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EMPIRICAL ESSAYS ON THE ECONOMICS OF FOOD PRICE SHOCKS:

MICRO-ECONOMETRIC EVIDENCE FROM UGANDA

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Contents

List of Tables, Figures, and Appendices

Tables

Figures

Appendices

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Summary and Overview

The vast majority of households in developing countries are located in rural areas and still depend on agriculture as their main income generating activity. Despite economic progress was recently achieved by many of these countries at the macroeconomic level, welfare indicators remain at critical levels for a large proportion of their populations. The absence of well-functioning insurance and credit markets coupled with the prominence of different covariate and idiosyncratic shocks (droughts, floods, inflation, conflicts, and health-related shocks) exacerbate the vulnerability of the poorest among these households. Under such circumstances, a general consensus among development practitioners has been that policy interventions will only be effective if they help households prepare for and protect themselves against stressors and shocks, mitigate ex post their potential losses, and reinforce their abilities to respond adequately to future threats to their well-being. This goal can only be achieved if we understand the deep causes that trigger those shocks and the ways in which they affect households with different initial conditions and characteristics, in particular the processes through which they prevent some households from moving out of poverty or thrust some others into spirals of destitution and poverty.

This thesis explores several issues related to our understanding of the causes, consequences, and households' responses to different shocks and stressors. One particular type of shocks is at the core of this dissertation, namely food price shocks. Indeed, the recent sharp increases in food and other commodity prices between 2006 and 2008 and again in 2011 have generated passionate debates about their potential drivers and consequences on households, especially in developing countries. Some of these countries reported social tensions and turmoil, food riots or social unrest as a direct result of rising food prices while simulations across different countries have revealed that many vulnerable households even reduced their calorie intakes (Bellemare, 2015). The four closely related studies of this thesis address respectively the following research questions:

1. What macroeconomic and environmental drivers explain changes in food price volatility observed in Uganda between 2000 and 2012? Subsequently, how strong is the evidence of spillover, asymmetry, and seasonality effects in these volatilities?
2. To what extent are the econometric estimates of welfare effects of food price shocks sensitive to models' assumptions, in particular to the incorporation of both labor market frictions and households' net positions in food and labor markets?

3. How do agricultural and market-related risks as well as farmers' expectations about future output prices and yield levels shape their crop choice and acreage allocation decisions?
4. How strong is the link between poverty traps and differential exposure and vulnerability to food price shocks?

This dissertation is motivated by the following gaps in both the theoretical and empirical literature on food price shocks that are epitomized in the above questionings. First, studies on food price volatility in developing countries in general, and in Sub-Saharan Africa (SSA) in particular, have mainly focused on the extent of price transmission between international and domestic markets and have applied simulation models to identify the poverty impacts of such price transmission. In regards to the drivers of the observed price volatilities, most empirical studies typically enumerate a list of potential candidates without quantifying the differential contribution of each of them. Accordingly, the main purpose of **essay I**, titled *Food price volatility in Uganda: Trends, Drivers, and Spillover effects,* is to fill this empirical gap by modeling changes over time of food price volatilities and identifying its potential drivers by means of time-series econometrics. The motivation that propelled this study in Uganda was guided by the observed increases in consumer food price indices since 2008 despite the landlocked position of the country and the relatively small price transmission from international to its domestic food markets, which is an indication that internal or regional rather than international factors might have been at work. Furthermore, Uganda is among the rare countries in SSA to have a rich history in gathering household and food price data.

This first essay has a fourfold objective. The first objective checks the claim that increases in food price levels since 2006 were also accompanied with rises in price volatilities. The second objective is to analyze the patterns of conditional food price volatilities between 2000 and 2012; the third is to model and test for the presence of spillover and leverage effects in food price volatilities and the fourth is to model the potential macroeconomic and environmental drivers of observed food price volatilities and uncover their differential effects.

The analysis is applied to six of the main staple foods produced and consumed in Uganda: *matooke*, cassava, maize, potatoes, beans, and millet flour. The graphical representation of consumer food price indices shows that food prices were astonishingly stable between 2000 and 2007 before starting a rapid upward trend thereafter. Results from variance equality tests further reveal that for the majority of commodities under investigation (5 out of 6), the *unconditional* price volatility (measured by the standard deviation of the price returns) did effectively increase since January 2008. This implies that from that period onwards, Ugandan households have entered phases of higher uncertainties and instabilities regarding food prices. And since high volatility generally implies large and/or rapid changes in food prices, it became more challenging for producers to make optimal decisions concerning input and land allocations, while consumers (most of them also producers) may have increased difficulties in planning their future consumption decisions. The empirical findings also indicate limited evidence in favor of asymmetric and leverage effects in food price volatilities for about half of the staples. In addition, no clear picture is portrayed in regards to the nature and extent of volatility spillover effects across food markets in Uganda, with most of them being only unidirectional. Finally, this first essay reveals that changes in consumer price indices, rainfall and fuel volatilities were the main drivers of observed changes in historical food price volatilities and their impacts were particularly important during periods of high price instabilities. Gven these findings, the essay highlights the importance of mixing actions that target primarily the agricultural sector with more global interventions likely to ensure price stabilization or, at least, reduce price volatility.

The second main research question is tackled in **essay II** (co-authored with Gabriella Berloffa) titled *Welfare effects of food price changes in Uganda under non-separability: How relevant is the net market position?* This study incorporates the insights from the agricultural households' literature (Singh et al., 1986; Strauss, 1986; de Janvry et al., 1991; Taylor and Alderman, 2002) to identify welfare effects of food price changes in Uganda. The study is motivated by the lack of both theoretical and empirical work that explicitly takes account of market failures when analyzing those effects. The study shows that although there exists an abundant empirical literature on welfare impacts of food price shocks (and especially since the global food price crisis of 2007/8), these studies generally fall short of recognizing a crucial feature of markets in developing countries, namely the presence of important market frictions and failures (Barrett and Carter, 2013) that may lead to deviations from the standard neoclassical model of rational consumers. The essay demonstrates theoretically that the effects of food price changes on consumption levels are not straightforward when we allow for the possibility of labor market imperfections and disaggregate households by their net positions in the food and labor markets. As a consequence, it becomes a priori impossible to identify the welfare effects of price changes which may be over- or under-estimated when we assume perfect functioning food and labor markets.

Methodologically, this second study uses household panel dataset collected in three waves (2005/6, 2009/10, and 2010/11) to investigate the impacts of allowing for labor market frictions and to identify groups of households that lost or gained from food price shocks. To that end, the essay estimates a panel stochastic production frontier function using the Battese and Coelli's (1995) Maximum likelihood estimator and applies the Sherlund et al.'s (2002) and Barrett et al.'s (2008) approaches to compute shadow wages for non-labor market participants. It tests for the separability hypothesis using the Kolmogorov-Smirnov and the Epps-Singleton tests of distributions' equality between market wages of off-farm workers and shadow wages of self-employed agricultural households.

In order to estimate the welfare effects of food price changes, the study relies on the econometrics of demand systems' estimation using the Quadratic almost ideal demand system (QUAIDS) of Banks et al. (1997). It is a flexible functional form that incorporates nonlinear effects and interactions of price and expenditures in the demand relationships. Furthermore, it is a hybrid model where some goods face a nonlinear expenditure specification (QUAIDS) while other goods face a linear specification (AIDS). I estimate expenditure and price demand elasticities for 10 key commodities and commodity groups plus leisure time using the QUAIDS model. The demand systems are estimated using a Non-linear Seemingly Unrelated Regression (NSUR) model taking account of censoring in food consumption and the endogeneity of both households' expenditures and shadow wage. The QUAIDS is estimated for each panel wave to check whether households reacted differently to food price changes in periods of low and high price volatility as outlined in the first essay.

Demand estimates are provided for each sub-group of households to take into consideration their potential heterogeneous behavior regarding price changes. Accordingly, households are categorized into 5 groups: non-agricultural households, significant net seller, significant net buyers, insignificant net sellers, and insignificant net buyers. These last 4 sub-groups are defined using a 50%-threshold rule: for instance, an agricultural household is a significant net seller (net buyer) if the total values of its crop sales (of *matooke*, maize, potatoes, cassava, beans, rice, millet, sorghum, fruits and vegetables) is at least 1.5 times larger (lower) than their total market purchases of the same crops.

Estimates of compensating variations using estimated price elasticities computed under perfect and imperfect labor markets reveal that the welfare effects of food price changes are globally lower in the non-separable model and different in signs and magnitudes for the sub-groups of households. In particular, the results show that the welfare effects even present opposite signs in the sub-period 2005/6-2009/10. Indeed, while Ugandan households as a whole have benefited from high food price increases between 2005/6 and 2009/10 by 15.4%

(meaning that they have to decrease their total expenditures of 2009/10 by 15.4% to reach the utility level achieved in 2005/6), they lost from these price increases by 9.7% if we incorporate virtual or shadow effects due to labor market frictions. By and large, the findings from this second essay indicate that non-agricultural, poor, and urban households have suffered from price increases while among agricultural households, only significant net sellers and, to a small extent, marginal net sellers have benefited from the price upsurges. However, the magnitudes of these welfare effects are found to be slightly less important than those obtained previously through price simulations.

In settings characterized by the prominence of shocks, the uncertainty about the future, and the quasi-absence of formal insurance and credit markets, agricultural households in most developing countries can only rely on informal mechanisms or crop diversification strategies to protect themselves against high variances in food prices (Fafchamps, 1992). **Essay III**, titled *How strongly do agricultural risks and farmers' expectations influence acreage decisions? Dynamic models of land use in Uganda*, explores the question of crop choices and land allocations in environments where farmers face uncertainties about end-of-season output prices and yield levels, weather variability, and formulate expectations about their future levels. In particular, this essay answers the following empirical questions: Are Ugandan farmers more sensitive to changes in expected prices or expected yields? Or is it the volatility of prices and yields that finally matters? Do farmers keep growing the same crop once it has been selected previously or do they instead take advantage of crop rotational effects? Which factors—household characteristics (such as education, sex, or household size), environmental factors (such as land quality, typology of soil, or irrigation practices), or agricultural and market-related risks—are most important when it comes to selecting and allocating land to particular crops?

To that end, I estimate two econometric models: a multivariate crop selection model that analyses the factors affecting the probability of selecting and growing different crops under market uncertainties and a conditional acreage share model that investigates how farmers allocate their agricultural land to different crops so that to maximize the expected utility of their profit. In these models, the choices that the farmers made in the past regarding the crops they grew and how much land they allocated to different crops are assumed to influence current farmers' choices, leading to dynamic crop choice and land allocation problems. Moreover, farmers' behavior is modeled as a generalized two-step Heckman-type approach consisting in a sequential decision: first they select the crop (s) to grow and second, they determine the proportion of land to share out among the selected crops. The model specifications allow to distinguish true state dependence in crop choice and land allocation from spurious state dependence (due to unobserved heterogeneity) and to check for the presence of inertia effects (if farmers do not change their previous crop choice patterns) or spillover/rotational effects (if choices made in the past by a farmer regarding one crop affect current decisions about competing crops). Both the selection and land share models are estimated for 6 crops or crop groups, *matooke*, cassava, maize, potatoes (both Irish and sweet potatoes), beans, and other cereals (rice, millet, and sorghum), as well as a residual category for all other crops not selected in the present analysis using panel dataset of 1,598 agricultural households over 4 periods.

To take account of initial observations problem posed by the dynamic nature of the farmers' decisions, I apply in both crop choice and acreage allocation models the Wooldridge's (2002) recommendation by including as an additional covariate the first observations of each dependent variable. Furthermore, to deal with farm and crop unobserved heterogeneity, I apply the Mundlak-Chamberlain approach by assuming that unobserved heterogeneity can be specified as a linear function of the average values of all time-varying independent variables. The crop selection problem is then modeled as a dynamic multivariate probit regression and estimated through Simulated Maximum Likelihood and the G (Geweke) H (Hajivassiliou) K (Keane) simulator; whereas the conditional acreage share model is estimated using a dynamic multivariate fractional logit model (Mullahy, 2011).

