implications are discussed. Section 3 describes the dataset used for the empirical analysis with a particular emphasis on the construction of a food price shock variable and household's asset index. In section 4, different estimation methods are discussed and empirical results are presented. Section 5 concludes the study.

2. CONCEPTUAL MODEL

This study focuses on the analysis of consumption growth, assets accumulation, and the identification of household-level poverty traps in an intertemporal framework where heterogeneous economic agents are maximizing their welfare and accumulating assets. As in Jalan and Ravallion (2002), and Elbers et al (2002), I use a variant of the Ramsey growth model of consumption.

However, in the present model, I am explicitly allowing agents (households) to face two types of shocks that directly affect their wealth accumulation: food price shocks θ_{ht}^{f}, through their impact on consumption levels and therefore household utility, and asset shocks θ_{ht}^{k}, through their effects on income levels.

Concretely, let the consumption level and capital/asset stock of a utility-maximizing household *h* for period *t* be c_{ht} and k_{ht}, respectively. For simplicity, I assume that the distributions of θ_{ht}^{f} and θ_{ht}^{k} are independent of each other and across time and their respective cumulative density functions denoted by $\Omega_{\theta^f}(.)$ and $\Omega_{\theta^k}(.)$ are known by the household when he decides on c_{ht} and k_{ht+1}. The relation between food price shocks and household consumption choices can be understood as follows: at the beginning of each period *t*, the household forms his expectations about both the probability of experiencing a price shock during period *t* and the magnitude of the shock given the information set at his disposal (current and past food price levels), expectations about future levels of food prices, and other constraints (labor, budget, or farm constraints). At the end of time *t*, after the realization or not of θ_{ht}^{f}, the household adapts his period *t*+1 decisions accordingly.

Formally, let $u(.)$be the instantaneous household's utility function, twice differentiable, strictly increasing, and strictly concave $(u'(.)>0; u''(.)<0)$. To incorporate the effect of a food price shock into the analysis, I assume, along the lines of Köszegi and Rabin (2006), that a household's utility depends on both the consumption bundle, *c*, and the realization or not of a food price shock $z(\theta^f)$, such that $U(c;\theta^f)=u(c)+v(c|z(\theta^f))$, where $u(c)$ is an intrinsic consumption utility and $v(c|z(\theta^f))$ is the utility gap or "gain-loss utility" function due to the realization of θ_{ht}^{f}. The utility-gap function is given by $v(c|z(\theta^f))=v[u(c)-u(c|z(\theta^f))]$, with $v(c|z(\theta^f=1))=0$, meaning that, in the absence of a price shock, $\theta^f=1$ and $U(c;\theta^f)$ reduces to the standard instantaneous utility function $u(c)$.

In terms of assets, the decision-maker accumulates a stock of assets at the end of each period t, k_{t+1}, with a depreciation rate δ, assumed constant over time. Unlike in the standard Ramsey model, the household assets are also exposed to shocks θ^k.

Each household h maximizes his expected lifetime utility and solves the following optimization problem:

$$\underset{c_t,k_{t+1}}{Max} \quad U\left(c;\theta^f\right) = \mathbf{E}_0\left\{\sum_{t=0}^{\infty}\beta^t\left[u(c_t)+\nu\left(u(c_t)-u\left(c_t\left|z\left(\theta_t^f\right)\right.\right)\right)\right]\right\}$$

subject to (1)

$$k_{t+1} = \theta_t^k\left[f(k_t)+(1-\delta)k_t\right]-c_t$$

k_0 given

where $\mathbf{E}_0(\bullet)$ is the conditional expectation $\mathbf{E}_0\left(\bullet|\Psi_0\right)$ with Ψ_0 the household's information set available at time 0; $\beta \in (0,1)$ is the time discount factor. Similarly to food price shocks, when $\theta^k = 1$, there is no asset shock while $\theta^k < 1$ implies a negative shock that depletes part of the household assets (Barrett et al, 2008). The value function derived from this problem in the presence of both food price and asset shocks can be defined as:

$$V\left(t,k_t\left|\Omega_{\theta_t}\right.\right) = \underset{c_s}{Max} \quad \mathbf{E}_t\left\{\sum_{s=t}^{\infty}\beta^s\left[u(c_s)+\nu\left(u(c_s)-u\left(c_s\left|z\left(\theta_s^f\right)\right.\right)\right)\right]\right\} \quad s.t \quad k_{t+1} = \theta_t^k\left[f(k_t)+(1-\delta)k_t\right]-c_t \tag{2}$$

The Bellman's principle of optimality associated with the value function in (2) for each t = 0, 1,2,… gives the following result:

$$V\left(t,k_t\left|\Omega_{\theta_t}\right.\right) = \underset{c_t}{Max}\left\{\beta^t\left[u(c_t)+\nu\left(u(c_t)-u\left(c_t\left|z\left(\theta_t^f\right)\right.\right)\right)\right]+\mathbf{E}_tV\left[t+1,\theta_t^k\left[f(k_t)+(1-\delta)k_t\right]-c_t\right]\right\} \tag{3}$$

It is straightforward to show that the first order conditions derived from the stochastic Bellman equation in (3) give the following Euler equation:

$$\mathbf{E}_t\left\{\theta_{t+1}^k\beta^{t+1}\left[f'(k_{t+1})+(1-\delta)\right]\times\left[u'(c_{t+1})+v'\left[g\left(c_{t+1};\theta_{t+1}^f\right)\right]\times\left(u'(c_{t+1})-u'\left(c_{t+1}\middle|z\left(\theta_{t+1}^f\right)\right)\right)\right]\right\}$$
$$=\beta^t\left\{u'(c_t)+v'\left[g\left(c_t;\theta_t^f\right)\right]\times\left(u'(c_t)-u'\left(c_t\middle|z\left(\theta_t^f\right)\right)\right)\right\} \tag{4}$$

where $g\left(c_t;\theta_t^f\right)=u(c_t)-u\left(c_t\middle|z\left(\theta_t^f\right)\right)$

The *Euler equation* (4) equates the discounted marginal benefit of consumption in period *t* under exposure to food price shock θ_t^f to the marginal cost, measured by the discounted marginal expected utility of potential consumption foregone in period *t*+1. The Euler equation (4) can be rearranged to give:

$$\frac{U'\left(c_t;\theta_t^f\right)}{\beta\mathbf{E}_t U'\left(c_{t+1};\theta_{t+1}^f\right)}=\theta_{t+1}^k\left[f'(k_{t+1})+(1-\delta)\right] \tag{5}$$

where

$$U'\left(c_t;\theta_t^f\right)=u'(c_t)+v'\left[g\left(c_t;\theta_t^f\right)\right]\times\left(u'(c_t)-u'\left(c_t\middle|z\left(\theta_t^f\right)\right)\right) \tag{6}$$

and

$$U'\left(c_{t+1};\theta_{t+1}^f\right)=u'(c_{t+1})+v'\left[g\left(c_{t+1};\theta_{t+1}^f\right)\right]\times\left(u'(c_{t+1})-u'\left(c_{t+1}\middle|z\left(\theta_{t+1}^f\right)\right)\right) \tag{7}$$

The left-hand side of (5) represents the intertemporal marginal rate of substitution in consumption under price instabilities, while the right-hand side is the marginal rate of transformation in production (*MRT*) when assets are subject to shocks. Accordingly, the Euler equation (5) provides two key messages regarding the effects of food price and asset shocks on household's intertemporal optimization problem. First, if exposure to food price shocks has no effect on household's consumption behavior (for example, in the case of autarkic households who do not participate into a food market, $g\left(c_t;\theta_t^f\right)=0\rightarrow u(c_t)=u\left(c_t\middle|z\left(\theta_t^f\right)\right),\forall t$, $U'\left(c_t;\theta_t^f\right)=u'(c_t),\forall t$), and assets are not affected by shocks ($\theta^k=1$), the left-hand side of equation (5) reduces to a standard Euler equation.

Second, if instead $u(c_t) \neq u\left(c_t \middle| z\left(\theta_t^f\right)\right), \forall t$, in other words, if food price shocks push a household to modify his consumption behavior (think for example of pure consumers, net sellers, or net buyers of agricultural products), then the marginal utility of consumption under θ_t^f becomes:

$$U'\left(c_t;\theta_t^f\right) = u'(c_t)\left\{1 + v'\left[g\left(c_t;\theta_t^f\right)\right]\right\} - u'\left(c_t \middle| z\left(\theta_t^f\right)\right)\left\{v'\left[g\left(c_t;\theta_t^f\right)\right]\right\} \neq u'(c_t), \forall t \qquad (8)$$

Hence, from equation (8), it is possible to get for some households $c_t \middle| z\left(\theta_t^f\right) < c_t$ while for others $c_t \middle| z\left(\theta_t^f\right) > c_t$, depending on their initial characteristics, attitude towards risk, preferences, or expectations about the future. Particularly, when $c_t \middle| z\left(\theta_t^f\right) < c_t$, a price shock, either its realization or household's anticipation about its future realization, reduces the level of consumption that the household would have achieved (attainable well-being). Repeated price shocks over time may thus trigger downward welfare spirals and increase the likelihood of a poverty trap, unless the household luckily receives a positive income shock (social transfers, inheritances, job opportunities,…) or policy interventions modify these price dynamics. Furthermore, in the presence of negative asset shocks $\left(\theta^k < 1\right)$, the standard marginal rate of transformation in output will be reduced the larger the magnitude of the asset shocks.

To uncover the expression of the growth path of consumption $\Delta \ln c_t = \ln c_t - \ln c_{t-1}$, let us assume that the level of consumption under food price shocks is proportional to the importance of the shock such that $U\left(c_t;\theta_t^f\right) = u\left(\left(\theta_t^f\right)^\pi c_t\right)$, where π is a time-constant and household-specific elasticity that captures the magnitude of the price shock. Furthermore, let the utility $u(c)$ be represented by a Constant Relative Risk Aversion (CRRA) utility function: $u(c) = \dfrac{c^{1-\rho}}{1-\rho}$ if $\rho > 0, \rho \neq 1$ and $u(c) = \ln(c)$ if $\rho = 1$; with ρ a measure of the degree of relative risk aversion. This implies that $U'\left(c_t;\theta_t^f\right) = \left(\theta_t^f\right)^{\pi(1-\rho)} c_t^{-\rho}$ and $U'\left(c_{t+1};\theta_{t+1}^f\right) = \left(\theta_{t+1}^f\right)^{\pi(1-\rho)} c_{t+1}^{-\rho}$. Expressing the Euler equation in (5) one period backwards and linearizing the resulting intertemporal marginal rate of consumption substitution, we get the following expression of the growth rate of consumption between *t* and *t*-1:

$$\Delta \ln c_t \equiv \ln\left(\frac{c_t}{c_{t-1}}\right) = \pi\left(\frac{1-\rho}{\rho}\right)\ln\left(\frac{\theta_t^f}{\theta_{t-1}^f}\right) + \frac{1}{\rho}\ln\left(\theta_t^k\right) + \frac{1}{\rho}\ln\left(\frac{1}{\beta}\right) + \frac{1}{\rho}\ln\left[f'\left(k_t\right) + \left(1-\delta\right)\right] \tag{9}$$

Equation (9), which will serve as the starting point to our empirical model, gives the consumption growth path when both food price and asset shocks are allowed to co-exist. It shows that the consumption path over time is affected not only by taste and preference shifters (time preference β and degree of risk aversion ρ) or marginal productivity of capital/assets net of depreciation rate (last term of 9) but also by the magnitude of relative changes in food price shocks $\Delta\theta_t^f = \frac{\theta_t^f}{\theta_{t-1}^f}$ and capital/asset shocks θ_t^k. In reduced form, equation (9) leads to the following specification:

$$\Delta \ln c_{ht} \equiv \ln\left(\frac{c_{ht}}{c_{ht-1}}\right) = \sigma_0 + \sigma_1 Z_{ht} + \sigma_2 \Delta \ln \theta_{ht}^f\left(X, Z\right) + \sigma_3 \ln\left(\theta_t^k\right) + \sigma_4 X_{ht} + \sigma_5 X_h + \eta_h + \mu_{ht} \tag{10}$$

where Z_{ht} is a vector of variables affecting taste and other preference shifters, X_{ht} and X_h are vectors of time-varying and time-invariant variables that influence household's asset levels and their marginal productivity; η_h is household-specific unobserved heterogeneity capturing household fixed effects; μ_{ht} is the error term; σ_i are unknown parameters to be estimated. Importantly, σ_2 measures the impact of variations in differential exposure to food price shocks on contemporaneous consumption growth, after controlling for other types of shocks, household characteristics, or unobserved heterogeneity. In particular, a negative coefficient of σ_2 will be indicative of consumption depletion consecutive to increases in the rate of exposure to price shocks, all other things equal.

3. DATA

This paper uses a four-wave panel dataset of the Uganda National Panel Surveys (UNPS) conducted in 2005/6, 2009/10, 2010/11, and 2011/2012 by the Uganda Bureau of Statistics (UBoS) as part of the Living Standard Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) of the World Bank. Among the 3,123 targeted households in 2005/9, the UBoS was able to track 2,888 households in 2009/10, among which only 2,566 had complete information (Ssewanyana and Kasirye, 2012), which represents an attrition rate of 17, 8%. And among the 2,566 households tracked in the 2009/10, 2,390 were re-interviewed in 2010/11 and 2,194 in 2011/12, with only 2,173 households having complete information in all the four waves. Hence, for this article, the final sample of each survey contains information on 2,173 balanced households[1], located in all the geographical regions of the country. Pooling these time series and cross-sectional data gives 8,692 observations.

All surveys were based on a two-stage stratified random sampling design. In the first stage, Enumeration Areas (EAs) were selected from the 4 geographical regions of the country and grouped by districts and rural-urban location (UBoS, 2010). In the second stage, ten households in each EA were selected by simple random sampling. Each household was then visited twice in order to capture seasonalities in the agricultural production module. The panel surveys provide detailed information on household demographics, production, consumption, landholdings and livestock ownership, types of shocks and coping strategies, among others.

(a) Construction of a food price shock variable

A key challenge in estimating equation (10) is to find a suitable definition of *being exposed to a food price shock*. Two practical problems emerge when engaging in such task. First, although the UNPS provide information on households' exposure to different types of shocks (health, agricultural, livestock or other asset shocks) as well as the responses in terms of coping strategies that households adopt, the surveys remain silent in regards to food price shocks. Second, price changes affect households differently depending on their tastes, preferences, composition, or their decision to participate or not into a food market. Hence, observing a "large" change in food prices in a specific district between two periods does not automatically imply that all households within that district will be identically affected. One way to overcome the above complications is "to locate shocks using a pure statistical definition" (Dehn, 2000: 8). Hence, in order to compute a food price shock variable, I follow the methodology first developed by Deaton and Miller (1995) and recently applied by Collier and Dehn (2001) and Combes et al. (2012) in their studies of countries' vulnerability to commodity price instabilities and shocks.

First, I compute a household-specific consumer price index to reflect households' heterogeneity in their consumption preferences. Theoretically, two approaches can be used to obtain these indices. One could estimate a food demand system and use the estimation results to compute a household-specific true cost of living (Cage et al., 2002); or instead, one could use a vector of market prices at a certain disaggregation level (village, district, or sub-region) and a vector of household-specific budget shares to construct the index. I will use the second approach given its evident computational simplicity.

Let CPI_{hct} be the food price index, specific to a household *h* living in cluster (village or district) *c* in period *t.* If p_{ct}^{i} represents the median unit market price of a commodity *i* observed in cluster *c* at time *t*, and $s_{hct}^{i} = p_{ct}^{i} C_{hct}^{i} / \sum_{i=1}^{I} p_{ct}^{i} C_{hct}^{i}$ is the food consumption share of the commodity *i*¸ then CPI_{hct}, based on price levels in period 0 (in this paper, 2005/6), can be computed as a modified *Laspeyres* formula:

$$CPI_{hct} = \sum_{i=1}^{I} s_{hct}^{i} \left(\frac{p_{ct}^{i}}{p_{c0}^{i}} \right) \tag{11}$$

where the basket of goods in equation (11) is made up of 7 food commodities or commodity groups considered as the most important in the Ugandan diet: *matooke*, potatoes (sweet and Irish potatoes), cassava, maize, beans, meat and fish, fruits and vegetables. Hence, although market prices are assumed on average identical for households within the same village (Deaton, 1988, 1997), the use of food consumption shares s^i_{hct} as individual weights makes the price index household-specific. Given CPI_{hct}, the second step consists in regressing the changes in each household's price index on its lagged values, time dummies *t*, and household's fixed effects κ as follows:

$$\Delta CPI_{hct} = \alpha_0 + \alpha_1 CPI_{hct-1} + \alpha_2 t + \kappa + \varepsilon_{hct}; \qquad t = 1,..., T \tag{12}$$

The residuals from equation (12), $\hat{\varepsilon}_{hct}$, are then standardized by subtracting their mean values $\bar{\varepsilon}_{hct}$ and dividing by their standard deviation $s_{\hat{\varepsilon}}$ (Combes et al., 2012). Hence, contrarily to many previous studies on shocks, this specification allows not only to answer *whether* there is a significant impact of exposure to food price shocks on consumption growth but also *how large* this impact is given the magnitude of the shocks experienced by the household. Owing to the emphasis of the paper on positive price shocks, I consider for now a household as having been exposed to a food price shock if its normalized residuals from equation (12) are positive. This definition will then be extended thereafter by including negative price shocks and varying cut-off points. The higher the values of the normalized residuals, the more important the scale of exposure to food price shocks. Using this definition, there are respectively 63.3, 51.7, and 34.2% households that were exposed to food price shocks in 2009/10, 2010/11, and 2011/12.

Table 1 presents some key household characteristics according to whether a household was exposed or not to a food price shock. Households are then subdivided into three categories, depending of the extent of their exposure to price shocks: *high* if the normalized $\hat{\varepsilon}_{hct}$ exceeds the 75$^{\text{th}}$ percentile of the sample value; *moderate*, if it lies between the median and the 75th percentile; and *low* if it is positive but below the median.

(table 1 *about here)*

Different features emerge from this table. First, the proportion of highly exposed households is the largest in 2009/10 (27.6% of surveyed households) and the lowest during the third survey (15.6% in 2010/11). Second, while the number of moderately affected households is decreasing over time, those of unexposed and with low exposure rates are increasing, reflecting the general tendency of food price changes in Uganda. Third, we also note that on average households' monthly real values of food consumption per adult equivalent were the highest when households were not exposed to food price shocks. Hence, unexposed households enjoyed an increase in their consumption relative to those exposed. Among the sub-sample of households exposed to price shocks, those at the highest vulnerability percentile reported on average a lower level of consumption compared to the baseline survey (2005/6), providing a first insight on a possible negative relationship between the degree of exposure to food price shocks and households' consumption levels. By and large, the less a household is exposed to food price shocks, the more important his level of consumption. Households likely to be highly exposed to food price shocks have on average larger household size, higher proportion of children, older heads and are run mostly by females.

Unsurprisingly, agricultural and poor households display a higher likelihood of being exposed to large food price shocks. For example, the proportion of agricultural households with low degree of exposure to price shocks is around 70%, compared to an average of 90% and 85% for high and moderate degrees, respectively. This feature was expected, particularly for agricultural households since they generally live in rural areas and dependent essentially on the levels of market prices for their income. When we disaggregate agricultural households by their net seller/net buyer status, it appears that globally the proportion of net sellers (buyers) of food staples is decreasing (increasing) with the degree of exposure. Finally, the fact that most poor households were highly exposed to price shocks is also in line with many empirical findings (Cudjoe et al, 2008; Headey and Fan, 2008; Ivanic and Martin, 2008; Boysen, 2009; Hella et al, 2011) and is indicative of increased risks of being trapped into persistent poverty for those households.

(b) Asset index

Although very informative on household welfare dynamics, consumption-based approaches fall short of distinguishing structural changes from stochastic variations in welfare (Barrett et al, 2006). To enrich the analyses from consumption and account for the underlying structural wellbeing of households, I also compute, in line with Carter and May (2001), Carter and Barrett (2006), McKay and Perge (2013), and Naschold (2013), an aggregate index of household assets. This index reduces the multivariate dimension of assets to a single dimension, thereby avoiding the "curse of dimensionality" problem in non-parametric estimations. I use the livelihood-weighted regression approach (Carter and May, 2001; Adato et al; 2006; Amare and Waibel, 2013) where a livelihood indicator, is regressed over a bundle of assets (human, physical, financial, or social) likely to shape household's wellbeing and the predicted value of the dependent variable is then used as the estimated asset index.

Similar to previous studies (McKay and Perge, 2013; Naschold, 2013), the components of the asset index include a set of productive and agricultural assets (land, livestock, agricultural equipments, small business machinery,…), physical assets (owned houses and buildings, household utilities,…), and human assets (household size, maximum years of schooling of the head, proportion of adults and children,…). Formally, this requires estimating the following regression model (Amare and Waibel, 2013):

$$\lambda_{ht} = \beta_0 + \sum_{i=1}^{I} \beta_i A_{ht}^i + \sum_{j,k}^{I} \beta_{jk} A_{ht}^j A_{ht}^k + \mathbf{Z'}\boldsymbol{\alpha} + \mathbf{D'}\boldsymbol{\omega} + \vartheta_h + \varepsilon_{ht} \qquad (13)$$

where the dependent variable $\lambda_{ht} = \frac{c_{ht}}{P_t}$ is the real monthly values of consumption per adult equivalent c_{ht} expressed at a percent of the official poverty line[2] P_t at time *t*. A_{ht}^i, A_{ht}^j, and A_{ht}^k are the amounts of physical or productive assets *i,j,* and *k* owned by household *h* in period *t*; $\mathbf{Z}$ is a vector of households' characteristics (human assets); $\mathbf{D}$ is a vector of district and time dummies included to account for geographical and time unobserved effects on assets accumulation, while ϑ_h stands for household-specific unobserved fixed effects. ε_{ht} is the error term. Equation (13) is estimated using a fixed-effects model and the predicted values $\hat{\lambda}_{ht}$ are interpreted as household-specific asset index. Deriving this index through a livelihood approach presents at least three appealing advantages. First, individual assets are included in the index based on their marginal contribution on the household's overall livelihood level. Second, scaled in Poverty Line Units (PLU), the index is easily interpretable: an index above 1 means that household's asset holdings would be expected to yield a livelihood level above the official poverty line. Finally, the asset index can be used to distinguish between stochastic and structural poverty.

In figure 1, I plot the asset index a_{ht} at current period against its one period lagged value. First, there seems to exist an equi-distribution of asset indices below and above the asset poverty line, particularly between 0.65 and 1.4, with only few observations (gray circles) located outside this interval. Second, there is evidence of households' heterogeneity regarding their assets' accumulation process: households whose asset holdings are below (above) the 45° line will be decumulating (accumulating) assets over time. Third, and probably the key take-away message from this bivariate analysis, is the evident absence of multiple critical thresholds in the assets accumulation process: Ugandan households seem to be converging towards a single asset equilibrium located slightly above the official poverty line.

(figure 1 *about here)*

4. ESTIMATION METHODS AND RESULTS

(a) Parametric models of consumption and asset dynamics

The starting point of our estimation strategy is given by equation (10). In line with existing studies (Jalan and Ravallion, 2002; Barrett et al, 2006; Kwak and Smith, 2010; Naschold, 2013), I allow for nonlinearities in welfare dynamics by estimating changes in consumption $\Delta \ln c_{ht}$ as a cubic polynomial function of lagged consumption c_{ht-1}, household characteristics $\mathbf{\Lambda}$, and changes in exposure to food price shocks $\Delta \ln \theta_{ht}^{f}$ and other asset shocks $\left(\theta_{t}^{k}\right)$. Hence, our baseline empirical model is given by:

$$\Delta \ln c_{ht} = \sigma_0 + \sum_{i=1}^{3} \beta_i \ln c_{ht-1}^{i} + \mathbf{\Lambda'\alpha} + \sigma_1 \Delta \ln \theta_{ht}^{f} + \sum_{j=1}^{3} \nu_j \theta_{t}^{kj} + \left(\eta_h + \mu_{ht}\right) \quad (14)$$

where the dependent variable c_{ht} represents monthly real values of consumption per adult equivalent in period *t*; $\mathbf{\Lambda}$ denotes a set of household characteristics, some of which are time-varying and others time-invariant, likely to influence household consumption levels. Specifically, I include in $\mathbf{\Lambda}$ household size $(hsize)$, dependency ratio $(dratio)$, age of the head (age), age squared $(age2)$, gender (sex), tropical livestock units (tlu)[3], years of education of the head $(educ)$, land size in acres $(land)$, household's poverty status ($povstatus$) as well as regional ($region$) and time ($year$) dummies to control for geographic and time effects, respectively. β_i are the coefficients of consumption polynomial terms; η_h is the time-invariant component of the error term indicating household's unobserved effects, potentially correlated with $\mathbf{\Lambda}$ but not with μ_{ht}; μ_{ht} is an independent and identically distributed (*iid*) error term; and the remaining right-hand side variables have been previously defined. Capital/asset shocks are subdivided into three categories: health shocks (θ_{ht}^{k1}) which take 1 if in the last 12 months a household member died, had severe injury or accident, had a serious illness, or if the household experienced the death of a member or close relative for whom it had to pay for the burial. Agricultural shocks (θ_{ht}^{k2}) equal 1 if the household experienced in the last 12 months droughts, floods, or pest attacks and diseases, causing output losses, or faced increases costs of agricultural inputs and theft of agricultural assets. Income shocks (θ_{ht}^{k3}) take 1 if in the last 12 months a household member lost a job or faced reduction of earnings.