The empirical findings suggest that price, yield, and weather risks are more important than their expected values in both crop choice and acreage share models. Farmers are found more sensitive to changes in expected yields and yield volatility than in expected prices or price volatility. Moreover, most conditional expected acreage share elasticities in the static models are overestimated compared to the dynamic models and finally, I find evidence of strong state dependence in farmers' crop choices and acreage allocations while the presence of rotational effects is relatively limited compared to inertia effects.

The final essay, titled *Welfare growth, poverty traps, and differential exposure to food price shocks: Evidence from Uganda*, explores the last main research question of this dissertation by investigating the link between poverty traps, poverty persistence, and differential exposure and vulnerability to food price shocks using four waves of Uganda National Panel Surveys (UNPS) spanning over the years 2005-2012. The motivation behind this last essay is the unproved claim that food price shocks, especially since the recent global food price crisis, might have thrust thousands, or even millions, of households in most developing countries into chronic poverty and have even exacerbated the risk of being trapped into poverty (Martin and Ivanic, 2008). The essay develops a modified Ramsey consumption growth model allowing for reference-dependent preferences and both food price and asset shocks to model theoretically the impact of shocks on welfare growth. To uncover the link between exposure to food price shocks and the patterns of welfare growth dynamics, the study first constructs both household-specific food price shocks' variable and asset index (using a livelihood-based regression model). Three types of econometric methods (parametric, non-, and semi-parametric) are then applied to check for the hypothesis of food-price-shocks-induced poverty traps.

Under parametric methods, consumption and asset dynamics are modeled as cubic polynomial regressions of lagged consumption levels and asset indices, respectively, and estimated by the two-step system Generalized Methods of Moments (S-GMM). During these estimations, I test for the existence of serial correlations of error terms using the Arellano-Bond first order AR (1) and second order AR (2) tests, and check for over-identification of the instruments through the Hansen *J* test. To allow for nonlinearities in the effects of food price shocks, I enter the price shocks' variable both linearly and interacted with the degree of the household's vulnerability to food price shocks. This latter is computed using the principal components analysis by incorporating three factors likely to determine the extent of this vulnerability, namely the food dependency ratio, the degree of market participation, and the level of household's income.

The results suggest the presence of nonlinearities in both consumption and asset dynamics. Furthermore, I find that changes in the degree of exposure to food price shocks tend to decrease the rates of both consumption and asset growth during the sample period, with the effects being more important in the consumption growth model. Concretely, the parametric results show 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 vulnerability threshold to food price shocks is found to be 1.364, meaning that on average the effect of food price shocks starts inducing detrimental impacts on consumption growth once the vulnerability index exceeds this level, and this was the case of around 58% of the surveyed households.

However, I did not find any evidence of food-price-shocks-induced poverty traps or bifurcated welfare dynamics necessary for the existence of multiple welfare equilibria.

Instead, graphical representations of the predicted consumption levels and asset indices reveal that Ugandan households are converging towards a single welfare equilibrium located slightly above the official poverty line, at around 29,000 Ugandan Shillings (UShs) for monthly real values of consumption per adult equivalent and 1.10 Poverty Line Units (PLUs) for asset index. Non-parametric (Kernel-weighted local polynomial smoothing and locally weighted scatterplot smoother, LOWESS) and semi-parametric methods (Ruppert et al's (2003) penalized spline regression estimation) also indicate the absence of poverty traps caused by exposure to food price shocks.

When households are disaggregated into different sub-groups sharing some similarities, the econometric results suggest that different household groups appear to be moving towards specific welfare equilibria. For instance, households exposed to food price shocks are moving towards a consumption threshold that is 6.5% lower than the equilibrium of their unexposed counterparts, with 30,260UShs of consumption values against 32,360UShs. Households located below the vulnerability threshold 1.364 (meaning less vulnerable households) are expected to reach a welfare equilibrium that is on average 57.1% greater than that of households beyond the estimated critical vulnerability index. Hence, although there is no evidence of food-price-shocks-induced poverty traps, the essay finds evidence of conditional convergence across groups of households with female-educated, less educated, highly exposed and vulnerable households to food price shocks converging towards lower consumption and asset equilibria, regardless of the selected econometric method.

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Essay I

Food Price Volatility in Uganda:

Trends, Drivers, and Spillover Effects

1.1 Introduction

The recent unprecedented shifts in global commodity prices observed between 2007 and the middle of 2008 and from 2010 to 2011 have revived interest and widespread concerns about their potential adverse consequences on households, especially in developing countries. Indeed, between 2005 and 2007, international prices of many staple foods rose drastically: milk powder by 90 percent, maize by 80 percent, wheat by 70 percent, and rice by 20 percent (Ivanic and Martin, 2008). Further, at the peaks of the crisis in mid-2008, the international prices of some food commodities - such as wheat, maize, and rice - had more than doubled (von Braun, 2008). While in developed countries the budget shares of food expenditures are relatively modest, in developing countries, most households not only are producers and consumers of food, but also consume all or part of the output of their productive activities.

In Uganda for example, agriculture provides about 42% of earning sources (UBoS, 2010), employs 65% of the total labor force of the country (World Bank, 2013) and the population relies primarily on staple foods as its main source of caloric intakes. To grasp the importance of the staples for the population, table 1.1 gives an overview of caloric intake and consumption of the most important staple foods in Uganda (*matooke*[1], cassava, maize, sweet and Irish potatoes, beans, rice, sorghum, millet, wheat, and groundnuts) between 2000 and 2011. Overall, *matooke* has been both the most consumed staple food with a per capita annual average of 154kg and the most contributing item in terms of caloric intake, averaging 16.33% throughout the sample period. Cassava, maize, and sweet potatoes also play an important role in both consumption and daily caloric intakes. They account respectively for 12.6, 11.6 and 8.8% of average caloric intakes. The remaining staples only contribute marginally to annual

[1] *Matooke* refers to starchy bananas that are cooked and consumed as staple (Haggblade and Dewina, 2010)

consumption and daily caloric intakes, revealing a diet highly diversified among the population with no staple food accounting for more than 20% of the daily caloric intakes.

In such an environment characterized by a high dependency of the population on staple foods for both consumption, caloric intakes and agricultural revenues, any substantial changes in food prices (both in levels and volatility) are likely to impact on household real income, particularly for agricultural households, and exacerbate food insecurity of the poor (Apergis and Rezitis, 2011). A visual inspection of the price volatility of these staple foods helps understand the need of investigating their behavior and identifying their main drivers.

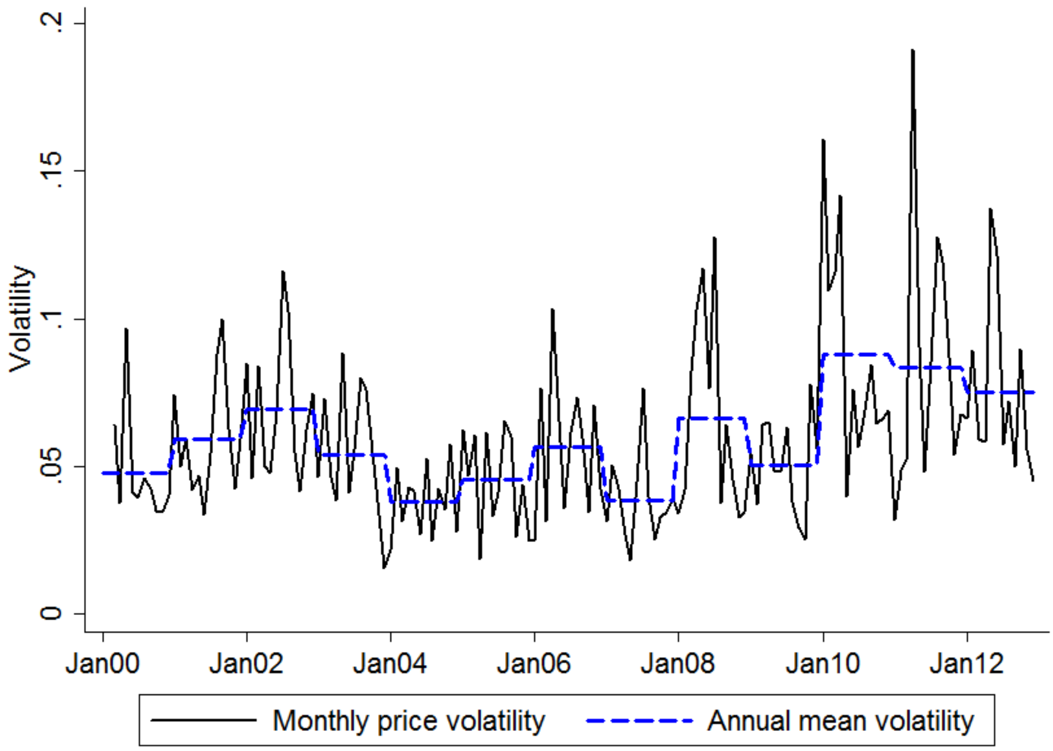
Table 1.1 *Caloric intakes and consumption of main staple foods (2000 – 2011)*

Staple foods	Caloric intakes (kcal/person/day)				Consumption (kg/person/year)		
	Average	%	min	max	Average	Min	Max
Matooke	375.75	16.33	318	439	154.06	130.3	180.2
Cassava	290.25	12.62	267	312	97.24	88.8	104.7
Maize	265.25	11.55	203	344	29.05	22.4	40.7
Sweet potatoes	202.67	8.81	162	225	77.16	61.8	85.6
Beans	124.58	5.51	91	166	13.42	9.8	17.9
Millet	94.17	4.08	39	127	14.82	5.4	18
Wheat	67.67	2.94	16	97	9.01	2	13.1
Groundnuts	55.08	2.39	49	69	3.65	2.8	4.6
Rice	45.25	1.97	34	54	4.64	3.5	5.6
Sorghum	41.25	1.79	30	50	4.96	3.5	5.8
Irish Potatoes	27.75	1.21	26	29	14.27	13.4	14.9
Others	670.33	29.16	569	749			
Total	2,299.83	100	2,250	2,380			

Source: FAO data, various years.

Indeed, the trend of monthly real food prices in Uganda between January 2000 and December 2012 suggests that price volatility (measured by the standard deviation of real price returns) has been time-varying over periods of both months and years and can be characterized by three main stylized features (Figure 1.1). Firstly, it has remained relatively low between January 2000 and December 2007, barely reaching 10 percent and averaging 7.8 percent. Secondly, food price volatility appeared particularly high during the sub-period January 2008 and December 2012, which coincides with the recent international food price turmoil. Finally, price volatility has peaked three times between January 2008 and December 2012: during the second quarter of 2008, the first quarter of 2009 and the last quarter of 2011, with respectively 13, 16, and 19 percent.

Figure 1.1 *Monthly real food price volatility, January 2000 – December 2012*



Note: Weighted index of 10 key food commodities in Uganda: *matooke*, cassava, maize grains and flour, sweet potatoes, beans, millet flour, rice, sorghum, and groundnuts. Nominal prices were deflated using the UBoS all items' consumer price index (2005/06=100).

Understanding factors that drive changes in food price volatility is of utter importance for both market participants and policy-makers. On the one hand, increases in food prices (both in mean and volatility) imply that farmers receive high but more instable revenues from food markets and that consumers not only have to pay consistently high prices but also cannot perfectly predict future market prices due to their highly unpredictable variability. On the other hand, high price volatility may be source of social tensions and conflicts, and may hamper the efficacy of policy responses[2].