In this baseline specification, food price shocks enter linearly the empirical dynamic welfare equation (14) which would suggest a homogeneous impact of price shocks. I extend this model by investigating the presence of non-linear effects of food price shocks on consumption growth in the following way. I assume that the impact of food price shocks will be different depending on the degree of a household's vulnerability to price shocks. Adapting the criteria of countries' vulnerability to commodity price instabilities as advanced by de Janvry and Sadoulet (2008) and applied by Combes et al. (2012), I identify three factors that might determine this vulnerability.

The first factor, food dependency, is related to the importance of food consumption in the household's budget. At a given period t¸ a household will be hit by food price instabilities the larger the share of food consumption in his budget. This degree of food dependency is approximated by the share of the total value of food consumption in the household's total expenditures.

The second factor concerns the extent of market participation in household consumption. Households that rely mainly on home production for consumption needs will be marginally affected than those constrained to purchase a large proportion of their food consumption, such as non-agricultural households or significant net buyers. Hence, the higher the degree of market participation, the higher the likelihood of being exposed to food price shocks. This second criterion is measured by the ratio of total food purchased to total food consumption.

Finally, food price shocks may have differential impact on households depending on whether they are rich or poor. Indeed, it has been shown that poor households are generally more vulnerable to shocks and lack sufficient resources to play as safety nets in case of shocks' occurrence (de Weerdt, 2004; Santos and Barrett, 2006). I measure this ability of households to mitigate the effects of price shocks by the level of monthly real income per adult equivalent. These three factors are then combined to compute a household's vulnerability index to food price shocks (vul_{ht}^{θ}) using the principal component analysis. The higher the value of the index, the more vulnerable the household to food price shocks. The variable of price shocks θ_{ht}^{f} is finally interacted with the vulnerability index as follows:

$$\Delta \ln c_{ht} = \sigma_0 + \sum_{i=1}^{3} \beta_i \ln c_{ht-1}^{i} + \mathbf{\Lambda'\alpha} + \sigma_1 \Delta \ln \theta_{ht}^{f} + \sigma_2 \left(\Delta \ln \theta_{ht}^{f} \times vul_{ht}^{\theta} \right) + \sigma_3 vul_{ht}^{\theta} + \sum_{j=1}^{3} \nu_j \theta_t^{kj} + \varepsilon_{ht} \qquad (15)$$

where $\varepsilon_{ht} = \eta_h + \mu_{ht}$

This specification allows the impact of food price shocks to differ between households given their degree of vulnerability to price shocks. The coefficient σ_1 captures the impact of price shocks due to the actual level of exposure while σ_3 provides the impact related to the household's predisposition to being vulnerable to price shocks. Furthermore, The total effect of changes in exposure to food price shocks on consumption growth rate is thus given by $\frac{\partial \Delta \ln c_{ht}}{\partial \Delta \ln \theta_{ht}^{f}} = \hat{\sigma}_1 + \hat{\sigma}_2 v\bar{u}l_h^{\theta}$,

where $\hat{\sigma}_1$ and $\hat{\sigma}_2$ are the estimated coefficients and $v\bar{u}l_h^{\theta} = \frac{1}{T} \sum_{t=1}^{T} vul_{ht}^{\theta}$ is the household's *h* average vulnerability index over the sample period. Hence, checking for non-linearity simply implies testing the null hypothesis that $\hat{\sigma}_2$ is statistically different from 0. The assumption that food price shocks have detrimental consequences on consumption growth is akin to having $\hat{\sigma}_1 + \hat{\sigma}_2 v\bar{u}l_h^{\theta} < 0$.

Finally, when $\hat{\sigma}_1$ and $\hat{\sigma}_2$ display opposite signs, it is possible to derive a threshold vulnerability index $\left(vul_h^{\theta} \right)^{\bullet} = -\frac{\hat{\sigma}_1}{\hat{\sigma}_2}$ above which food price shocks start hurting households (reducing their consumption growth).

The estimation of the non-linear dynamic panel model in (15) poses some practical problems. First, the construction of our food price shock variable suggests that θ_{ht}^{f} will be endogenously determined since it is correlated with household characteristics $\mathbf{\Lambda}$. To solve this problem, one could use an instrumental variables' estimation (such as Two Stage Least Squares, 2SLS). However, with weak instruments, the fixed-effects IV estimators will be biased. Second, it is well known that OLS will yield inconsistent estimates since the polynomial terms in consumption $c^{i}_{ht-1}, \forall i = 1,...,3$ will be correlated with the error term $(\eta_h + \mu_{ht})$. As a result, the coefficients β_i will be inflated upwardly (Hsiao, 1986; Bond, 2002), leading again to potential endogeneity problems and estimation instability. A possible way-out to reduce this upward panel bias is through a within-groups (fixed effects) transformation that wipes out household-specific time-invariant effects η_h. However, given the structure of our panel dataset (small *T*, large *N*), this solution is also unsatisfactory as it has a tendency towards downward panel bias (Nickell, 1981). The panel bias will be captured by introducing the first difference, which purges the fixed effects η_h. To estimate the consumption growth model, I use the System Generalized Methods of Moments (S-GMM) of Arellano-Bover (1995) and Blundell-Bond (1998). Indeed, the S-GMM reduces the problem of finite sample biases associated with weak instruments and estimates a system of equations both in first differences and in levels. Blundell and Bond (1998) suggest that *lagged levels* of the variables are suitable instruments in the difference equation, whereas in the levels equation, *lagged differences* are used as appropriate instruments. The implementation of S-GMM depends on the satisfaction of serial correlation and over-identification tests. The Sargan/Hansen test checks whether the set of instruments as a group are properly identified and valid. Therefore, the higher the *p*-value of this statistic, the better. The Arellano-Bond test for autocorrelation AR(2) detects autocorrelation in levels and failure to pass test implies that the S-GMM estimator is inconsistent.

Table 2 reports the two-step S-GMM estimation results of consumption growth model using four different specifications. Model I leaves aside shock variables (food price, health, agricultural, and income shocks) and regional and time dummies. Model II extends Model I by allowing for location and time dummies; the third specification takes account of both different shock variables and regional and time effects but only assumes linear effects of food price shocks. The last specification (Model IV) allows for potential non-linear effects of price shocks. Specification tests were performed using both serial correlation and over-identification tests.

(table 2 *about here)*

In all the three models, the null hypothesis of the Arellano-Bond test of autocorrelation in first differences AR(1) is rejected while the test of AR(2) indicates that the S-GMM estimators are consistent in all models. The *Hansen J* statistic concludes that our instrumental variables, as a group, are valid.

The effects of the polynomial terms on households' consumption growth reveal some interesting features. First, the results show that the coefficients of one-period lagged consumption expenditures affect households' consumption growth negatively and significantly in all model specifications, which indicates that households' consumption growth between periods *t*-1 and *t* tend to decrease the higher the levels of consumption in *t*-1. Particularly, these estimated coefficients exceed one in all specifications and are the lowest when regional and time dummies are excluded from the consumption growth model. Second, the quadratic and cubic polynomial terms are respectively positive and negative in all models but simultaneously insignificant only in Model I, which implies a linear consumption growth path. In the other models, the hypothesis of nonlinearities in the growth rate of consumption is not rejected at 5% significant level in the richer specifications.

All shock variables are both negative and significant at 5% levels, implying that being exposed to food price shocks lowers the rate of consumption growth. In model III, the coefficient $\hat{\sigma}_1$ associated with food price shocks is -0.18%, thereby indicating that a 1% increase in the growth rate of food price shocks is followed on average by a 0.18% decrease in consumption growth.

The last column of table 2 (Model IV) reveals that allowing for nonlinear effects of the impact of food price shocks modifies considerably the estimation results. Indeed, the *p*-value of the joint significance test of $\hat{\sigma}_1$ and $\hat{\sigma}_2$ rejects the hypothesis of linearities of price shocks. Hence, once we allow for the presence of these non-linear effects, the coefficient $\hat{\sigma}_1$ becomes amplified to -0.78 while the coefficient $\hat{\sigma}_2$ for the interaction between price shocks and the vulnerability index is positive and significant at 5%. These results suggest that the consumption growth rate is on average marginally decreasing with the degree of exposure to food price shocks, and this effect is increasing with the extent of household's vulnerability. The higher the vulnerability index, the lower the growth rate of consumption once a household is hit by a food price shock. The destabilizing effect of food price shocks is consequently reinforced by higher food dependency, higher degree of market participation, and lower income levels. However, being potentially vulnerable to food price shocks does not necessarily imply that a household will be negatively affected if the price shock effectively occurs. In the lower part of table 4, I thus report the level of vulnerability index above which exposure to food price shocks has detrimental effect on consumption growth rate. Given the estimated coefficients $\hat{\sigma}_1$ and $\hat{\sigma}_2$, the threshold vulnerability index $\left(vul_h^{\theta}\right)^{\bullet}$ is set at 1.364, which means that the consumption levels of households reporting an vulnerability index above that threshold would be negatively affected in case of exposure to food price shocks. The percent of households beyond this critical vulnerability level is given in the last line of table 2. Hence, the majority of households should have been particularly concerned by food price shocks because around 57.7% of surveyed households had a vulnerability index greater than 1.364. Over time, this percent has been however decreasing, from 69.6% in 2009/10 to 40.3% in 2011/12.

In terms of asset/income shocks, being exposed to health shocks (θ_{ht}^{k1}) has a negligible effect, while the occurrence of agricultural (θ_{ht}^{k2}) and income shocks (θ_{ht}^{k3}) reduces consumption growth in Model IV by 0.04 and 10%, respectively.

Many household-level variables have also contributed significantly to the consumption growth rates and present the expected signs. I find life-cycle effects in consumption growth: it tends to increase with age but only up a certain point before eventually declining. Similarly to Jalan and Ravallion (2002), the estimation results reveal that larger households tend to have higher consumption growth rates. Moreover, there are significant gender differences insofar as female-headed households are likely to have lower growth rates of consumption expenditures. Moreover, I find evidence that households with more TLUs, larger dependency ratio, and more educated heads, displayed higher growth rates, whereas poor households have significantly lower subsequent rates of consumption growth.

Finally, as expected, increases in land holdings are translated into increases in growth rates of consumption. This result perfectly characterizes the Ugandan economy where the majority of households are not only engaged in agricultural activities but also use the products of their farm for subsistence consumption. Therefore, more lands to cultivate imply more food for home consumption. And given that food consumption often represents the largest share of household's total expenditures, this situation ultimately leads to an increase in consumption growth rates.

The above analyses of changes in growth rates of consumption give first insights on household welfare dynamics in Uganda. However, as pointed out by Barrett et al. (2006), restricting the analysis to consumption prevents us from identifying structural and stochastic patterns of welfare dynamics and distinguishing the characteristics of one from another. Hence, to focus on the structural part of household's welfare, they suggest instead the study of asset dynamics, less likely to be sensitive to transitory variations. These dynamics may be determined by both household accumulation behavior and various asset shocks. Similarly to the above consumption growth model, the assets accumulation process can be described through a cubic polynomial regression model as follows:

$$\begin{aligned}\Delta \ln a_{ht} &= \beta_0 + \sum_{i=1}^{3} \beta_i \ln a_{ht-1}^{i} + \mathbf{\Lambda}'\boldsymbol{\gamma} + \beta_4 \Delta \ln \theta_{ht}^{f}(\mathbf{\Lambda}) \\ &\quad + \beta_5 \theta_t^k + \beta_6 a_{h,0} + \beta_7 \theta_t^k * apovstatus \quad + (\tau_h + \mu_{ht})\end{aligned} \tag{16}$$

where θ_t^k is a composite asset shock constructed by summing health (θ_{ht}^{k1}), agricultural (θ_{ht}^{k2}), income (θ_{ht}^{k3}), and other asset shocks (θ_{ht}^{k4}). It thus ranges from 0 (household did not face any type of asset shocks in the last 12 months) to 4 (household experienced each asset shock). Accordingly, asset shocks are incorporated linearly into the assets accumulation growth equation (16). They are also interacted with household asset poverty status *apovstatus* (which takes 1 if household asset index is below 1 and 0 otherwise) to allow for heterogeneous patterns in the effects of asset shocks across households. $a_{h,0}$ stands for household's initial asset index.

Table 3 displays the estimation results of equation (16) using a two-step S-GMM regression of Arellano-Bover (1995) and Blundell-Bond (1998).

(table 3 *about here)*

All model results reveal that the coefficients associated with the first and cubic polynomial terms are negative whereas the quadratic term is significantly negative, which implies, similarly to the consumption growth model, nonlinearities in growth rates of assets accumulation. In the richer model (III), all selected household characteristics significantly affect the growth rate of assets accumulation which tends to increase with household size, the age of the household head – but up to a certain age -, the years of education, and decrease with initial asset holdings or when households are female-headed or have a high dependency ratio.

In terms of the impact of shocks on assets accumulation growth, our results suggest that, although being exposed to food price shocks significantly reduce the assets growth rates, their impact appears relatively marginal compared to changes in consumption growth rates. Indeed, a 10% increase in the degree of exposure to a food price shock would be expected to decrease the assets growth rate by only 0.14%, largely lower than the 2.07%[4] fall in consumption growth rates. Hence, the marginal effects of changes in food price shocks' exposure are much more important on consumption growth than on assets accumulation. Moreover, the results show that the effects of asset shocks are much more important than those of food price shocks. However, these impacts appear non-linear across asset poverty status and the number of asset shocks faced by the households. Households who are structurally poor are found not only more sensitive to the occurrence of asset shocks but also their sensitivity increases with the number of asset shocks. The results reveal for example that the growth rates of assets accumulation of structurally poor households fell on average by 0.15, 0.16, and 0.18% when they faced one, two, and three types of asset shocks, respectively. Despite being also sensitive to shocks, assets accumulation rates of structurally non-poor households are only marginally affected. As pointed out by Amare and Waibel (2013), these households are generally engaged in high-return livelihood activities which increase their resilience to different shocks. Indeed, the growth rate of their assets will shrink by only 0.07% in case of exposure to three types of asset shocks against 0.18% for structurally poor. These results outline the inability of structurally poor households to maintain the welfare levels in the wake of shocks and other stressors and therefore shed light on the increased likelihood of being trapped into poverty or converging towards low level welfare equilibrium.

(b) Testing for poverty traps

The results of the parametric models of consumption growth and assets accumulation process have revealed the existence of nonlinearities in household welfare dynamics. However, finding these nonlinearities does not necessarily imply the presence of poverty traps or guarantee welfare multiplia equilibria (Kwak and Smith, 2010). To test for the existence of poverty traps, I first predict the values of consumption expenditures and asset indices using the estimation results presented in tables 4 and 5. I add to these results the lagged values of consumption c_{ht-1} and asset a_{ht-1} to get the predicted consumption levels and asset index. The relationship between these predicted values against their lagged values are then portrayed graphically through a scatterplot. If there are multiple welfare dynamic equilibria, then we must find an *S*-shaped curve or non-convex welfare dynamics characterized by the existence of multiple stable equilibria (with at least one equilibrium below the poverty line) and at least one unstable dynamic equilibrium (Barrett and Carter, 2013).

Figure 2 shows markedly linear welfare dynamics with the absence of any *S*-shaped curve or bifurcated welfare dynamics necessary for the existence of multiple critical thresholds. On the contrary, the 45 degree line cuts both consumption and asset dynamics' curves at one point, suggesting a *single* dynamic welfare equilibrium at around 29,000UShs for monthly real values of consumption per adult equivalent and 1.10 PLUs for asset index. These equilibria are at relatively low level, slightly above the poverty line of 23,760UShs for per capita real monthly consumption.

(figure 2 *about here)*

(c) Non- and semi-parametric models of consumption and asset dynamics

One of the main drawbacks of parametric methods is that they require the researcher to specify pre-determined functional forms for the welfare dynamics process. Contrary to parametric methods, the appeal of non-parametric approach stems from letting the data determine the appropriate model specification without imposing any parametric assumptions on the data generating process. The functional form to be estimated is then unknown by the researcher and can be expressed as:

$$y_{ht} = f(y_{ht-1}) + \varepsilon_{ht}, \quad y_{ht} = \{c_{ht}, a_{ht}\} \tag{17}$$

with $\varepsilon \sim N(0;\sigma_\varepsilon^2), \quad 1 \le h \le N, \quad and \quad 2 \le t \le T$

The non-parametric bivariate relationship between the current welfare level y_{ht} and its lagged values portrayed in equation (17) can be estimated using various non-parametric methods such as Kernel-weighted local polynomial smoothing, locally weighted scatterplot smoother (LOWESS), or different types of splines. In figures 3 and 4, I present the results of consumption (figure 3) and asset (figure 4) dynamics using location polynomial smoothing and LOWESS estimates. For each welfare indicator, I first report the LOWESS estimates and then the local polynomial smoothing diagrams (using an Epanechnikov kernel function with 3 degrees). The dashed lines stand for the 45 degree line and helps locate welfare threshold equilibria. Moreover, the range of the consumption graphs has been truncated at the 99th percentile under the assumption that all extreme values are either outliers or due to measurement errors. Two features emerge from these non-parametric estimations. First, while consumption and asset dynamics paths are not exactly linear, they do not exhibit a typical *S*-shaped curves hypothesized by the theory of poverty traps (Carter and Barrett, 2006).

(figure 3 *about here)*

(figure 4 *about here)*

Similarly to parametric methods, there is evidence of a single welfare dynamic equilibrium characterizing consumption expenditures and assets accumulation paths in Uganda. The 45° lines cross the consumption and assets curves at around 31,000UShs and 1.07 PLUs, respectively, slightly above the poverty lines. Second, as of the LOWESS curves, although the observations appear widely distributed, consumption and asset plots do not show any substantial division of observations (represented by gray circles) into distinct subgroups with heterogeneous welfare characteristics, contrarily to the theory of bifurcated welfare dynamics of Carter and Barrett. Conversely, household asset holdings and consumption growth are distributed along the LOWESS curves, with some evidence of clustering of observations below 60,000UShs threshold for consumption.

Semi-parametric methods include both parametric components (such as time dummies and other explanatory variables), and a non-parametric component $f\left(y_{ht-1}\right)$, with $y_{ht-1} = \{c_{ht-1}, a_{ht-1}\}$. By incorporating control variables and allowing the data to dictate the shape of the relationship between current welfare indicators and their previous values, semi-parametric methods gain in precision and robustness (Libois and Verardi, 2013). They often avoid unobserved heterogeneity problems arising from excluding control variables in non-parametric techniques (Naschold, 2013). They are often referred to as partially linear models with the following general specification:

$$y_{ht} = \mathbf{X_{ht}}\boldsymbol{\beta} + f(y_{ht-1}) + \eta_h + \mu_{ht} \tag{18}$$

where η_h is the household h's random or fixed effects and X is a vector of household characteristics such as age, gender, household size, and education. I run the Ruppert and al.'s (2003) semi-parametric penalized splines estimator. The semi-parametric estimations of the relationship between the current welfare levels (consumption levels and asset indices) and their lagged values using the Ruppert and al.'s (2003) estimator are displayed in figure 5

(figure 5 *about here)*

What is evident from these figures is that despite nonlinearities in both consumption expenditures and assets accumulation, the recursion diagrams are in line with the results from (non-) parametric methods: they reveal the absence of multiple dynamic equilibria characterizing households' welfare paths. They show instead that households are converging towards a single welfare equilibrium located approximately at 31,500UShs for monthly consumption and 1.13 PLUs for asset index.

(d) Shifts in welfare equilibria, exposure to food price shocks, and regional heterogeneity

So far, our estimation results relied on the assumption that all the sampled households share fundamentally similar dynamic welfare accumulation paths. However, different factors may lead households to display significantly different welfare trajectories or converge towards different welfare equilibria. As highlighted by Jalan and Ravallion (2002) through the concept of geographical poverty traps, regional heterogeneity in terms of access to certain facilities (roads, transportation means, health structures,…) may be a powerful tool in explaining heterogeneous welfare dynamics within a country. Furthermore, high exposure to food price shocks may also undermine households' efforts to climb out of poverty or increase their likelihood of falling into poverty (Ivanic and Martin, 2008), and therefore ensnare them at lower welfare equilibria. The net seller/net buyer status may also discriminate households regarding their welfare equilibria, while households below and above the vulnerability threshold might converge towards different equilibria.

To assess the possibility of heterogeneous welfare dynamics and shifts in equilibria consecutive to differentials in the degrees of exposure and vulnerability to food price shocks, regional heterogeneity, and other households' observed characteristics, I locate welfare equilibria from different econometric methods when households are grouped into categories sharing similar features. Graphically, the shapes of welfare recursion diagrams were globally similar to those of the full sample inasmuch as they display single dynamic equilibria. However, they do differ in the location of those equilibria. Tables 4 and 5 report the estimated approximate locations of welfare dynamic equilibria by sub-groups of population.

(table 4 *about here)*

In terms of consumption, table 4 reveals that sub-groups of the Ugandan population are moving towards different welfare thresholds, regardless of the specified econometric method. For instance, male-headed households are expected to converge to higher consumption levels than their female counterparts. On average, their dynamic welfare equilibrium is 4.4%[5] higher than what female-headed households could reach. Education of the household head is also positively correlated with the welfare equilibrium: the higher the level of education attained by the household head, the higher the dynamic equilibrium he is expected to reach in the long run. Particularly, everything held constant, non-educated heads are found to converge consistently to lower welfare equilibria. Heads with university education are expected to settle at an equilibrium that is on average 8.44, 31.98, and 50.97% higher than that of non-educated and heads with primary and secondary education, respectively.

Moreover, differences between agricultural and non-agricultural households, on the one hand, and on the other, poor and non-poor households, is particularly striking. On average, agricultural households will move to an equilibrium that is 19.6% lower than that of non-agricultural households. This significant difference can be explained by two related facts: first, since most households in the surveys are subsistence farmers and net buyers, the degree of their market participation and therefore their market purchases, is relatively limited compared to non-agricultural households; second, food consumption expenditures, which often represent the largest share of household total consumption expenditures, are substantially lower for agricultural households. On the other hand, non-poor households are expected to attain an equilibrium that is 45.8% higher than that of poor households, with an average monthly consumption of 35,100UShs against 24,080UShs for poor households.

The location of consumption equilibria is found negatively correlated with the exposure to food price shocks. Hence, households exposed to food price shocks are moving towards a consumption threshold that is 6.5% lower than that of their unexposed counterparts, with 30,260UShs of consumption values against 32,360UShs. Furthermore, the more the household is affected by food price shocks, the lower its attainable welfare equilibrium. Concretely, households with lower exposure rates (with degree of exposure below the sample median) can expect to reach a long term consumption dynamic equilibrium that is 15.1% higher than that of households with high exposure rates (above the 75 percentile of the sample value) and 5.8% higher than households with moderate exposure rates (between the median and the 75 percentile). Hence, the higher the degree of exposure to food price shocks, the lower the level of attainable welfare equilibrium.