There exists a rich body of literature that has investigated the determinants of food price volatility. Macroeconomic factors such as inflation rates, adverse weather conditions, increasing fuel and energy prices, exchange and interest rates, yield and stock levels, have generally been identified among the key contributing factors of changes in commodity price volatility (Pindyck and Rotemberg, 1990; Ai et al., 2006; Balcombe, 2009; Roache, 2010;

[2] For example, Berazneva and Lee (2013) found that between 2006 and 2008, food riots occurred in at least 14 African countries: Guinea, Mauritania, Morocco, Senegal, Cameroon, Mozambique, Burkina Faso, Cote d'Ivoire, Ethiopia, Egypt, Madagascar, Somalia, Tunisia, and Zimbabwe. Bellemare (2015) is another example of recent studies on the impact of high prices (both price levels and price volatility) on social unrest.

Dong et al., 2011; Apergis and Rezitis, 2011; Karali and Power, 2013). Notwithstanding the vast number of theoretical and empirical studies on commodity volatility, they have overwhelmingly focused on spot and futures markets in developed or at least in some emerging countries. By contrast, in developing countries and especially in Sub-Saharan Africa, although different factors have been listed as potential causes of agricultural price volatility, existing studies only present a qualitative, rather than a quantitative, evaluation of these factors and are therefore unable to identify the specific contribution of each factor to observed or historical price volatility (FAO, 2009; FAO, 2011; Minot, 2012; Gouel, 2013).

The aim of this first study is to fill this empirical gap with a twofold objective. Firstly, the paper models conditional price volatility of the main staple foods in Uganda and examines the extent to which volatility in principal food markets in Uganda spills over each other. This is particularly important in the Ugandan setting insofar as previous studies (see, Rashid, 2004; Conforti, 2004; and Boysen, 2009)[3] have shown that different food markets across the country are rather integrated. The evidence of spillover effects across food markets would therefore imply that price stabilization policies should primarily focus more on global solutions instead of favoring market-specific measures. Furthermore, the study addresses the question of asymmetric effects in price volatility. Although largely analyzed in regards to financial markets where good and bad news of the same magnitude generally have different effects, recent studies have also found evidence of such asymmetric effects in agricultural markets (Carpantier, 2010; Piot-Lepetit, 2011).

Secondly, the present study investigates the differential impacts of various factors in driving changes in food price volatility in Uganda between 2000 and 2012. More specifically, the paper aims at answering the following question: How does agricultural price volatility react to changes in macroeconomic fundamentals and environmental factors, on the one hand, and to own- and cross-price shocks, on the other?

[3] For example, Rachid (2004) analyzes internal integration of Ugandan maize markets in the years following the agricultural market liberalization in the early 1990's. Using weekly wholesale price data for 8 district markets over the periods from 1993, week 1 to 1994, week 40 and from 1999, week 40 to 2001, week 30, he finds that the majority of the district markets are integrated and that integration with Kampala improved from the first to the second period.

The Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models are employed to investigate both the conditional price volatility and the presence of asymmetric or leverage effects in food price volatilities. The Vector Autoregressive (VAR) models are used to explore the extent of spillover effects in food markets across the country and to identify the responsiveness of food price volatilities when shocks occur in their own markets or in others. Finally, the Seemingly Unrelated Regression (SUR) model is applied to estimate the impact of macroeconomic variables and seasonality factors on observed food price volatilities. The analysis is conducted for six key staple foods consumed by Ugandan households between January 2000 and December 2012, namely *matooke*, cassava, maize, sweet potatoes, beans, and millet flour.

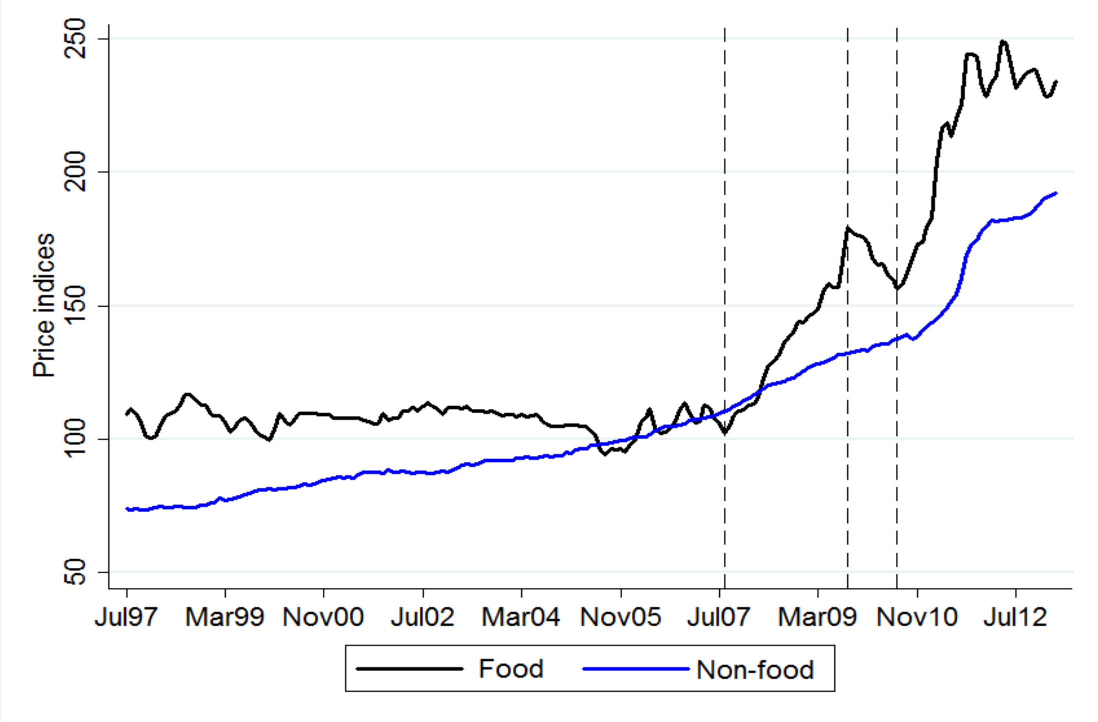
This study, including the preceding introduction, has five sections. The foregoing has highlighted the importance of understanding price volatility in countries largely dependent on food consumption. In the next section, I provide a graphical overview of the patterns of food price indices between 1997 and 2012. In section 3, I present different econometric models for analyzing successively conditional price volatility, asymmetric and leverage effects in food price volatilities, spillover effects across commodity markets, and factors driving the observed or historical price volatility. Section 4 describes the data and constructs volatility variables. Section 5 presents and discusses the results of the GARCH, VAR, and SUR models. Finally, Section 6 concludes the paper and discusses the policy implications of the key findings.

1.2 Patterns of food price indices in Uganda

In this paragraph, I analyze the evolution of monthly consumer price indices in Uganda between July 1997 and December 2012 and identify their main patterns. As shown in figure 1.2, while non-food price indices[4] were continuously increasing, the monthly price indices of food commodities reveal four different patterns in their evolution between July 1997 and December 2012.

[4] Here, non-food price indices represent the weighted average of six commodity groups: clothing and footwear; rent, fuel, and utilities; household and personal goods; transport and communication; education; and health and other commodities.

***Figure 1.2** Monthly consumer price indices, July 1997 – December 2012 (Base: 2005/06=100)*



Source: Own computation based on UBoS data, various years

***First phase:** Stability of food price indices (July 1997 – September 2007)*

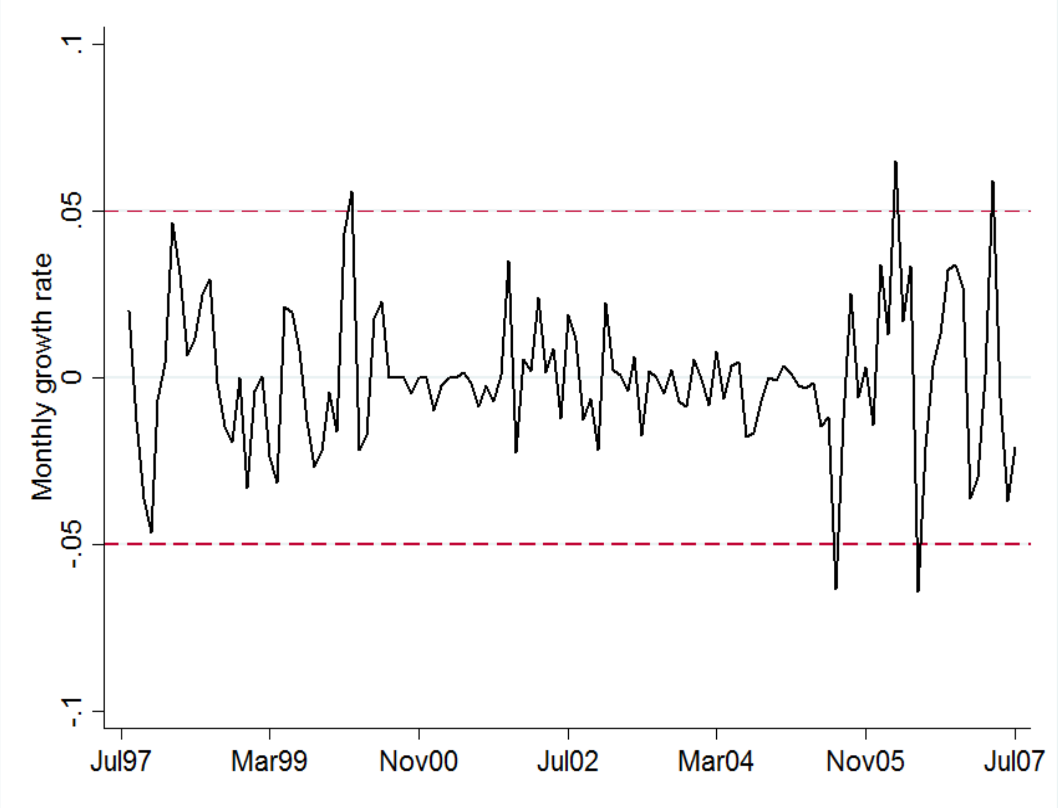
During this phase, the food price index is remarkably stable, around the 2005/06 level. At the macroeconomic level, the Ugandan government has launched substantial economic reforms that contributed to sustaining the economic growth (6.7% on average between 1997 and 2007) and to stabilizing the economy. Indeed, in 1999, the government introduced Poverty Reduction Strategic Papers (PRSPs) with the aim of making the economic performance more pro-poor. The liberalization of the economy during that period improved the incentive of the private sector to invest into the economy which boosted the private capital formation at the expense of public investments[5]. Other reforms included the Medium-Term Competitive Strategy for the Private Sector (MTCS) in 2000 aiming at improving the performances of the private sector[6]; the Plan for the Modernization of Agriculture (PMA) in 1997 whose objective was to eradicate poverty through competitive and sustainable agriculture and agri-business

[5] For example, the share of private capital formation rose from 7% of GDP in 1989/90 to 13% in 1998/9, whereas the public capital formation fell from 7 to 5% during the same period (Devarajan et al., 2001).

[6] Among its objectives, it tried to enforce prudential requirements in the banking system and carry out supervision of the financial sector, to reduce the incidence of corruption and improve the general investment climate.

sector; and the Strategic Export Intervention Program (SEIP) whose primary interest was to increase the competitiveness of Ugandan exports. Consequently, the overall inflation rate was very low during this period, around 5% while it reached 16.6% on average in the early 1990s. The growth rate of the monthly food consumer price indices was relatively stable during this period as visualized in figure 1.3.

Figure 1.3 *Growth rates of monthly consumer food price indices (July 1997 – September 2007)*



Source: Own computation based on UBoS data, various years

Second phase: *Steep increase of food price indices (October 2007 – September 2009)*

This period covers the international food price crisis of 2007/2008. Uganda food price indices were continuously increasing with an average monthly growth rate of 2.3% against -0.005% during the previous period. This observed pattern led several authors to analyze the potential links between the world and Ugandan food prices and they generally came up with the conclusion that, although the world and Ugandan domestic markets were integrated, the price transmission was not only imperfect but also highly dependent of the type of commodities analyzed.

For example, Conforti (2004) and Boysen (2009) analyzed how an increase in food prices impacts on poverty in Uganda. Although they focused on different items in their respective studies[7], they both found that world and Ugandan domestic markets were integrated. The same results were obtained by Rapsomanikis et al. (2003), Dorosh et al. (2003) and Bussolo et al. (2007) who restricted their study to the analysis of the Ugandan coffee markets over various periods and found a significant link between the world and Ugandan coffee markets. Kaspersen and Føyn (2010) analyzed the impact of the world prices' increases on the Ugandan domestic markets of Robusta coffee and sorghum. They used wholesale weekly prices of Foodnet, collected at the main local markets in four districts (Gulu, Jinja, Mbale and Soroti). Contrarily to previous studies, their paper found that sorghum markets in Uganda, unlike the Robusta coffee's markets, were not integrated into the world markets. Their empirical analysis also indicated that rising food prices (of little-traded crops) in world markets would not have a direct effect on food prices in Uganda. Finally, Benson et al. (2008) assessed the potential impact of rising world food prices in 2007/2008 on the welfare of Ugandan households. They suggested that only domestic prices of internationally traded goods (in their study, rice and wheat) were directly affected by international market prices.

By and large, these studies suggest that international food prices were imperfectly transmitted to Ugandan local markets and among the reasons usually put forward, we have high transaction costs due to the insulation of the country from international markets (Benson et al., 2008) and the relatively large quantity and range of staples consumed from home production (Boysen, 2009). Therefore, the observed increases in Ugandan food prices during this period have been attributed, without formal tests of the proposed explanations, to diverse factors, including the global rise in oil prices, the post-election crisis in Kenya at the beginning of 2008 that has increased the demand for Ugandan products, new demands from DR Congo and southern Sudan, and localized production problems, for example floods in the Teso region between July and October 2007 (Benson et al., 2008).

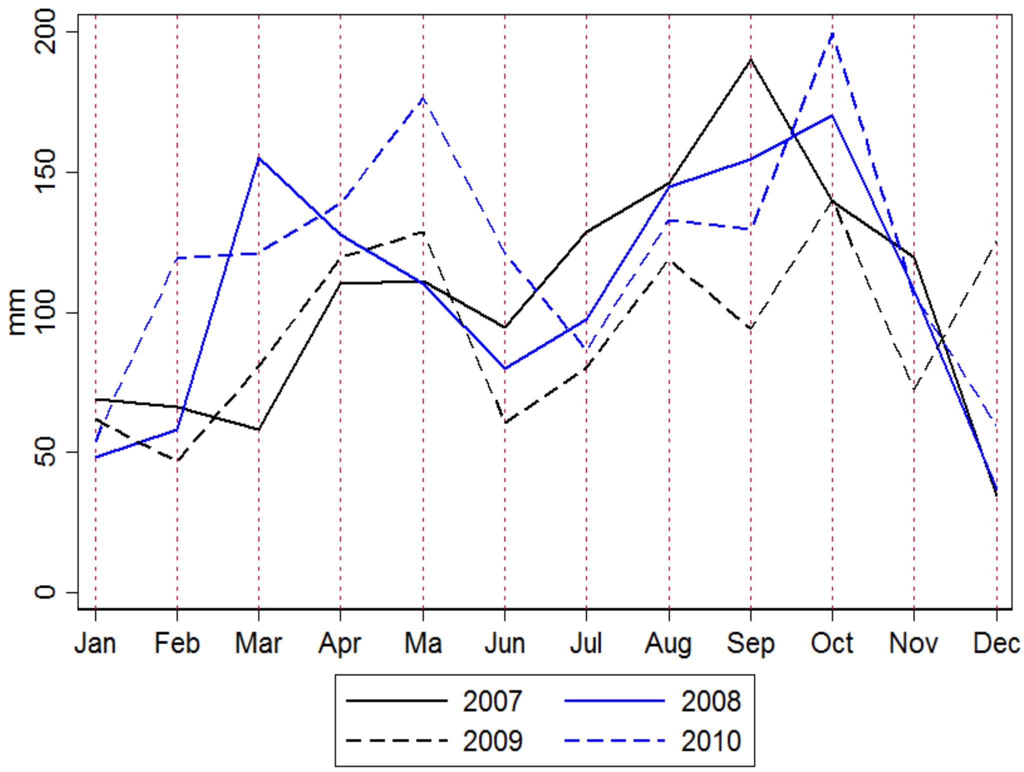
Third phase: *Sharp decline in food price indices (October 2009 – June 2010)*

Between October 2009 and June 2010, food inflation ceased off its upward trend characterizing the previous spell but still remained higher than during the period July 1997 -

[7] Wheat, sorghum, milk powder, sorghum, maize, rice, cassava, soybean, poultry and pork meat for Conforti and *matooke*, cassava flour, millet flour, cassava fresh, sweet potatoes, rice, dried beans Nambale, dried beans Kanyebwa, Irish potatoes, maize flour and "unpounded" groundnuts for Boysen.

September 2007. Among the potential causes of this food price deflation, we may find the combined effects of good harvest periods in major cereals (especially, maize and rice) and relatively lower fuel prices. With regards to rainfall variability, this period which covers almost all the four agricultural seasons[8] in Uganda enjoyed particularly good average rainfall levels. Indeed, from figure 1.4, it appears that rainfall levels between January and June 2010 were globally higher than the corresponding months of 2007, 2008, and 2009 which led to relatively important production during the first harvest season.

Figure 1.4 *Average rainfall levels (in mm) in Uganda (2007 – 2010)*



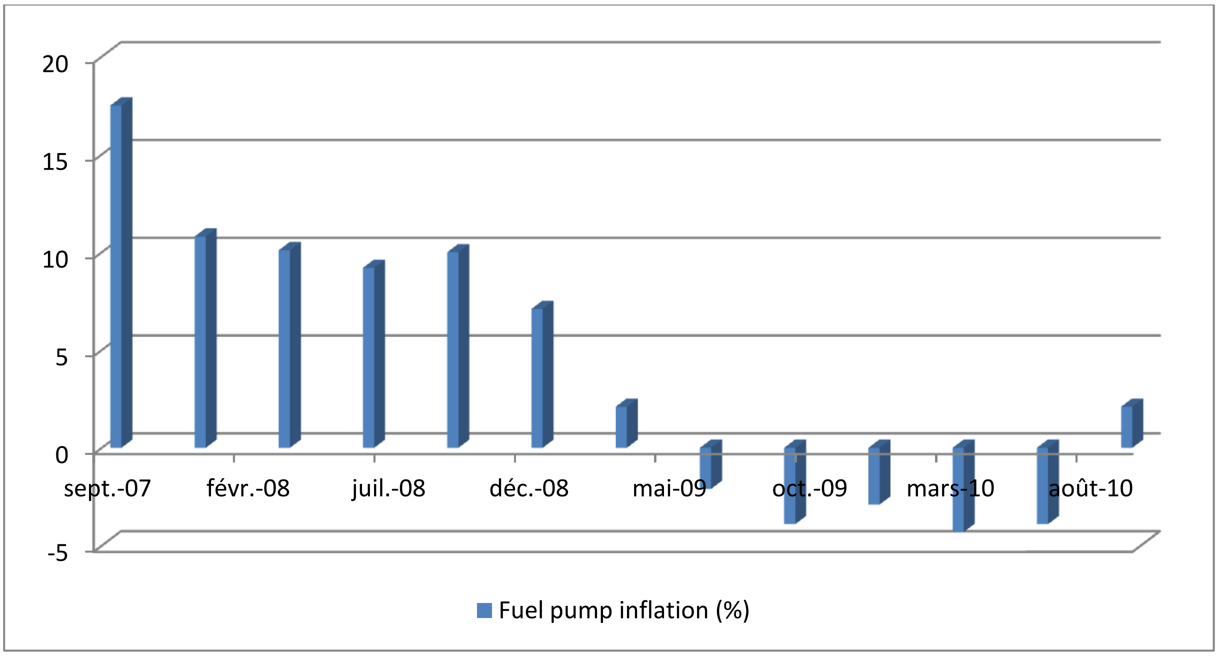
Source: Sector economic performance reports of the Ministry of Energy and Mineral Development of Uganda, various years.

On the other hand, although rainfall was lower in October and November 2009 comparatively to other years, it started increasing since December 2009 with an impact on the production during the second harvest period.

[8] The second planting season, which usually starts from September and goes until November, the second harvest period which covers the period December to February, the first planting season over the months of March to May, and the first month of the first harvest period (Asiimwe and Mpuga, 2007).

Furthermore, fuel prices could have played an important role in explaining the downward trend in food price indices. Indeed, many Ugandan farmers are located in remote areas, far from the main roads of the country. Access to food and input markets therefore requires relatively important transport costs that may be detrimental for small farmers and increase food prices charged by producers due to higher production costs. Fuel price inflation as depicted in figure 1.5 remained high in 2008 (around 10% quarterly) but sharply decreased between January 2009 and June 2010. During this period, the average quarterly fuel inflation was -3.75% against 8.1% between September 2007 and June 2009.

Figure 1.5 *Evolution of quarterly fuel pump inflation in Uganda, September 2007 – September 2010*



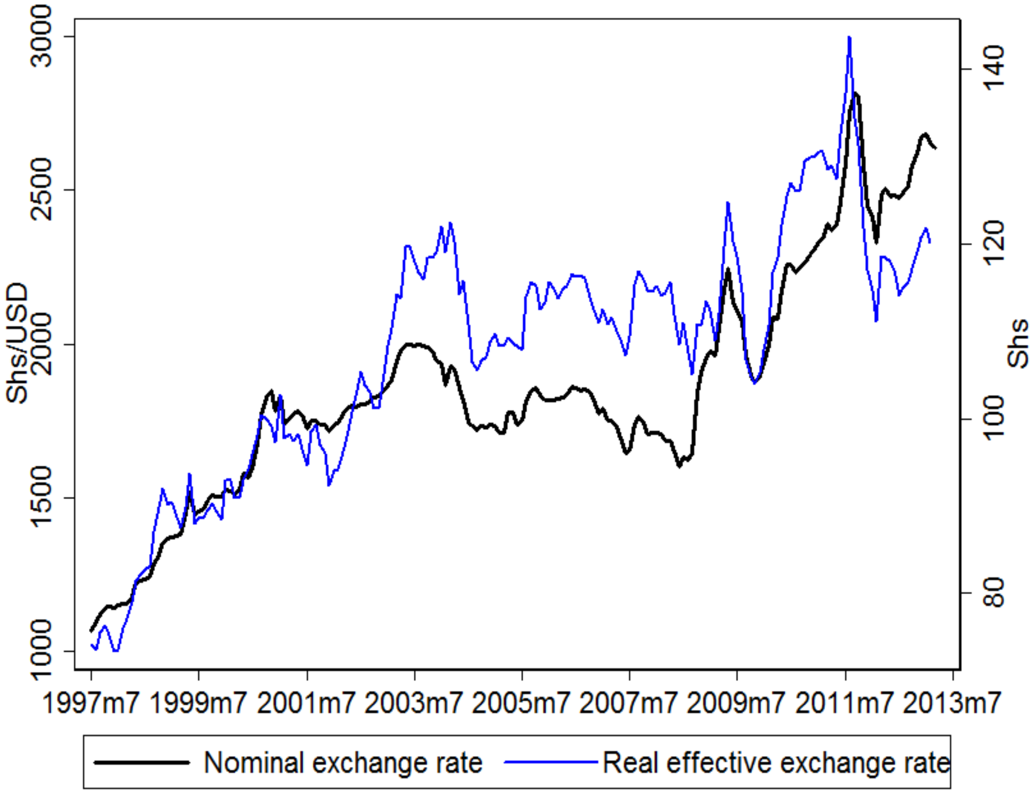
Source: Bank of Uganda's Quarterly macroeconomic reports, various years.