Households located below the vulnerability threshold $\left(vul_h^{\theta}\right)^{\bullet}$ can expect to reach a welfare equilibrium on average 57.1% greater than that of households beyond the estimated critical vulnerability index. Finally, table 4 shows that the geographical location also matters in explaining the levels of consumption equilibria. For instance, the northern region of Uganda, which is traditionally more vulnerable and with the largest proportion of poor households, is characterized by the lowest consumption threshold at 27,180UShs on average, whereas the better-endowed central region converges to the highest welfare level at an average of 35,420UShs.

In terms of assets accumulation process, table 5 reveals some similar patterns in welfare equilibria to those of consumption: female-headed households are expected to reach lower asset equilibria; the more educated the household head, the higher the likelihood of attaining higher asset equilibria; non-poor households consistently converge towards higher asset thresholds than poor households; while structurally poor regions (Northern region and to a smaller extent eastern region) are characterized by lower asset equilibrium levels. As of dissimilarities between the two welfare indicators, agricultural households are now moving to higher asset equilibria than non-agricultural ones, with an asset index 1.15 against 1.12. Finally, there seems to be only a marginal correlation between being exposed to food price shocks and the levels of asset thresholds. Hence, the difference in asset equilibrium between exposed and unexposed households is on average of 1.5%, compared to 7.6% when it comes to consumption expenditures. This consistently holds when I disentangle households by their degree of exposure to food price shocks: the asset level at equilibrium of low exposed households exceeds that of moderately and highly exposed only by 2% and 3.3%, respectively. Net sellers are moving towards higher asset levels than net buyers, and households below the threshold of the vulnerability index have on average higher asset levels than those beyond $\left(vul_h^{\theta}\right)$.

(table 5 *about here)*

(e) Sensitivity of estimation results to the definition of shock variable

In this last section, I examine whether our estimation results are sensitive to the definition of the food price shock variable. In the previous sections, a household was assumed exposed to food price shocks if its normalized residuals from equation (12) are positive. I now extend this shock definition by including both negative price shocks and different cut-off points. Indeed, although the sample period is characterized by increases in food prices, it is well conceivable that some households in specific villages or districts enjoyed remarkably average low prices between survey rounds. On the other hand, varying the cut-off for the shock definition helps check the robustness and stability of our results as the definition of food price shocks becomes more (less) severe. The cut-off points ψ range from 1 to 25% of observations falling into each tail region. For instance, with the 1% cut-off, a household is considered as having experienced a food price shock if its standardized residuals from (12), $\hat{\varepsilon}_{hct}$, is either below the 1st or above the 99th percentile. The approximate welfare equilibria for each selected cut-off point and econometric estimation method are presented in table 6.

(table 6 *about here)*

Overall, the different equilibria follow the same structure that our default measure of food price shock: for each cut-off point ψ, *exposed* households are expected to reach a lower equilibrium than their unexposed counterparts. Furthermore, as the cut-off point increases (decreases) or the definition of the price shock becomes less (more) severe, the welfare thresholds increase (decrease), from 31,325UShs to 32,750UShs at $\psi = 1\%$ and $\psi = 25\%$, respectively, when households experienced food price shocks. Finally, at lower level cut-off points, the location of consumption equilibria of exposed households appears insensitive to shifts in the cut-off points, contrarily to asset holdings. For instance, the equilibrium levels of consumption (assets) increase by 1.36% (2.7%) for exposed households and by 3.4% (1.74%) for unexposed households when ψ shifts from 1 to 5%.

5. CONCLUSIONS

This paper has tested the assumption that households that faced large increases in food prices were likely to experience high risks of being trapped into poverty or converging towards lower welfare equilibria. In order to shed light on the likely effects of differential exposure to food price shocks on welfare growth and risks of poverty traps, this study combines advanced methods in parametric, non-, and semi-parametric dynamic panel models using longitudinal data collected in Uganda between 2005 and 2012 on around 2,200 households.

By means of monthly real values of consumption per adult equivalent and asset indices as measures of welfare indicators, our empirical findings from a cubic polynomial regression model estimated through a two-step system GMM method suggest the existence of both nonlinearities in welfare dynamics and conditional convergence operating at the district level. Household characteristics such as household size, gender of the household head, land size as well as the changes in exposure to food price shocks are found to influence negatively the growth rates of consumption expenditures. Particularly, the results show that the higher the degree of exposure to food price shocks, the lower the rates of consumption growth, and the decreases in these rates are more important than those consecutive to exposure to health, agricultural, or income shocks. Furthermore, and similarly to previous studies (Dercon and Christiaensen, 2011; Amare and Waibel, 2013), the assets dynamic model indicates that structurally poor households were more vulnerable to asset shocks than structurally non-poor and that the larger the number of assets shocks, the lower the assets accumulation growth rates.

However, contrarily to most studies of welfare dynamics based on either consumption growth or asset-based approaches, I find no evidence in favor of multiple welfare equilibria or bifurcations of welfare trajectories. In contrast, consumption and asset recursion diagrams reveal the presence of a single dynamic welfare equilibrium towards which Ugandan households are converging. The empirical insights from parametric methods are relatively consistent with non- and semi-parametric evidences in which welfare equilibria are located slightly above the official poverty line. Accordingly, welfare equilibria were located at around 30,500UShs and 1.14 PLUS for consumption and asset indices, respectively.

There are different potential explanations about the absence of any consumption- or assets-based poverty traps in Uganda, such as potential measurement errors, lack of information on other important aspects of household life (social network, kinship ties, membership to different organizations,...) (Giesbert and Schindler, 2012). But, as pointed out by Naschold (2013), studies that do find evidence of poverty traps are generally characterized by relatively long panel spells, likely to pick up long term welfare dynamics and significant differential processes, particularly if consumption expenditures or assets holdings are moving slowly. In our setting, although the time span between the baseline survey (2005/6) and the second survey (2009/10) is reasonably acceptable, the follow-up surveys were conducted annually, a particularly short period to uncover significant changes in long-run welfare dynamics.

Finally, I split the household sample into sub-groups of population to consider the possibility of shifting welfare equilibria related to differential exposure to food price shocks, regional location, or other households' observables. My results suggest that, regardless of the estimation methods selected, being exposed to food price shocks was not sufficient to push Ugandan into poverty traps, as recently hypothesized. However, I do find that households exposed to price shocks are expected to converge towards lower welfare equilibria (in terms of consumption and assets holdings) than unexposed households, though still above the poverty line. Furthermore, the higher the degree of exposure to price shocks, the lower the attainable equilibrium. The effects of these differential degrees of exposure to price shocks are substantially larger on consumption than assets accumulation, at 7.6% against 1.5%.

Households living in better-off Ugandan regions, such are the Central and Western regions, are found to settle at higher welfare equilibria than those in poor Northern regions. There is also evidence of gender differences in welfare trajectories, with female-headed households consistently moving to lower welfare thresholds, while highly educated and non-poor households enjoyed higher welfare equilibria.

These empirical findings have straightforward policy implications. First, the fact that the welfare equilibria of most households are located just slightly above the poverty lines (official and asset-based poverty lines) implies that policy interventions should primarily focus not only on keeping current households located above these thresholds from falling below but also on helping them move towards higher welfare levels. As of those already below these thresholds, and potentially below the poverty lines, safety nets mechanisms need to be enforced in order to extricate them from the low welfare levels they are truck in.

The second implication is related to the impacts of both price and asset shocks, which are found to negatively affect consumption expenditures and assets holdings. As is well documented in the literature, when hit by shocks, poor households may deteriorate their already-critical welfare conditions by modifying for example their consumption behavior to smooth their assets (Amare and Waibel, 2013). One possible way might be to build their resilience to these shocks and other stressors by increasing *ex ante* their capacities to manage risks and by helping them *ex post* to minimize the adverse consequences of shocks. Stimulating households to engage into diversified activities (for example, combination of farm and non- or off-farm activities) or developing targeted programs that aim at improving the structural characteristics of the country such as better access to land, credit, or insurance markets, improvements in health coverage or infrastructure coverage may well reduce the vulnerability of households to both food price and asset shocks.

NOTES

1. To test for a potential attrition bias, I applied the attrition probits' tests of Fitzgerald et al (1998), and the pooling tests of Becketti, Gould, Lillard and Welch (1988). The correction of attrition bias was then done through the *inverse probability weighting* (IPW) procedure (Fitzgerald et al, 1998; Wooldridge, 2002).

2. 1 USD PPP per capita/ per day converted into Uganda Shillings (UShs).

3. The concept of Tropical Livestock Unit (TLU) represents a way of quantifying and aggregating a wide range of different types of livestock types/sizes into a single number by applying different exchange ratios among species. In this paper, I used: 1 TLU = Camels 1.0; Cattle 0.7; Sheep/Goats: 0.1.

4. The sum of $\hat{\sigma}_1$ and $\hat{\sigma}_2$ in model IV.

5. The average value from the different estimation methods in table 6.

REFERENCES

Adato, M., Carter, M.R., and J., May (2006), "Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data", *Journal of Development Studies,* 42 (2): 226–247.

Amare, M. and H. Waibel (2013), "Geographical capital, shocks, and asset poverty traps in rural Vietnam", Selected Paper prepared for presentation at the AEL (Research Committee on Development Economics) Conference, Munich, June 21-22, 2013.

Antman, F. and D. McKenzie (2007), "Poverty Traps and Nonlinear Income Dy-namics with Measurement Error and Individual Heterogeneity", *Journal of Development Studies*, 43 (6): 1057–1083

Arellano, M. and O. Bover (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics,* 68(1):29-51.

Azariadis, C. and Stachurski, J. (2005), "Poverty Traps", in Aghion, P. and S. Durlauf (ed.), *Handbook of Economic Growth*, volume 1, chapter 5. Elsevier.

Barrett, C.B. and M.R. Carter (2013), "The economics of poverty traps and persistent poverty: Empirical and policy implications", *The Journal of Development Studies*", 49 (7): 976-990.

Barrett, C.B., M.R. Carter, and M. Ikegami (2008), "Poverty traps and social protection", Social Protection Discussion Papers. Series 42752. The World Bank.

Barrett, C.B, P.P. Marenya, J. Mcpeak, B. Minten, F. Murithi, W. Oluoch-Kosura, F. Place, J.C. Randrianarisoa, J. Rasambainarivo, and J., Wangila (2006), "Welfare dynamics in rural Kenya and Madagascar", *The Journal of Development Studies* 42 (2): 248–27.

Bond, S. 2002. "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice." *Portuguese Economic Journal* 1 (2): 141–162.

Boysen, O. (2009), "Border price shocks, spatial price variation, and their impacts on poverty in Uganda", Discussion paper, Institute of International Integration Studies, 306.

Blundell, R. and S. Bond (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics, 87*(1): 115–143.

Cage, R. A., T. I. Garner, and J. Ruiz-Castillo (2002), "Constructing household specific consumer price indexes: An analysis of different techniques and methods", US Department of Labor, Bureau of Labor Statistics, Working Paper, 354.

Carter, M.R. and C.B. Barrett (2006), "The economics of poverty traps and persistent poverty: An asset-based approach", *The Journal of Development Studies,* 42 (2): 178–199.

Carter, M.R. and J. May (2001), "One kind of freedom: Poverty dynamics in post-apartheid South Africa", *World Development,* 29 (12): 1987–2006.

Collier, P. and J. Dehn (2001), "Aid, shocks, and growth", World Bank Policy Research Working Paper, Series n° 2688. The World Bank.

Combes, J.L., C. Ebeke, M.N. Etoundi, and T. Yogo (2012), "Are foreign aid and remittance inflows a hedge against food price shocks?", *IMF Working Paper,* 12/67.

Cudjoe, G., Breisinger, C., and Diao, X. (2008), "Local impacts of a global crisis: Food price transmission and poverty impacts in Ghana", Working paper, International Food Policy Research Institute, 842.

Deaton, A. (1997), *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy,* John Hopkins University Press for the World Bank, Washington DC, Baltimore and London.

Deaton, A. (1988), "Quality, quantity and spatial variation of price", *American Economic Reciew,* 78: 418-430.

Deaton, A. J. and R. I. Miller (1995), "International commodity prices, macroeconomic performance, and politics in Sub-Saharan Africa", Princeton Studies in International Finance, 79.

Dehn, J. (2001), "Commodity Price Uncertainty and Shocks: Implications for Economic Growth", Paper presented at the Royal Economic Society Annual Conference 2001, University of Durham 9th-11th April 2001.