Fourth phase: *Skyrocketing food price indices (July 2010-December 2012)*

During this last phase, Uganda has experienced the second remarkable increase in its food price inflation. Indeed, food inflation, which accounts for around 27.2% in the overall inflation, drastically increased from -2.8% in the second quarter of 2010 to 12% in the first quarter of 2011 (Bank of Uganda, 2011). Furthermore, since April 2011, food inflation has not stopped rising, peaking in October 2011 and April 2012, with an index of around 250. This surge in food prices may result from various and intertwined factors.

First, international crude oil prices accelerated since March 2011 and reached 123$ per barrel in April 2011. Second, the rise in food crop inflation might have resulted from periods of droughts that adversely affected agricultural production in most growing food regions of the country. Third, increased fuel prices coincided with the depreciation of the Uganda Shilling/US dollar exchange rate (figure 1.6). Finally, increased inflation in Uganda's trading partners, particularly in Kenya, Euro area, China, and the United Kingdom, may have been translated into rising food prices. For example, in Kenya, a country that accounted for around 19% of the total Uganda exports between 2010 and 2013, the overall annual inflation rate increased from 4% in 2010 to 14% in 2011, while in the Euro area, China, and the United Kingdom, it rose from 1.5, 3.3, and 3.3% in 2010 to 3.3, 5.4, and 4.5% in 2011, respectively (World Bank , 2013).

Figure 1.6 *Evolution of nominal and real effective exchange rates UShs/$US (July 1997- March 2013)*



Source: Own computation based on Bank of Uganda (2013)

1.2 Econometric models of conditional volatility, asymmetric and spillover effects, and drivers of price volatility

In this section, different econometric models of evaluating conditional food price volatility, testing for the presence of asymmetric and spillover effects of price volatilities across

Ugandan commodity markets, and examining the differential impact of potential drivers of observed volatilities are successively presented.

1.2.1 Conditional volatility model

To analyze historical food price volatility in Uganda, I draw on the Autoregressive Conditional Heteroscedastic (ARCH) model introduced by Engle (1982) and the generalized ARCH (GARCH) model by Bollerslev (1986). The ARCH model is specified so that the current price volatility will be positively affected by the more recently observed shocks whereas the GARCH model assumes a positive impact of both previous shocks and volatilities.

Consider the following general $\mathrm{ARMA}(p,q)$ process with autoregressive order *p* and moving average order *q*:

$$\rho(L^p)(Y_t - X_t\beta) = \theta(L^q)\varepsilon_t \tag{1.1}$$

where

$$\begin{aligned} \rho(L^p) &= 1 - \rho_1 L - \rho_2 L^2 - \ldots - \rho_p L^p \\ \theta(L^q) &= 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q \\ L^j Y_t &= Y_{t-j} \end{aligned} \tag{1.2}$$

with Y_t, the dependent variable, is a food price volatility time-series ; Y_{t-j} , j = 1, 2,…, p, its lagged dependent variables; X_t are independent variables; L is the lag operator; and ε_t are the error terms assumed to be white noise. The mean equation (1.1) does not take account of heteroscedasticity of the time series process generally observed in the form of fat tails and leverage effects (Würtz et al, 2006). To solve this problem, Engle (1982) defines the error terms in (1.1) as an autoregressive conditional heteroscedastic process, giving the following $\mathrm{ARCH}(q)$ process:

$$Y_t = \mathbf{X}_t'\boldsymbol{\beta} + \varepsilon_t \tag{1.3}$$

where

$$\begin{aligned} \varepsilon_t \,|\, \Omega_{t-1} &\to N(0, \sigma_t^2) \\ \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \end{aligned} \tag{1.4}$$

with σ_t^2 is the time-varying variance of the error term ε_t; Ω_{t-1} is the information set available at time *t*-1. In the $\mathrm{GARCH}(p,q)$, the lagged values of σ_t^2 are now included into the model which gives:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{1.5}$$

where ω is the mean of σ_t^2; α_i and β_j are the ARCH and GARCH terms, respectively.

For the $\mathrm{GARCH}(p,q)$ to be stationary, the following restrictions are sufficient:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1, \quad \omega > 0, \quad \alpha_i, \beta_j > 0, \quad \forall i, \forall j \tag{1.6}$$

I introduce two types of variables in the mean equation (1.3). First, to check whether the conditional price volatility has significantly changed since 2008, I include in the vector ***X*** a dummy variable *Dum* which takes the value 1 during periods of structural breaks in food price series and 0 otherwise (see next section). The sign of this variable is expected to be positive, implying a significant increase in conditional price volatility associated with these turning points.

Second, one of the common features of agricultural food markets is the presence of seasonality in volatility patterns. Food prices tend to fluctuate across the agricultural season, rising during the planting season as the stocks of commodities are depleting and declining during the harvest period (Buguk et al., 2003). To incorporate deterministic seasonal components into the volatility models, I follow Goodwin and Schnepf (2000) by adding a sum of trigonometric functions corresponding to the t^{th} month of the year into the vector ***X***. Concretely, if m_t represents the month of the year associated with the observation *t*, the seasonal component s_t can be written as:

$$s_t = \sum_{k=1}^{K} \left[\theta_k \cos\left(\frac{2\pi * k * m_t}{12} \right) + \varphi_k \sin\left(\frac{2\pi * k * m_t}{12} \right) \right] \tag{1.7}$$

where θ_k and φ_k, $\forall k = 1,\ldots,K$, are parameters to be estimated.

Through this specification, the unknown seasonal function is expressed as a k^{th}-order Fourier approximation within a period of one year. The presence of seasonal patterns into price volatility can then be assessed by testing the significance of the estimated values of θ_k and φ_k. Following Goodwin and Schnepf (2000) and Buguk et al. (2003), k = 3 is used in deriving the seasonal component.

1.2.2 Asymmetric and leverage effects

One of the limitations of a standard GARCH (1, 1) model is its assumption of symmetric impacts of good and bad news on volatility. However, empirical evidence, originated from financial markets and stock exchange, extensively shows that not only is there an asymmetric response of price volatility to positive and negative past returns (asymmetric effects) but also increases in volatility appear to be larger when previous returns were negative than when they were positive with the same magnitude (*leverage* effects) (Black, 1976; French et al., 1987; Nelson, 1991a, b; Engle and Ng, 1993; Villar, 2010; Apergis and Rezitis, 2011). In terms of food prices, this would mean that households would not react identically to unanticipated increases and decreases in food prices of the same magnitude. To test for the robustness of the GARCH (1, 1) estimation results, I now allow price volatility to react asymmetrically to both positive and negative shocks. To that end, I estimate an Exponential GARCH model proposed by Nelson (1991b)[9]. In addition to accounting for asymmetry in the responsiveness of food price volatility to shocks of opposite signs, the EGARCH model does not impose any restrictions on the parameters to guarantee a positive variance as do standard GARCH models (Villar, 2010). The EGARCH (1, 1) model specifies the conditional variance σ_t^2 of equation (1.5) as follows:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\ln\left(\sigma_{t-1}^2\right) \tag{1.8}$$

where the ratio $h_t = \varepsilon_t / \sigma_t$ represents the standardized shock for time *t*. The parameters α and γ capture the presence of asymmetric and leverage effects in food price volatility whereas β reports persistence in volatility. Since the EGARCH (1, 1) model is based on the standardized residuals h_t, the regularity condition is satisfied if $|\beta| < 1$.

The model will be symmetric if $\gamma = 0$ and in that case the model reverts to the standard GARCH (1, 1). It will exhibit asymmetric effects if γ is statistically significant. When $\gamma < 0$

[9] Other possibilities include Asymmetric power ARCH (A-PARCH) models first proposed by Ding et al. (1993) or Threshold ARCH (TARCH) models of Zakoian (1994).

and significant, then there exist leverage effects, meaning that negative shocks on price volatility have larger impact than positive shocks of the same magnitude. The effects of high- (unexpected price increases) and low-price news (unexpected price decreases) on the conditional variance will be given respectively by $\alpha+\gamma$ and $\alpha-\gamma$ (Zheng et al., 2008). If $|\alpha-\gamma|>|\alpha+\gamma|$, then low-price news have more effects on the conditional variance than high-price news of the same magnitude.

1.2.3 Volatility spillover model

To examine the possibility of spillover effects from one market to another within the country, I specify a multivariate framework in which the current price volatility of a commodity *i* is allowed to depend on both past own shocks and price shocks to other commodities. To that end, I use a Vector AutoRegressive (VAR) specification of Sims (1982) which identifies how each endogenous variable (i.e. food price volatility) reacts over time to own shocks and to shocks from other food markets. I estimate the following VAR model:

$$\begin{pmatrix} Y_t^i \\ Y_t^{-i} \end{pmatrix} = \begin{pmatrix} A_k \\ a_k \end{pmatrix} + \begin{pmatrix} \sum_{k=1}^{p} B_k Q \\ \sum_{k=1}^{p} b_k q \end{pmatrix} + \begin{pmatrix} \sum_{k=1}^{p} C_k Y_{t-k}^i \\ \sum_{k=1}^{p} c_k Y_{t-k}^i \end{pmatrix} + \begin{pmatrix} \sum_{k=1}^{p} D_k Y_{t-k}^{-i} \\ \sum_{k=1}^{p} d_k Y_{t-k}^{-i} \end{pmatrix} + \begin{pmatrix} U_t \\ u_t \end{pmatrix} \tag{1.9}$$

where Y_t^i is the price volatility of commodity *i* and Y_t^{-i} is a vector of price volatilities of other commodities which effects are assumed to spill over the market of the commodity i ; Q is a vector of dummy variables capturing structural breaks; A_k, B_k, C_k, and D_k and their lowercase counterparts are the vector of coefficients in Y_t^i and Y_t^{-i} equations, respectively. Schwartz information criterion was used to select the appropriate lag length.

1.2.4 Model of drivers of food price volatility

One of the questions arising when inspecting figure 1.1 is whether the blame of the upward trend in food price volatility in Uganda could be put on the international food price turmoil of 2007/8. The answer depends crucially on how integrated are Ugandan domestic markets to global commodity markets. By and large, the existing studies tackling this issue have come up with the conclusion that international food prices were imperfectly transmitted to Ugandan local markets. As previously outlined, high transaction costs due to the insulation of Uganda from international markets (Benson et al., 2008; Kaspersen and Føyn, 2010) and the relatively large quantity and range of staple foods consumed from home production (Boysen, 2009) are the reasons usually advanced to explain these results. Here, I take a more formal approach by identifying and analyzing the differential contributions of the key drivers to the observed price upswings in the main Ugandan markets.

Economic theory predicts that changes in price volatility will depend to a larger extent on factors directly affecting the decisions of buyers and sellers of commodities analyzed and to a smaller extent on indirect factors. Direct determinants will generally include supply shocks (such as weather variability, changes in input prices, yield variability, and changes in stock levels) and demand shocks (like changes in income or consumption habit persistence) whereas indirect causes may result from speculative behavior, volatility in market prices of substitute or complement commodities, exchange rate volatility, or inflation rates.

The choice of the potential determinants of food price volatility is mainly guided here by economic theory, results of other empirical studies, and data availability constraints. To analyze the impact of macroeconomic and environmental variables on changes in price volatility, I estimate the Seemingly Unrelated Regression (SUR) model introduced by Zellner (1962):

$$\begin{aligned} CPV_{i,M} &= a_i + b_i \Delta CPI_M + c_i ERV_{M,Shs/\$} + d_i FPV_M + e_i IRV_M + f_i RFV_M \\ &\quad + h_i Harvest1 + k_i Harvest2 + l_i Planting2 + \varepsilon_{i,M}\,, \\ &\quad M = 2000m1, \ \ldots, 2012m12; \quad i = 1,\ldots,6 \end{aligned} \tag{1.10}$$

where $CPV_{i,M}$ is the food price volatility of the commodity *i* in month *M;* a_i, b_i, c_i, d_i, e_i f_i, h_i, k_i, l_i are parameters to be estimated; $\varepsilon_{i,M}$ are the error terms.

Among the explanatory variables, I include the inflation rate volatility ΔCPI_M, real effective exchange rate volatility between the Uganda Shilling and the US dollar $ERV_{M,Shs/\$}$, fuel price volatility FPV_M, interest rate volatility IRV_M, and rainfall variability RFV_M as well as dummy variables for different agricultural seasons in the country *Harvest*1, *Harverst*2, and *Planting*2.

The variable ΔCPI_M captures the impact of the overall food inflation on the price movements of a particular commodity. I expect a positive correlation between the changes in consumer price index and individual price volatility (Roache, 2010; Azad et al., 2012).

Volatility in the exchange rates increases the riskiness of both the returns of the exporters and the prices of imported goods. Including this variable into the model will help discriminate the effects of regional and international forces on domestic price variations of each commodity (Gilbert, 1989; IMF, 2008). I adopt a standard measure of exchange rate volatility $ERV_{M,Shs/\$}$ of a particular month M by taking the standard deviation of the percent changes of the real effective exchange rate RE_M between the Uganda Shilling and the US dollar over a three-month window width (Chowdhury 1993; Hau, 1999; Arezki et al., 2012)[10]:

$$ERV_M = \left[\frac{1}{3} \sum_{i=1}^{3} (\ln RE_{M+i-1} - \ln RE_{M+i-2})^2 \right]^{\frac{1}{2}} \qquad (1.11)$$

The effective exchange rate is computed in such a way that a decline of its value implies a real appreciation of the domestic currency. I assume that the impact will be higher and significantly positive for commodities which are more regionally and/or internationally traded by Uganda, such as maize, millet flour, and beans.

The rainfall volatility variable RFV_M captures the impact of weather shocks on price volatility. Weather variability is among the main causes of production shortfalls, particularly in developing countries where agricultural plots are predominately rain-fed. As suggested by the storage model, supply shocks (here consecutive to weather shocks) are likely to be important factors of agricultural price volatility (Deaton and Laroque, 1992, 1996). I hypothesize that the more rainfall-dependent the commodity, the larger the impact of weather variability on its price instability.

Interest rate volatility IRV_M is used as a proxy for commodity stocks given the absence of monthly data. It therefore represents the opportunity costs of holding potential commodity stocks (Balcombe, 2009; Azad et al., 2012; Karali and Power, 2013).

Transaction costs and particularly transportation costs are also obvious candidates as drivers of food price volatility in Uganda. Fuel price volatility FPV_M is used as proxy of these costs. Indeed, farmers often have to choose between selling their products at the farm gate and therefore earn less or carrying these products to markets and incur a transport cost (Fafchamps and Hill, 2005). When a crop has a low value-weight ratio (such as *matooke* or cassava), these

[10] I also used other alternatives window widths (1, 4, and 6 months) to check for the robustness of the volatility measures but results did not significantly change.

costs may represent a non-negligible component of the market prices and fuel their volatility. It is thus hypothesized that the impact of fuel price volatility will be more important the heavier the commodity. Similarly to the exchange rate volatility, I measure inflation rate, interest rate, rainfall and fuel price volatilities as the standard deviation of their growth rate with a three-month window width.

Finally, it is likely that food prices exhibit important seasonalities, being relatively higher and lower during planting and harvest seasons, respectively (Koekebakker and Lien, 2004). To account for that possibility, I include seasonal dummy variables corresponding to different harvest and planting seasons in Uganda: *Harvest*1 takes 1 if the corresponding months are June, July and August, and 0 otherwise; *Harvest*2 has 1 if months are December, January and February, and 0 otherwise; and *Planting*2 takes 1 if the corresponding months are September, October and November, and 0 otherwise. The first planting season (March, April, and May) has been used as baseline.

1.3 Data

In all the estimated models, the dependent variables are the food price volatilities. There exist different ways of measuring historic food price volatility. For example, O'Connor and Keane (2011) and Piot-Lepetit (2011) used the coefficient of variation (CV) which is the ratio of the standard deviation over the mean. However, as pointed out by Minot (2012), given the non-stationarity in most food prices, the estimates of price variability derived from the standard deviation approach are dependent on the sample size and may be particularly large when the time period approaches infinity. To avoid this undesirable feature, I follow Gilbert and Morgan (2011) and use instead the standard deviation of price returns, where returns stand for the proportional change in logarithm prices. Therefore, the average monthly price volatility of the i^{th} commodity in the t^{th} month $CPV_{i,t}$ can be formalized as follows (Balcombe, 2009; Minot, 2012):

$$CPV_{i,t} = \sqrt{\sum_{t=1}^{N} \frac{1}{N-1} \left(r_{i,j,t} - \bar{r}_{i,t}\right)^2} \tag{1.12}$$

where

$$r_{i,j,t} = \ln(p_{i,j,t}) - \ln(p_{i,j,t-1}) \quad and \quad \bar{r}_{i,t} = \sum_{t=1}^{N} \frac{1}{N} r_{i,j,t} \tag{1.13}$$

$p_{i,j,t}$ and $r_{i,j,t}$ are respectively the real price and price return of the i^{th} commodity in the j^{th} week of the month *t*. $\bar{r}_{i,t}$ stands for the average monthly price return of the i^{th} commodity. N represents the number of weekly price information available for each month.

I use data obtained from different sources: exchange and interest rates are obtained from Bank of Uganda; consumer price indices, inflation rates, and rainfall data are collected from various issues of *Statistical abstracts* of the Uganda Bureau of Statistics (UBoS) and the Background to the Budget of the Ministry of Finance, Planning, and Economic Development. Fuel pump prices are obtained from the Agriculture Market Information System (AGMIS) Uganda. Monthly nominal food prices of the selected commodities come from time series' prices collected by the Foodnet market price information project of the International Institute of Tropical Agriculture (IITA). The dataset contains weekly wholesale price series for around twenty Ugandan markets across all the geographical regions[11] and for more than 25 staple foods from September 1999, week 40 to December 2012, week 52. For each series, nominal prices were deflated by the UBoS all items' consumer price index (2005/06=100) to take account of potential changes in the purchasing power of Ugandan households.

Table 1.2 reports the values of unconditional price volatility of 6 food commodities, namely *matooke*, cassava, maize, sweet potatoes, beans, and millet flour between January 2000 and December 2012 (see Appendix A.1 for individual volatility plots). The data are divided into two sub-periods (January 2000 to December 2007 and January 2008 to December 2012), which gives 96 and 60 monthly observations, respectively. A standard *F*-test of variance equality is presented in the penultimate column and its implications in terms of significance rise or fall in unconditional volatility are summarized in the last column.

The table reveals that monthly food prices have been globally more volatile since January 2008, rising from 8.4 to 11.7%, which represents an average growth rate of 38.8% between the two sub-periods. The distribution of food price volatility across commodities shows that beans and sweet potatoes were the most volatile respectively in the first and second sub-periods.

[11] Arua, Gulu, Kitgum and Lira in the Northern region; Luwero, Masaka, Rakai, Kiboga, and Kampala (Kisenyi, Owino, Nakawa, Kalerwe) in the Central region; Iganga, Mbale, Jinja, Soroti, and Tororo in the Eastern region; and Jinja, Kabale, Kibale, Kasese, Hoima, and Mbarara in the Western region

Table 1.2 *Unconditional price volatility of key food commodities in Uganda (2000m1 –2012m12)*

	2000m1-2007m12	2008m1-2012m12	Growth rate	2000m1-2012m12	*F*-test (*p*-value)	Conclusion
Matooke	0.099	0.134	0.354	0.112	1.617 (0.037)	Significant rise
Cassava	0.056	0.108	0.929	0.076	3.699 (0.000)	Significant rise
Maize	0.101	0.127	0.257	0.111	1.757 (0.014)	Significant rise
Sweet potatoes	0.097	0.154	0.588	0.120	3.171 (0.000)	Significant rise
Beans	0.112	0.114	0.018	0.112	0.993 (0.989)	Insignificant rise
Millet flour	0.040	0.064	0.600	0.049	3.437 (0.000)	Significant rise
Average	0.084	0.117	0.388	0.065	2.714 (0.000)	Significant rise

Note: The growth rate of each price volatility is defined as $(b-a)/a$, where *a* and *b* are respectively the mean volatility during the first and the second sub-periods. Source: Analysis based on price data from FoodNet project.

Globally, price volatility is the lowest for millet flour (4.9%) and cassava (7.6%) and the highest for sweet potatoes (12%), *matooke* (11.2%), and maize (11.1%). Furthermore, all commodities but beans have exhibited a significant increase in the variance of their unconditional volatility since January 2008.

1.4 Empirical results

1.4.1 Conditional price volatility

Unconditional price volatility assumes that the stochastic processes generating the data on price returns are independent and identically distributed and therefore, the data may be considered as random draws from the same (unconditional) distribution. In the *conditional* volatility model, the stochastic process has now a time-varying volatility (Green, 2012). The model thus estimates a conditional variance at each date in the time series given current and past price information (Gilbert and Morgan, 2011).

A prerequisite for estimating conditional volatility through GARCH models is the stationarity of the process being analyzed. However, since our sample covers periods of recent food price turmoil, I suspect the possibility of breaks and shifting trends in Ugandan price series. In case of evidence in favor of structural breaks in price series, standard econometric tests (Augmented Dickey-Fuller, Phillips-Perron, or Dickey-Fuller Generalized Least Squares) become biased because of their potential confusion of structural breaks in the series as evidence of non-stationarity (Baum, 2005; Ghoshray et al., 2014). Hence, before performing unit root tests, I first identify the potential breaks or turning points in food price trends, following testing procedures proposed by Clemente, Montañés, and Reyes (1998) (henceforth, CMR) and Bai and Perron (2003) (henceforth, BP).

Detecting structural breaks in commodity food prices

The behavior of food commodity prices depicted in previous paragraphs highlighted the possibility of breaks and shifting trends in Ugandan price series. However, relying strictly on visual inspection of data plots to detect the presence of structural breaks may be misleading due to its inherent impossibility to disentangle a simple level shift from real shocks. Hence, since Prebisch (1950) and Singer (1950), researchers such as Perron (1989), Zivot and Andrews (1992), Vogelsang and Perron (1998), Clemente, Montañés, and Reyes (1998), Bai and Perron (2003), Harvey et al. (2009), Perron and Yabu (2009a, b), and Ghoshray et al. (2014) have developed various econometric procedures to detect breaks in the level and/or the scope of commodity trends and estimate both the number and locations of break dates. Although the primary motivation behind these studies and their methodological procedure has been to test the Prebisch-Singer hypothesis[12], they can also be used to differentiate real structural breaks from pure level shifts identified in the previous sections.