Dehn, J. (2000), "Commodity price uncertainty and shocks: implications for economic growth", The Centre for the Study of African Economies Working Paper Series, 2000-10.

de Janvry, A. and E. Sadoulet (2008), "The global food crisis: Identification of the vulnerable and policy responses", Agricultural and Research Economics Update, Special Issue: Causes and Consequences of the Food Price Crisis, 18 – 21.

de Weerdt, J. (2004), "Risk-sharing and endogenous network formation", in S. Dercon (ed.), *Insurance against Poverty,* Oxford: Oxford University Press for WIDER.

Dercon, S., and L., Christiaensen (2011), “Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia”, *Journal of Development Economics,* 96 (2): 159–173.

Dutta, S. (2014), “Identifying Single or Multiple Poverty Trap: An Application to Indian Household Panel Data”, *Social Indicators Research,* DOI 10.1007/s11205-014-0586-x.

Elbers, C., J.W. Gunning, and B. Kinsey (2002), “Convergence, shocks, and poverty”, *Tinbergen Insitute,* Discussion Paper, 2002-035/2

Ferreira, F.H., Fruttero, A., Leite, P., and Lucchetti, L. (2011), “Rising food prices and household welfare: evidence from Brazil in 2008”, ECINEQ Working paper, 200.

Fitzgerald, J., P. Gottschalk, and M. Moffit (1998), “An analysis of sample attrition in panel data”, *Journal of Human Resources,* 33(2): 251-299.

Geromini, V., L. Matthieu, P. Schembri, and A. Taranco (2006), “Poverty traps: Instabilities do matter”, Conference AFSE, 14 and 15 September 2006, Paris.

Giesbert, L. and K. Schindler (2012), “Assets, shocks, and poverty traps in rural Mozambique”, *World Development,* 40(8): 1594–1609.

Headey, D. and S. Fan (2008), “Anatomy of a crisis: the causes and consequences of surging food prices”, *Agricultural economics*, 39 (s1): 375-391.

Hella, J. P., R. Haug, and I.M. Kamile (2011), “High global food prices – crisis or opportunity for smallholder farmers in Tanzania?”, *Development in Practice*, 21 (4-5), 652-665.

Hsiao, C. (1986). *Analysis of panel data*. (1st ed.). Cambridge University Press.

Ivanic, M. and W. Martin (2008), “Implications of higher global food prices for poverty in low-income countries”, *Agricultural economics,* 39 (s1): 405-416.

Jalan, J. and M. Ravallion (2002), “Geographic poverty traps? A micro-model of consumption growth in rural China, *Journal of Applied Econometrics,* 17 (4): 329–346.

Koszegi, B. and M. Rabin (2006), “A model of reference-dependent preferences”, *The Quarterly Journal of Economics,* 121 (4): 1133-1165.

Kwak, S and S. C. Smith (2010), “What kind of poverty trap? An investigation of single and multidimensional traps with Ethiopian household panel data”, IIEP Working Paper Series, 04.

Libois, F. and V. Verardi (2013), "Semiparametric fixed-effects estimator", *The Stata Journal*, 13 (2): 329 – 336.

Lokshin, M. and M. Ravallion (2004), "Household income dynamics in two transition economies", *Studies in Nonlinear Dynamics and Econometrics*, 8 (3): 1-31.

Lybbert, T. J., C.B. Barrett, S. Desta, and D.L. Coppock (2004), "Stochastic wealth dynamics and risk management among a poor population", *The Economic Journal*, 114(498):750-777.

McKay, A. and E. Perge (2013), "How strong is the evidence for the existence of poverty traps? A multi-country assessment", *Journal of Development Studies*, 49 (7): 877 - 897.

Naschold, F. (2013), "Welfare dynamics in Pakistan and Ethiopia: Does the estimation method matter?, *The Journal of Development Studies*, 49 (7): 936 – 954.

Naschold, F. (2005), "Identifying asset poverty thresholds – New methods with application to Pakistan and Ethiopian", Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27, 2005.

Nickell, S. (1981), "Biases in dynamic models with fixed effects", *Econometrica*, 49 (6): 1417–1426.

Ruppert, D., M. P. Wand, and R.J. Carroll (2003), *Semiparametric regression*, Cambridge: Cambridge University Press.

Santos, P., and C.B. Barrett (2006), "Informal insurance in the presence of poverty traps: Evidence from southern Ethiopia", Mimeo, Cornell University.

Ssewanyana, S. and I. Kasirye (2012), "Poverty and inequality dynamics in Uganda: Insights from the Uganda National Panel Surveys 2005/6 and 2009/10", *EPRC Research Series*, 92.

Uganda Bureau of Statistics (2013), Uganda National Panel Survey 2010/2011: Wave II Report. Available at: http://www.ubos.org/onlinefiles/uploads/ubos/UNPS/wave2/UNPS%20Report%20wave2.pdf. Accessed on 15 August, 2014.

Uganda Bureau of Statistics (2010), Uganda National Household Survey 2009/2010: Report on the Socio-Economic Module. Available at: http://www.ubos.org/onlinefiles/uploads/ubos/UNHS0910/UNHS%202009_2010%20socio-economic%20Report.pdf. Accessed on 10 November, 2012.

United Nations (2014), *Millennium Development Goals Report 2014*. Available at: http://www.un.org/millenniumgoals/2014%20MDG%20report/MDG%202014%20English%20web.pdf. Accessed on 20 September, 2014.

van Campenhout, B. and S. Dercon (2012), "Nonlinearities in the dynamics of livestock assets: Evidence from Ethiopia", International Food Policy Research Institute, Working paper, 01215.

Vu, L. and P. Glewwe (2011), "Impacts of rising food prices on poverty and welfare in Vietnam", *Journal of Agricultural and Resource Economics*, 36(1): 14-27.

World Bank (2013), World Development Indicators, Washington, DC: The World Bank.

Wooldridge J.M. (2002), *Econometric Analysis of Cross-sectional and Panel Data*, Cambridge MA: MIT Press

Table 1. *Household characteristics by exposure to food price shocks*

	Base survey:	High			Moderate			Low			None		
	2005/6	2009/10	2010/11	2011/12	2009/10	2010/11	2011/12	2009/10	2010/11	2011/12	2009/10	2010/11	2011/12
Observations	2173	599	338	492	726	703	101	50	82	150	798	1,050	1,430
Monthly real food cons.	34,955	32,067	25,056	32,911	33,184	27,875	27,529	33,598	28,885	37,735	34,403	29,443	37,659
	(30,359)	(25,607)	(17,167)	(21,703)	(26,867)	(22,727)	(18,524)	(22,134)	(23,686)	(22,802)	(23,864)	(21,170)	(29,893)
Household size	5.78	6.67	7.49	7.62	6.77	7.45	7.74	6.96	7.80	7.86	6.42	7.01	7.06
	(3.03)	(3.34)	(3.78)	(3.68)	(3.88)	(3.45)	(3.63)	(3.46)	(3.27)	(4.85)	(3.17)	(3.53)	(3.93)
Proportion of children	0.54	0.58	0.57	0.54	0.55	0.55	0.51	0.58	0.54	0.49	0.53	0.54	0.51
	(0.23)	(0.22)	(0.23)	(0.22)	(0.23)	(0.22)	(0.22)	(0.24)	(0.21)	(0.23)	(0.23)	(0.22)	(0.22)
Years of education	5.25	4.73	5.40	5.73	5.11	5.35	4.90	4.38	5.54	8.00	5.39	5.59	5.00
	(3.94)	(3.88)	(4.15)	(4.41)	(4.12)	(4.26)	(3.88)	(3.64)	(3.97)	(5.74)	(4.11)	(4.29)	(3.96)
Age of the head	42.79	47.44	47.74	47.40	46.81	47.58	47.71	43.62	47.96	48.29	46.51	47.00	48.58
	(15.00)	(15.19)	(15.10)	(14.89)	(14.73)	(15.61)	(13.06)	(14.62)	(15.25)	(15.53)	(14.91)	(15.02)	(14.76)
% of female-headed	0.28	0.29	0.31	0.33	0.30	0.32	0.33	0.20	0.24	0.23	0.28	0.31	0.31
% of agr. households	0.83	0.93	0.92	0.86	0.87	0.85	0.84	0.74	0.76	0.57	0.78	0.75	0.84
% of net sellers*	0.27	0.28	0.20	0.09	0.29	0.25	0.21	0.34	0.32	0.14	0.25	0.21	0.37
% of net buyers*	0.55	0.61	0.66	0.65	0.58	0.62	0.61	0.57	0.60	0.43	0.53	0.54	0.49
% of poor households	0.28	0.32	0.27	0.23	0.23	0.27	0.25	0.18	0.13	0.14	0.20	0.22	0.21

Note: * Net sellers (buyers) are defined as agricultural households whose total values of crop sales are greater (lower) than the total values of consumption of those crops (*matooke*, cassava, potatoes, maize, beans, rice, millet, sorghum, fruits, and vegetables). Standard deviations into brackets