Clemente, Montañés, and Reyes' model

The CMR procedure allows for up to two distinct and endogenous structural breaks using two different models: the additive outliers model (the AO model) which identifies a sudden change into a time series and the innovative outliers model (the IO model) that tests for a gradual shift in the mean of the time series (Baum, 2005). The AO model is defined as follows:

$$y_t = \alpha_0 + \alpha_1 DU_{1t} + \alpha_2 DU_{2t} + v_t \tag{1.14}$$

where

$$v_t = \sum_{i=1}^{k} \beta_{1i} DT_{b1,t-i} + \sum_{i=1}^{k} \beta_{2i} DT_{b2,t-i} + \eta v_{t-i} + \sum_{i=1}^{k} \theta_i \Delta v_{t-i} + e_t \tag{1.15}$$

[12] The Prebisch-Singer hypothesis states that the time series of primary commodity prices relative to manufactured goods present a downward trend in the long run. Theoretical explanations of such declining relative commodity prices include "…a low income elasticity of demand for primary commodities, lack of differentiation among commodity producers (…), productivity differentials between North (industrial) and South (commodity producing) countries, and asymmetric market structure (…)" Harvey et al. (2010:2)

In equation (1.14), y_t is the commodity price (in levels or logged) at time *t;* $DU_{it} = 1$ if $t > TB_i$ and 0 otherwise, with $i = 1,2$. There are two potential break points, TB_1 and TB_2, unknown ex ante and determined by grid search. The residuals from (1.14), v_t, are then estimated in equation (1.15) using their lagged values, lagged differences, and a set of dummy variables for the test tractability. In equation (1.15), $DT_{bi,t} = 1$ for $t = TB_i + 1$ and 0 otherwise, with i = 1,2. The model is then estimated over different feasible couples of TB_1 and TB_2, seeking for the minimum *t*-ratio for the null hypothesis $\eta = 1$. Perron and Vogelsang (1992) provided critical values that will then be compared with the value of the minimum *t*-ratio.

The IO model uses an ARMA representation to express the shocks affecting the price series in the following formulation:

$$v_t = \alpha_0 + \alpha_1 DU_{1t} + \alpha_2 DU_{2t} + \omega_1 DT_{b1,t} + \omega_2 DT_{b2,t} + \eta v_{t-1} + \sum_{i=1}^{k} \theta_i \Delta y_{t-i} + e_t \qquad (1.16)$$

In both AO and IO models, an estimate of $\eta < 1$ will indicate that the price series has not a unit root. The appropriate lag order of k is determined using sequential *F*-tests[13].

Bai and Perron's model

Two important weaknesses may bias the results from the CMR model. Indeed, imposing a predefined number of potential breakpoints (here, maximum two) to the data generating process while in reality there are more can render the tests inefficient and either cause spurious appearance of non-stationarity of the price series in a trend stationary process (Perron, 1989) or incorrectly suggest stationarity in a non-stationary process (Leybourne et al., 1998). To address this problem, Bai and Perron (2003) developed AO and IO models that account for multiple breaks. They test the null hypothesis of absence of breakpoints vs *k* breaks and *k* vs *k* + 1 breaks using an efficient algorithm to obtain the global minimisers of the sum of the squared residuals. Their dynamic programming algorithm allows, on the one hand, for both pure and partial structural changes, where all (respectively some) coefficients

[13] Stata routines `clemao2` and `clemio2` implement the AO and IO models of CMR procedure for two breakpoints, respectively.

are subject to changes, and on the other, the construction of confidence intervals of breakdates[14].

In both the CMR and BP models, I apply the following procedure. First, I test for one structural break in the slope of the trend function while allowing for the intercept to change. Second, given the evidence in favor of one structural change in a time series, I then test for one against two or more break points in the data. I choose between the AO and IO models for each food commodity based on the value of the minimum *t*-statistics of dummy variables introduced in the models. Specifically to the BP test, I select the optimal number of break dates that minimizes the Bayesian Information Criteria.

Table 1.3 reports the results for the 6 food price series using the Clemente, Montañés, and Reyes (1998) and Bai and Perron's (2003) models for endogenously determined break points in each price series.

Table 1.3 *Optimal endogenous break dates of food price series in Uganda*

Commodity	Clemente et al. (1998)					Bai and Perron (2003)		
	One break		*Two breaks*			*One break*	*Two breaks*	
	k	TB_1	k	TB_1	TB_2	TB_1	TB_1	TB_2
Food*	-	-	2	**2008m8**	2011m5	-	2008m5	**2008m8**
*Matooke**	-	-	1	2005m1	**2008m3**	-	**2008m3**	2011m1
*Cassava**	-	-	2	2008m7	2009m8	-	2008m10	2011m1
*Maize**	3	**2008m3**	-	-	-	-	**2008m3**	2011m3
Sweetpotato**	-	-	1	2008m2	2009m9	-	2008m4	2009m1
*Beans***	3	**2007m10**	-	-	-	-	**2007m10**	2011m2
Millet flour**	4	2009m2	-	-	-	2009m7	-	-

Note: * and ** mean that the AO or IO models have been applied in the CMP and BP procedures, respectively.

The results from table 1.3 show that all selected commodities contained either one or two breaks in the slope. Out of the 6 food commodities, respectively 1 and 3 commodities were found to exhibit one structural change in the BP and CMR models. A number of interesting features can be derived from these results.

[14] Zeileis et al. (2003) developed the package `strucchange` in the `R` system that performed all tests developed in Bai and Perron (2003).

First, the AO model was more efficient in explaining the price behavior of *matooke*, cassava, and maize which reveals that breaks in the scope of these series took place rapidly rather than gradually. Second, both CMR and BP models detect similar break points for 2 commodities – *matooke* and beans– and for the consumer food price index. Hence, December 2007 and March 2008 were selected as optimal endogenous break dates by both models for beans, *matooke*, and maize, respectively. In December 2007, monthly real prices of beans exceeded for the first time 1,000UShs, growing by 11.5% from the previous month while since March 2008, *matooke* prices have consistently been above 400UShs.

Third, discrepancies between the break points identified by both models are more or less important depending on each commodity. Indeed, while the CMR model selects January 2005 and March 2008 as optimal dates of *matooke,* the BP model instead started with March 2008 as first break point and January 2011 as the second one. Furthermore, CMR model only identified one break point in the case of maize and beans against two break dates in BP's. However, as stated above, the BP model is more robust in case of conflicting results with the CMR since it does not impose any limit to the number of potential breaks which can be selected *a posteriori* using either the BIC or RSS criteria (Ghorshay et al., 2014).

To sum up, despite discrepancies between CMR and BP models, a general conclusion emerging from the above analysis is that key commodity food prices in Uganda have been characterized by shifting trends since 2008. In fact, the estimated break dates have globally occurred when significant internal, regional, and international events took place in food commodity markets. An important number of break dates were observed in the first and last quarters of both 2008 and 2009 as well as the first semester of 2011.

Unit root tests

Given evidence of structural breaks in all price series, I perform Bai-Perron's unit root tests (table 1.4). It appears that even when accounting for the presence of structural breaks in the time series, all the prices are difference stationary $I(1)$ variables. I then apply the Box-Jenkins methodology to determine the values of p and q in the ARMA (p,q) process through the Bayesian information criteria (BIC).

Table 1.4 *Bai-Perron's unit root tests in the presence of structural breaks in food prices*

Commodities	TB1 ; TB2	*supF-stat*	Conclusion
Matooke	2008M3 ; 2011M1	3.049	I(1)
Cassava	2008M10 ; 2011M1	2.046	I(1)
Maize	2008M3 ; 2011M3	4.758	I(1)
Sweetpotato	2008M4 ; 2009M1	8.042	I(1)
Beans	2007M10 ; 2011M2	7.805	I(1)
Millet flour	2009M7	3.435	I(1)
Food price index	2008M5 ; 2008M8	5.716	I(1)

Note: The critical values for 15% trim, 5% significant levels, and 1 regressor (each commodity price) are 8.58 and 7.22 for one and two break dates, respectively (Bai and Perron, 2003).

GARCH (1, 1) estimation results

Table 1.5 shows the GARCH (1, 1) estimation results with structural breaks and seasonality in price volatility. Since the turning points occurred during the first quarters of 2008 and 2011 for most commodities, the Dum variable takes 1 for those months and 0 otherwise. All ARCH coefficients (α) are significant at 10% level and positive, thereby satisfying the necessary and sufficient conditions for the validity of the ARCH specifications. Furthermore, the GARCH (1, 1) estimated coefficients for all the commodities satisfy the covariance stationary condition since $\alpha + \beta < 1$ for each staple food. The sum of the ARCH and GARCH terms helps analyze the persistent nature of shocks to food price volatility. The closer the sum of these terms to one, the more persistent the shocks to food price volatility. The results reveal that shocks are more persistent for most commodities, suggesting that once a shock occurs, price volatility tends to persist for a long period (Apergis and Rezitis, 2011), particularly for *matooke*, cassava, and beans.

With regards to the impact of structural breaks on estimated conditional price volatility, the empirical results (coefficients of the variable Dum) indicate that, at a 1% significance level, the mean of the conditional volatility has increased for half of the commodities analyzed, namely cassava, sweet potatoes, and millet flour. As shown in table 1.2, these commodities were characterized by the most important growth rates in their unconditional price volatility. Moreover, they are generally traded regionally which, as predicted by trade or spatial equilibrium models, implies that their prices would be more sensitive than others to breaks or shifting trends associated with internal or regional market events.

The presence of deterministic seasonal components in price volatility can be analyzed through the estimated trigonometric seasonality terms θ_k and φ_k. For each commodity, only around half of the seasonal components are statistically significant, suggesting a relatively moderate seasonality effect on conditional mean volatility.

Table 1.5 *Results of the GARCH (1, 1) model estimation*

	Matooke	Cassava	Maize	Sweet potatoes	Beans	Millet flour
Mean equation : $Y_t = \text{constant} + \lambda Dum + \theta_1 \cos_1 + \theta_2 \cos_2 + \theta_3 \cos_3 + \varphi_1 \sin_1 + \varphi_2 \sin_2 + \varphi_3 \sin_3 + \varepsilon_t$						
Constant	0.002	0.002	0.002	0.004	0.005	0.003
	(0.006)	(0.003)	(0.006)	(0.007)	(0.008)	(0.003)
Dum	0.012	0.038	0.011	0.106	-0.040	0.017
	(0.042)	(0.014)***	(0.036)	(0.030)***	(0.073)	(0.007)**
θ_1	0.004	-0.002	-0.005	-0.010	-0.001	-0.002
	(0.002)**	(0.005)	(0.007)	(0.010)	(0.009)	(0.001)**
θ_2	0.002	-0.007	0.005	0.021	-0.020	-0.001
	(0.009)	(0.004)**	(0.003)*	(0.010)**	(0.009)**	(0.000)**
θ_3	0.004	-0.007	-0.010	-0.007	0.004	-0.000
	(0.001)***	(0.005)	(0.008)	(0.011)	(0.002)**	(0.000)*
φ_1	0.004	0.001	0.003	0.007	0.004	-0.000
	(0.007)	(0.000)***	(0.001)**	(0.004)**	(0.010)	(0.003)
φ_2	0.002	0.002	-0.009	-0.008	-0.005	0.001
	(0.007)	(0.005)	(0.005)**	(0.010)	(0.009)	(0.000)**
φ_3	0.017	0.001	0.002	0.010	0.026	0.004
	(0.009)*	(0.000)***	(0.008)	(0.004)**	(0.009)***	(0.004)
Variance equation: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$						
ω	0.001	0.001	0.002	0.003	0.014	0.001
	(0.001)	(0.000)**	(0.001)**	(0.001)**	(0.001)***	(0.000)**
α	0.155	0.214	0.339	0.269	0.033	0.290
	(0.088)*	(0.111)*	(0.194)*	(0.163)*	(0.017)*	(0.162)*
β	0.761	0.769	0.463	0.496	0.871	0.559
	(0.131)***	(0.219)***	(0.100)***	(0.219)**	(0.027)***	(0.264)**
$\alpha + \beta$	0.916	0.983	0.802	0.765	0.904	0.849

Note: Standard errors are given into brackets with ***, **, and * denoting significance at 1, 5, and 10% levels, respectively. Y_t is the food price volatility in month *t*. β is the GARCH term, α is the ARCH term. $\cos_k = \cos[(2\pi * k * m_t)/12]$ and $\sin_k = \sin[(2\pi * k * m_t)/12]$, $k = 1,2,3$.