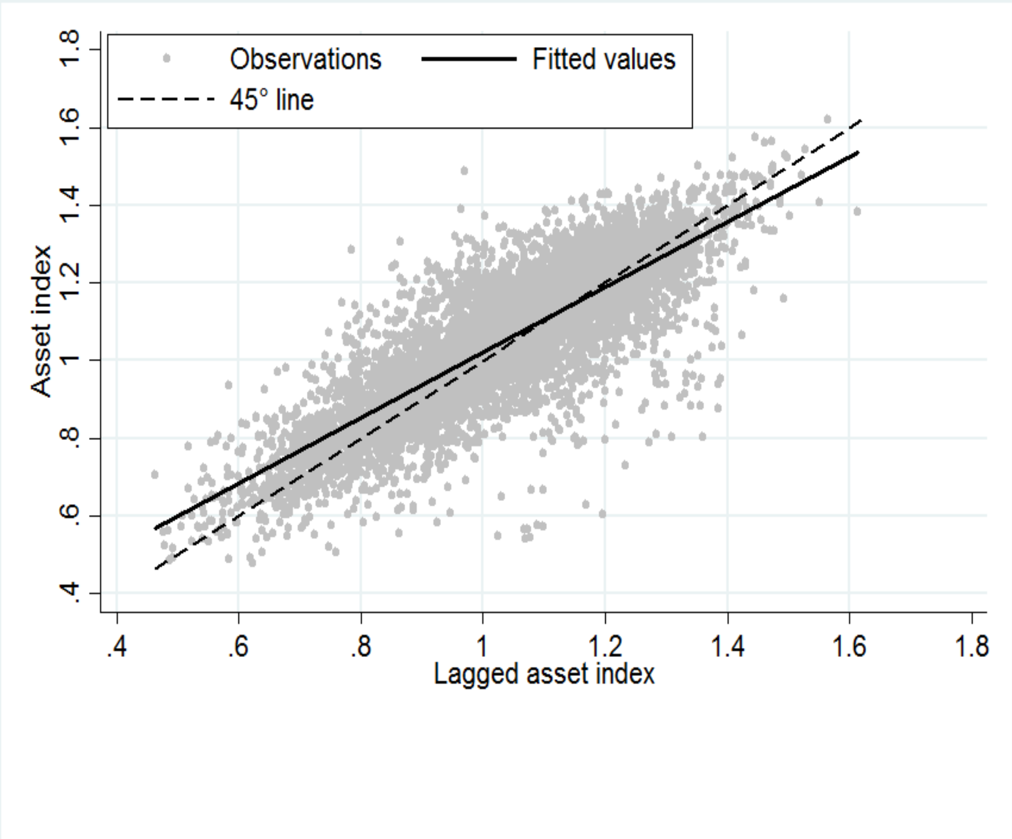

Figure 1. *Scatterplot of asset index*

Table 2. *Two-step system GMM estimation of consumption growth model*

Dependent variable: $\Delta \ln c_{ht}$				
	Model I	Model II	Model III	Model IV
Polynomial terms				
c_{ht-1}	-1.268 (0.009)***	-2.395 (0.315)***	-2.972 (0.084)***	-2.795 (0.087)***
c_{ht-1}^2	0.562 (0.455)	0.315 (0.022)***	0.256 (0.077)***	0.765 (0.264)***
c_{ht-1}^3	-0.056 (0.049)	-0.075 (0.024)***	-0.074 (0.025)***	-0.025 (0.009)***
Household characteristics				
hsize	0.015 (0.001)***	0.071 (0.007)***	0.063 (0.006)***	0.039 (0.007)***
dratio	0.032 (0.017)*	0.131 (0.064)***	0.129 (0.059)**	0.313 (0.77)***
age	0.025 (0.062)	0.142 (0.038)***	0.099 (0.031)***	0.050 (0.030)*
age^2	-0.002 (0.006)	-0.001 (0.004)***	-0.001 (0.000)***	-0.000 (0.000)*
sex	-0.010 (0.040)	-0.085 (0.028)***	-0.082 (0.028)***	-0.041 (0.023)*
tlu	-0.007 (0.002)***	0.008 (0.002)***	0.008 (0.003)***	0.001 (0.001)
educ	0.042 (0.019)**	0.020 (0.002)***	0.019 (0.004)***	0.000 (0.003)
land	0.005 (0.021)	0.052 (0.014)***	0.056 (0.001)***	0.021 (0.013)*
Sensitivity to food price and asset shocks				
$\Delta\theta_{ht}^{f}$			-0.183 (0.079)**	-0.775 (0.239)***
$\Delta\theta_{ht}^{f} \times vul_{ht}^{\theta}$				0.568 (0.225)**
vul_{ht}^{θ}				-0.207 (0.094)**
θ_{ht}^{k1}			-0.047 (0.021)**	-0.010 (0.018)
θ_{ht}^{k2}			-0.106 (0.031)***	-0.040 (0.019)**
θ_{ht}^{k3}			-0.045 (0.005)***	-0.096 (0.056)*
povstatus				-0.572 (0.245)***
region	No	Yes	Yes	Yes
year	No	Yes	Yes	Yes
Specification tests				
$AR(1)$	0.016**	0.093***	0.000***	0.000***
$AR(2)$	0.147	0.175	0.661	0.378
Hansen J	0.386	0.935	0.156	0.725
Joint significance test: $\hat{\sigma}_1 = 0$ and $\hat{\sigma}_2 = 0$, *p*-value				0.002
Vulnerability threshold: $\left(vul_h^{\theta}\right)^{\bullet}$				1.364
Percent of households above $\left(vul_h^{\theta}\right)^{\bullet}$ by survey ([a])				57,65 (69.61; 62.80; 40.53)

Note: ([a]) The percents of households above the vulnerability threshold are related to the surveys 2009/10, 2010/11, and 2011/12. The average percent throughout the sample is first reported and then disaggregated by survey round (into brackets). Robust standard errors into brackets. . ***, **, and * denote statistical significance at 10, 5, and 1% levels, respectively.

Table 3. *Two-step system GMM estimation of asset index growth model*

Dependent variable: $\Delta \ln a_{ht}$			
	Model I	Model II	Model III
Polynomial terms			
a_{ht-1}	-0.711 (0.074)***	-0.715 (0.067)***	-0.984 (0.190)***
a_{ht-1}^{2}	0.155 (0.106)	0.135 (0.115)	0.235 (0.119)**
a_{ht-1}^{3}	-0.029 (0.016)**	-0.026 (0.017)	-0.035 (0.016)**
Household characteristics			
hsize	0.028 (0.007)***	0.022 (0.008)***	0.034 (0.007)***
dratio	-0.093 (0.030)***	-0.084 (0.023)***	-0.279 (0.113)**
age	0.103 (0.058)*	0.057 (0.067)	0.179 (0.060)***
age^2	-0.001 (0.000)*	-0.001 (0.001)	-0.002 (0.001)***
sex	-0.042 (0.022)*	-0.025 (0.025)	-0.072 (0.022)***
educ	0.032 (0.003)***	0.028 (0.003)***	0.034 (0.004)***
$a_{h,0}$			-0.247 (0.125)*
Sensitivity to food price and asset shocks			
$\Delta\theta_{ht}^{f}$			-0.014 (0.002)**
$\theta_t^k = 0 \,\&\, apovstatus = 1$			-0.102 (0.015)***
$\theta_t^k = 1 \,\&\, apovstatus = 0$			-0.009 (0.017)
$\theta_t^k = 1 \,\&\, apovstatus = 1$			-0.152 (0.014)***
$\theta_t^k = 2 \,\&\, apovstatus = 0$			-0.024 (0.021)
$\theta_t^k = 2 \,\&\, apovstatus = 1$			-0.157 (0.024)***
$\theta_t^k = 3 \,\&\, apovstatus = 0$			-0.074 (0.023)***
$\theta_t^k = 3 \,\&\, apovstatus = 1$			-0.177 (0.028)***
region	No	Yes	Yes
year	No	Yes	Yes
$AR(1)$	0.005***	0.008***	0.008***
$AR(2)$	0.125	0.312	0.344
Hansen	0.118	0.509	0.411
Observations	6,519	6519	6519

Note: Robust standard errors in brackets. ***, **, and * denote statistical significance at 10, 5, and 1% levels, respectively.

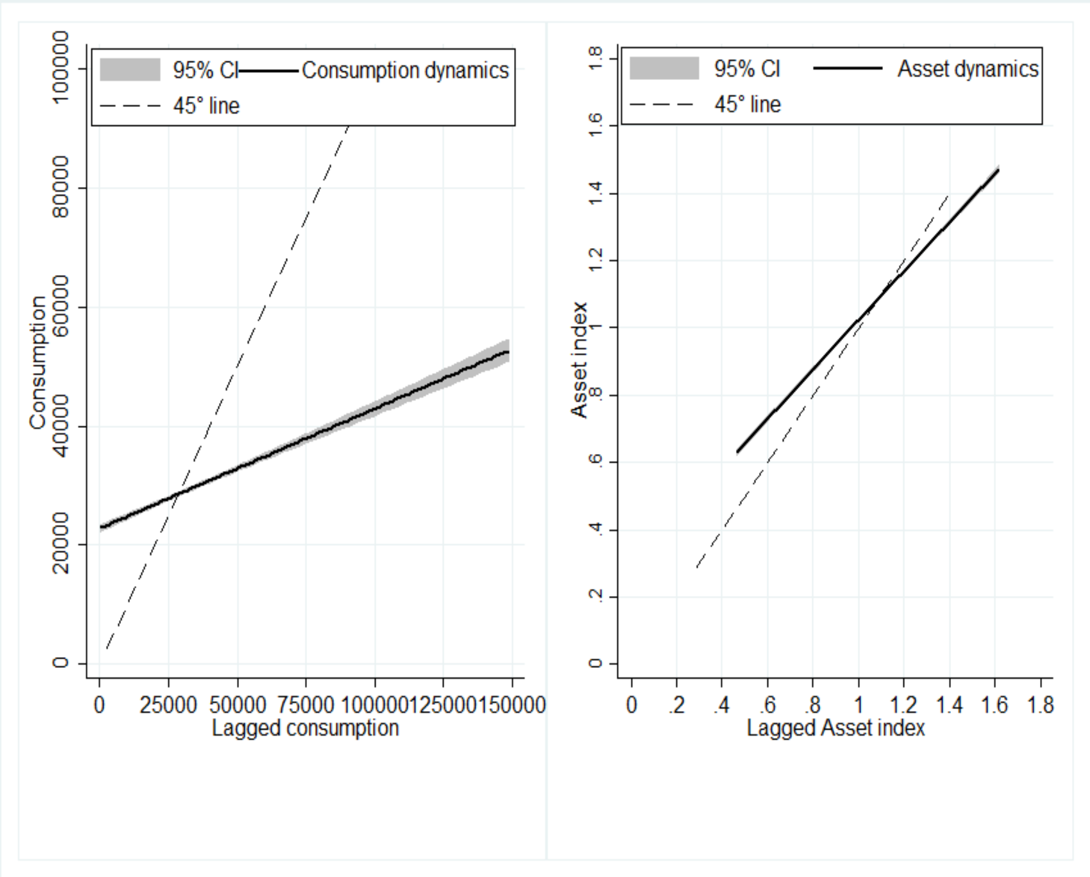

Figure 2. *Consumption and asset dynamics: Predicted values using parametric methods*

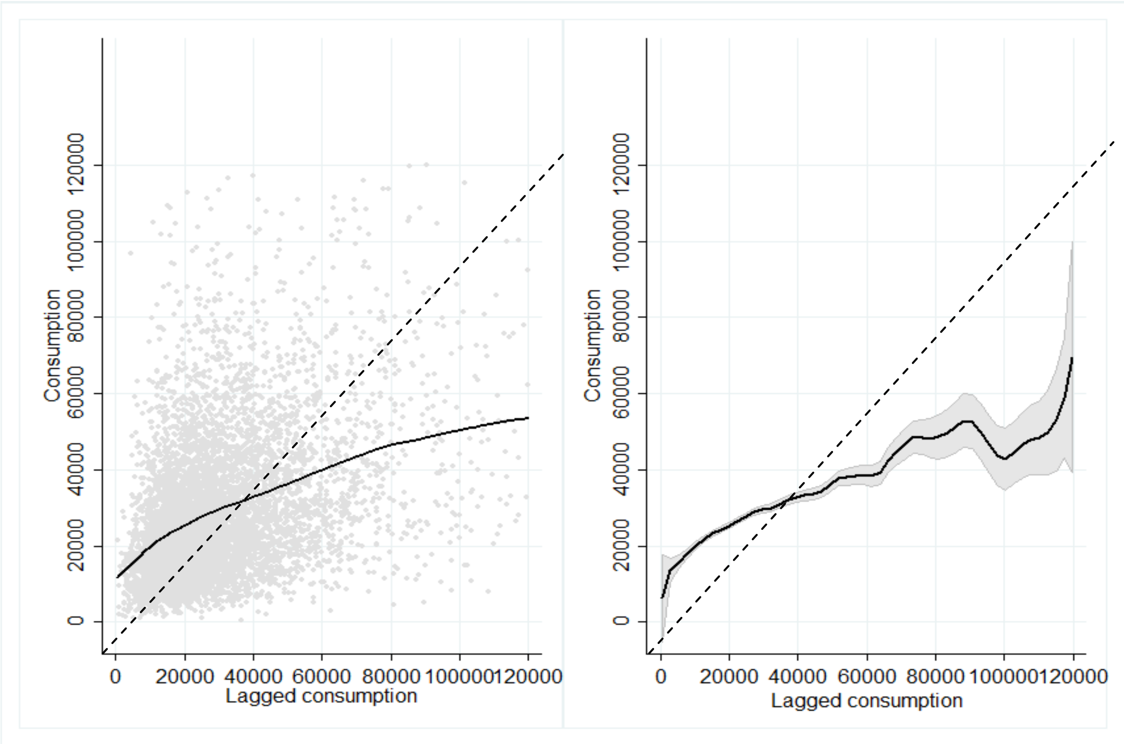

Figure 3. *Consumption dynamics: LOWESS estimates and Kernel-weighted local polynomial smooth*

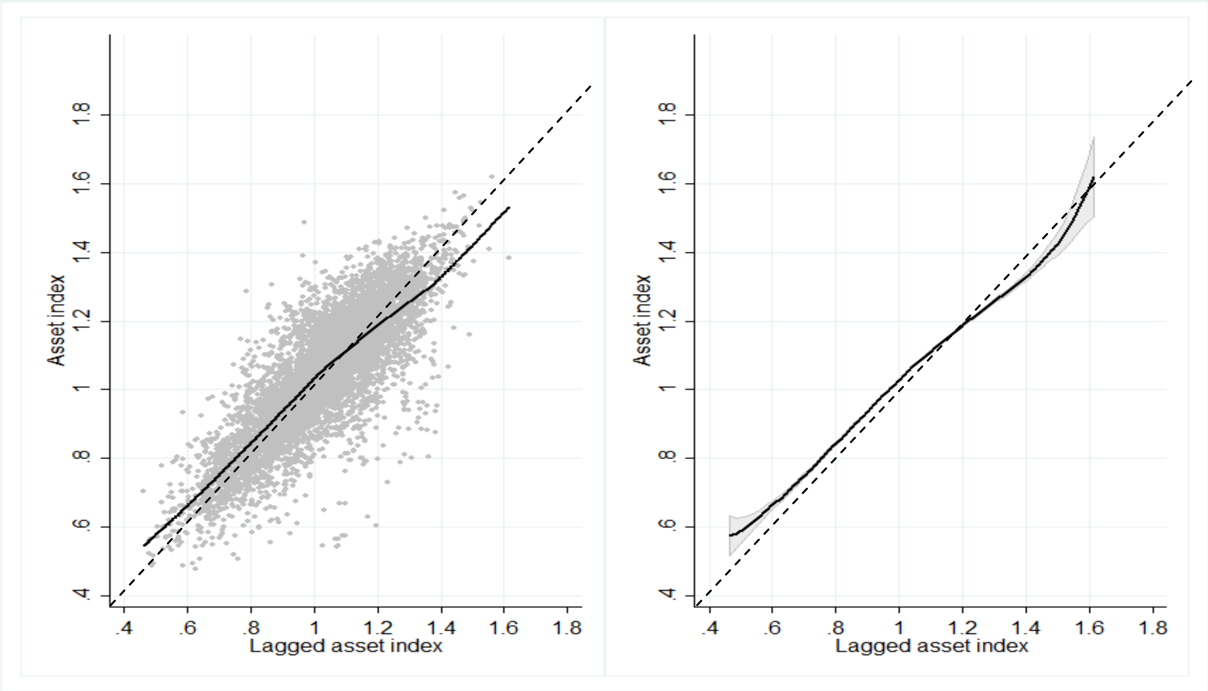

Figure 4. *Asset dynamics: LOWESS estimates and Kernel-weighted local polynomial smooth*

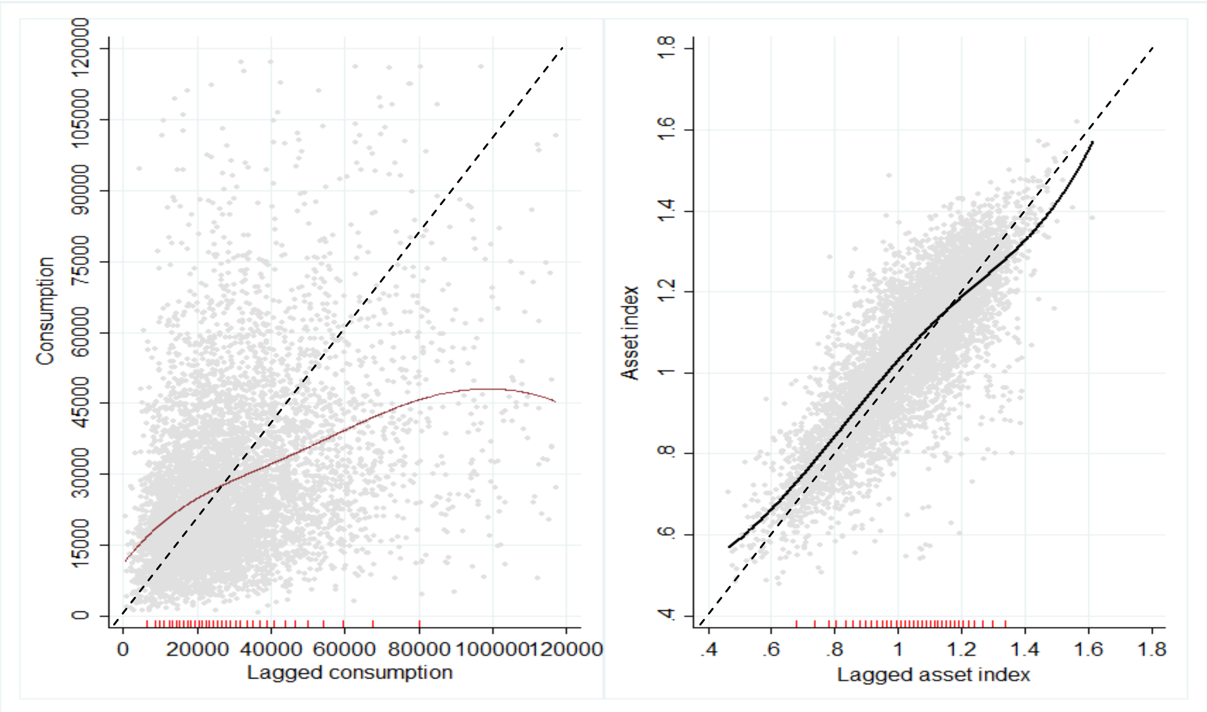

Figure 5. *Semi-parametric penalized spline regression estimation: Consumption and asset dynamics*

Table 4. *Approximate locations of real consumption equilibria by estimation methods*

	Non-parametric methods					Cubic parametric regression (S-GMM)	Ruppert et al.'s penalized splines
	LOWESS	Kernel linear Polynomial regression		Kernel cubic polynomial regression			
	Mean	Mean	CI	Mean	CI	Mean	Mean
All sample	30,000	31,000	[28,000;32,500]	30,500	[29,000;32,000]	29,000	31,500
Male-headed households	30,000	32,000	[28,700;33,500]	31,000	[29,500;32,000]	29,900	31,600
Female-headed hhds	29,000	30,000	[27,300;31,600]	29,800	[27,200;30,400]	28,000	31,200
Head with no educ.	25,000	23,000	[20,500;26,200]	25,000	[23,800;26,500]	27,000	29,300
Head with primary educ.	29,000	29,000	[26,500;33,600]	28,800	[27,000;29,200]	30,000	31,100
Head with sec. educ.	37,000	38,000	[35,300;41,100]	36,900	[31,000;38,500]	34,500	33,600
Head with higher educ.	42,500	42,500	[33,500;47,800]	43,000	[38,500;50,000]	32,000	35,200
Agric. Household*s*	28,000	29,000	[25,000;33,000]	29,800	[26,700;31,500]	29,800	30,800
Net sellers	28,000	31,200	[24,100;34,800]	33,000	[27,000;34,000]	28,000	28,000
Net buyers	29,000	28,000	[26,500;32,700]	28,900	[24,000;30,000]	30,000	29,000
Non-agric. households	42,500	33,000	[28,000;38,000]	37,000	[30,000;40,000]	36,000	34,900
Poor households	24,000	24,000	[20,100;32,700]	24,200	[21,000;25,000]	20,000	28,200
Non-poor households	36,500	33,800	[29,000;36,000]	35,000	[30,000;37,200]	37,500	32,700
Exposed to price shocks	30,000	29,000	[24,000;36,800]	30,000	[26,000;34,200]	30,500	31,800
High exposure	28,300	27,000	[24,400;30,000]	28,500	[26,500;33,000]	28,000	29,800
Moderate exposure	30,000	31,000	[25,200;33,000]	31,200	[26,000;36,000]	31,000	30,800
Low exposure	31,500	33,000	[29,000;37,000]	33,500	[28,300;35,000]	32,000	32,900
Unexposed to price shocks	32,000	32,600	[26,500;36,000]	32,000	[28,000;36,500]	32,000	33,200
Above the vulnerability threshold	21,000	22,000	[17,000;21,000]	20,000	[18,000;22,000]	21,000	23,000
Below the vulnerability threshold	34,000	34,000	[30,000;37,000]	34,100	[32,000;36,000]	34,000	32,000
Central region	36,000	37,000	[31,000;40,200]	35,000	[33,500;38,500]	35,000	34,100
Eastern region	27,500	28,000	[25,200;35,800]	28,200	[25,000;29,000]	28,000	31,000
Northern region	27,200	26,000	[20,000;31,300]	25,700	[24,000;26,700]	27,800	29,200
Western region	30,000	28,500	[25,000;31,000]	29,000	[27,000;32,000]	30,000	31,300

Note: Extreme or outlier household expenditures were defined as those beyond the 99th percentile and replaced by values observed at that percentile. CI stands for confidence intervals.

Table 5. *Approximate location of asset index (in PLUs) equilibria by estimation methods*

	Non-parametric methods					Cubic parametric regression (S-GMM)	Ruppert et al.'s penalized splines
	LOWESS	Kernel linear polynomial regression		Kernel cubic polynomial regression			
	Mean	Mean	CI	Mean	CI	Mean	Mean
All sample	1.15	1.18	[0.90;1.20]	1.15	[1.00;1.17]	1.10	1.13
Male-headed households	1.19	1.20	[1.15;1.22]	1.19	[1.17;1.20]	1.13	1.15
Female-headed households	1.09	1.07	[1.02;1.10]	1.10	[1.08;1.12]	1.02	1.05
Head with no education	1.12	1.15	[1.00;1.20]	1.14	[1.12;1.17]	1.05	1.10
Head with primary educ.	1.12	1.13	[1.12;1.15]	1.15	[1.13;1.18]	1.07	1.11
Head with secondary educ.	1.23	1.22	[1.20;1.24]	1.23	[1.21;1.25]	1.18	1.19
Head with higher educ.	1.21	1.21	[1.17;1.22]	1.20	[1.16;1.21]	1.20	1.18
Agricultural households	1.15	1.15	[1.13;1.16]	1.14	[1.13;1.15]	1.16	1.14
Net sellers	1.22	1.22	[1.20;1.23]	1.21	[1.19;1.23]	1.10	1.03
Net buyers	1.12	1.13	[1.12;1.14]	1.14	[1.13;1.15]	1.07	1.00
Non-agr. households	1.11	1.11	[1.10;1.13]	1.12	[1.10;1.14]	1.12	1.12
Poor households	1.00	0.97	[0.70;1.00]	1.00	[0.98;1.10]	1.09	1.11
Non-poor households	1.19	1.19	[1.17;1.20]	1.18	[1.17;1.19]	1.12	1.12
Exposed to price shocks	1.11	1.12	[1.10;1.14]	1.13	[1.12;1.14]	1.05	1.10
High exposure	1.09	1.10	[1.07;1.13]	1.10	[1.10;1.15]	1.03	1.08
Moderate exposure	1.10	1.11	[1.09;1.14]	1.12	[1.11;1.13]	1.04	1.10
Low exposure	1.12	1.13	[1.10;1.17]	1.15	[1.14;1.20]	1.07	1.11
Unexposed to price shocks	1.13	1.14	[1.14;1.10]	1.14	[1.10;1.21]	1.07	1.12
Above the vulnerability threshold	1.06	1.00	[0.08;1.02]	1.05	[1.03;1.06]	1.15	0.97
Below the vulnerability threshold	1.18	1.18	[1.17;1.20]	1.17	[1.15;1.19]	1.07	1.01
Central region	1.25	1.23	[1.21;1.24]	1.22	[1.21;1.25]	1.21	1.20
Eastern region	1.11	1.12	[1.10;1.13]	1.13	[1.12;1.14]	1.09	1.11
Northern region	0.89	0.89	[0.85;0.90]	0.90	[0.89;0.91]	0.85	0.88
Western region	1.11	1.13	[1.12;1.14]	1.14	[1.13;1.15]	1.011	1.12

Table 6. *Sensitivity of welfare equilibria to the definition of the price shock variable*

	Exposed to food price shocks							
	$\psi = 1\%$		$\psi = 5\%$		$\psi = 10\%$		$\psi = 25\%$	
	c^e	a^e	c^e	a^e	c^e	a^e	c^e	a^e
LOWESS	30,600	1.12	30,500	1.15	30,000	1.15	31,000	1.17
Cubic Kernel	30,200	1.12	31,000	1.14	31,500	1.15	32,500	1.17
GMM	31,500	1.08	32,500	1.11	33,000	1.13	33,800	1.16
Penalized splines	33,000	1.12	33,000	1.15	34,000	1.16	33,700	1.17
Average	31,325	1.11	31,750	1.14	32,125	1.15	32,750	1.17
Observations	130		651		1,304		3,259	
	Unexposed to food price shocks							
	$\psi = 1\%$		$\psi = 5\%$		$\psi = 10\%$		$\psi = 25\%$	
	c^e	a^e	c^e	a^e	c^e	a^e	c^e	a^e
LOWESS	29,900	1.15	31,000	1.17	32,500	1.18	36,000	1.19
Cubic Kernel	31,000	1.15	32,500	1.18	31,700	1.17	34,500	1.20
GMM	32,000	1.16	33,500	1.16	33,500	1.17	33,800	1.18
Penalized splines	33,500	1.14	33,700	1.15	34,500	1.18	33,500	1.18
Average	31,600	1.15	32,675	1.17	33,050	1.18	34,450	1.19
Observations	6,389		5,868		5,215		3,260	

Note: c^e and a^e denote the approximate equilibrium locations of consumption expenditures and asset index.