Indeed, when we look, for example, at the patterns of price volatility for each agricultural season in Uganda (see Appendix A.2), there is no clear picture of whether price volatilities were higher during planting seasons as one would expect. The last row of the Appendix A.2 reveals that for some commodities, the average monthly volatility was higher during planting seasons (the case of cassava and beans) while for others harvest periods were associated with greater volatility (for example *matooke* and maize). This lack of strong seasonality in price volatility has also been found by Buguk et al. (2003) and Balcombe (2009).

1.4.2 Asymmetric and leverage effects in food price volatility

Table 1.6 summarizes the estimated results of the EGARCH (1, 1) model for each food commodity. The Lagrange Multiplier (LM) statistic for a joint test for the significance of ARCH/GARCH effects (parameters $\alpha, \beta,$ and γ**)** is also provided. The effects of high- (unexpected price increases) and low-price news (unexpected price decreases) on the conditional variance as well as the existence of the leverage effects are shown in the last three rows of the table.

Table 1.6 *EGARCH (1, 1) estimation results, Monthly data, 2000 – 2012*

Parameters	*Matooke*	Cassava	Maize	Sweet potatoes	Beans	Millet flour
ω	-8.125	-2.872	-2.245	-0.600	-1.071	-2.288
	(1.191)***	(0.895)***	(0.951)**	(0.179)***	(0.256)***	(1.093)**
γ	0.122	-0.038	0.065	0.719	-0.970	0.260
	(0.084)	(0.141)	(0.152)	(0.173)***	(0.202)***	(0.151)*
α	0.311	1.103	0.696	0.315	0.605	0.600
	(0.163)*	(0.212)***	(0.238)***	(0.105)**	(0.157)***	(0.273)**
β	-0.556	0.510	0.615	0.865	0.773	0.661
	(0.229)**	(0.152)***	(0.166)***	(0.046)***	(0.058)***	(0.161)***
LM stat	22.47***	51.91***	35.63***	70.72***	77.06***	70.84***
$\alpha+\gamma$	0.433	1.065	0.761	1.034**	-0.365***	0.860**
$\alpha-\gamma$	0.189	1.141	0.631	-0.404**	1.378***	0.340**
Leverage effect?	No	No	No	*Inverse*	*Standard*	*Inverse*

Note: Standard errors into brackets with ***, **, and *denoting significance at 1, 5, and 10%, respectively. The Lagrange Multiplier statistic computed under the null hypothesis that γ, α, and β are jointly zero.

Interesting features are highlighted in table 1.6. First, it reveals that price volatility reacts symmetrically to positive and negative past shocks for half of the commodities under investigation, *matooke*, cassava, and maize, but asymmetrically to positive and negative shocks for sweet potatoes, beans, and millet flour. Second, the estimated value of α is statistically significant for all food commodities which indicates that the absolute size of past shocks affects current food price volatility. The effects were the largest for cassava and maize with respectively 1.10% and 0.70% increases of current price volatility due to past shocks. Third, once asymmetric effects of innovations or shocks are accounted for, only beans exhibited standard leverage effects, meaning that negative shocks had more impact on price volatility than positive shocks of the same magnitude. Indeed, an unexpected price decrease measured by a unit decrease in the standardized residuals $\varepsilon_{t-1}/\sigma_{t-1}$ decreases the price volatility of beans by 1.38 %, while an unexpected price increase of the same magnitude increases its price volatility by only 0.37%. However, for sweet potatoes and millet flour, increases in volatility appear to be larger when previous returns were positive than when they were negative of the same magnitude. Hence, past positive shocks (unanticipated price increases) rise price volatility of sweet potatoes and millet flour by respectively 1.03 and 0.86% and negative past shocks (price decreases) reduce price volatility of sweet potatoes by 0.40% and increase that of millet flour by 0.34%. This type of leverage effect has been named *inverse* leverage effects or "inventory effects" by Carpantier (2010) since they do not display the expected sign. The economic interpretation of such effects can be found in the theory of storage (Deaton and Laroque, 1992, 1996). Increases in commodity prices may act as a signal of the depletion of the commodity inventories and therefore positive price shocks may induce more volatility while negative price shocks may indicate an excess of supply over demand, reducing thereby current volatility.

1.4.3 Volatility spillover effects

Appendix A.3 reports the estimated results of the multivariate VAR model from equation (1.9). The optimal lag length of 2 in the VAR model was chosen using the Schwartz criterion. Results show that current price volatilities are positively and significantly impacted by past own-price shocks. Hence, higher volatility in the previous months leads to more volatility in the current one, suggesting persistence in price volatility (Balcombe, 2011). With regards to volatility spillovers across Ugandan markets, the estimated results indicate that there is no clear picture about the presence of spillover effects. We note for example that cassava volatility is affected positively by shocks to sweet potatoes' volatility but negatively by *matooke* volatility. Maize volatility declines following shocks to cassava and millet flour volatilities but increases in reaction to shocks to beans volatility. Furthermore, these volatility spillover effects are globally unidirectional, except for cassava and sweet potatoes. The matrix of pairwise correlations across different food price volatilities (Appendix A.4) also gives a similar picture. Although half of the pairwise correlations are statistically significant, their magnitude is relatively small, below 35%.

Finally, the results from the VAR system can also be used to understand the dynamic behavior of price volatility through the computation of impulse response functions (IRFs). An IRF gives the impact of one standard deviation (SD) shock of own- and cross-price volatility to food price volatility after a certain period of time (here after x months). However, because the disturbances obtained from VARs may be correlated, I first orthogonalized the innovations through a Cholesky decomposition in order to get a causal interpretation of the estimated impulse response functions (Hossain and Latif, 2007). Table 1.7 reports the responses after one month of food price volatility to Cholesky one SD shock to own- and cross-volatility as well as the number of months before the effects of the shocks disappear.

Table 1.7 *Responses after one month of price volatility to Cholesky one SD shocks*

	Response variable					
Commodities	*Matooke*	Cassava	Maize	Sweet potatoes	Beans	Millet Flour
Matooke	**0.040** **[6]**	0.002 [3]	0.001 [1]	0.002 [4]	-0.011 [3]	0.001 [3]
Cassava	-0.001 [3]	**0.034** **[5]**	-0.014 [3]	0.022 [3]	-0.025 [4]	-0.005 [1]
Maize	-0.001 [2]	0.003 [4]	**0.023** **[5]**	0.007 [2]	0.004 [2]	-0.002 [1]
Sweet potatoes	0.006 [3]	0.008 [5]	0.003 [2]	**0.036** **[4]**	0.006 [2]	0.001 [4]
Beans	-0.001 [3]	-0.003 [3]	0.007 [3]	0.003 [2]	**0.033** **[4]**	-0.001 [1]
Millet flour	0.005 [3]	-0.003 [1]	-0.007 [3]	0.002 [4]	-0.001 [1]	**0.019** **[5]**

Note: The number of months before the effects of the shocks disappear are reported into brackets.

A closer look at the table suggests an asymmetric pattern in the distribution of volatility shocks. First, for all commodities, the effects of shocks to own-price volatility are both positive and relatively large, implying that food price volatility in Uganda was "*self-feeding*". For example, a one standard deviation shock to *matooke* and cassava volatilities has led to 4 and 3.4% increases of their own-price volatility after one month relative to their equilibrium levels. Second, there is no clear evidence of strong market integration across Uganda. Indeed, the estimated results show that shocks to price volatility of different markets within the country only have a very marginal and insignificant impact on price volatility in the other markets, these effects being in all markets less than 1%. Third, in terms of the persistence of these effects, the table indicates that they last longer when shocks originated from own markets. For all markets, the effects of one SD shock from own-price volatility take on average at least four months to disappear against around one quarter in case of shocks to cross-price volatilities.

1.4.4 Effects of macroeconomic factors on changes in food price volatility

Table 1.8 reports the estimates and robust standard errors of the determinants of price volatility for 6 commodities using the Seemingly Unrelated Regression (SUR) method. Since we have 6 commodities and 96 months in the first sub-period (2000m1-2007m12) and 60 in the second (2008m1-2012m12), a total of 576 and 360 observations, respectively, are available in the SUR system. The sample is divided into two sub-periods to check for differential impacts of the potential determinants in periods of low and high volatility.

With regards to the first sub-period (2000m1-2007m12), table 1.8a shows that the coefficient of ΔCPI_M is positive and significant for all commodities which suggests that changes in consumer price index in Uganda have affected the volatility of food commodity prices. A 1% increase in the monthly consumer price index is associated with an increase in price volatility ranging from 0.17% in the case of millet flour to 1.84% for maize, with an average inflation effect of 0.94%. In periods of high volatility (table 1.8b), the impact of inflation is also significant and positive for all commodities. On average, the magnitude of the changes in price volatility during this sub-period is of 1%, higher than that of the relatively stable period. These results are consistent with other empirical findings that have suggested that not only is the commodity price volatility generally increasing with changes in consumer price index but also the impact will be greater in periods of higher price instability (Cashin and McDermott, 2001; Engle and Rangel, 2008; Roache, 2010; Karali and Power, 2013). For example, Karali and Power (2013) found that a 1% increase in inflation led to 0.76% in the low-frequency volatility of heating oil in the US.

Real effective exchange rate volatility ERV_M is not statistically significant for all commodities in the first sub-period while in the second its effect is only significant for maize and sweet potatoes. This insignificance for the majority of the commodities may result from at least two factors. First, Uganda is relatively self-sufficient in terms of staple foods it consumes, which limits the influence of changes in exchange rate insofar as financial transactions within the country are primarily realized in the local currency. Although some commodities are imported (such as rice, cassava, or beans), the significance of these imports is quiet marginal (Benson et al., 2008). Second, the Ugandan economy is rather imperfectly integrated to international food commodity markets (Conforti, 2004; Atingi-Ego et al., 2008; Boysen, 2008; Benson et al., 2008). And since most contracts in international commodity trade are settled in USD, the role played by exchange rate volatility in shaping domestic food price volatility is therefore limited.

As expected, fuel price volatility FPV_M has a positive impact on monthly volatilities of most commodities. However, between 2000m1 and 2007m12, the effect is only significant for two commodities – *matooke* and cassava – while between 2008m1 and 2012m12, the effect is positive and significant for all commodities. In both sub-periods, the impact of 1% increase was the highest for *matooke* (0.36 and 1.25%, respectively). All the commodities for which fuel price volatility has a significant effect are characterized by a lower value-to-weight ratio and given the long distances across different population centers and the poor transport infrastructure, fuel price variability is likely to transmit to market prices of these commodities (Dillon and Barrett, 2014).

Real interest rate volatility IRV_M is a poor predictor of food price volatility in Uganda during both periods and for almost all commodities, its coefficient is insignificant. Unlike the well-functioning futures markets in developed or some emerging countries, this result is not surprising for Uganda where the majority of both internal and regional agricultural transactions are realized out of the banking system and where despite the emergence of microfinance institutions in the country, credit markets are still in their infancy.

***Table 1.8** Determinants of changes in food price volatility in Uganda – SUR model*

	Matooke	Cassava	Maize	Sweet potato	Beans	Millet flour
a. Sample period: January 2000 – December 2007						
Intercept	0.013	0.003	-0.055	0.017	0.048	0.006
	(0.013)	(0.007)	(0.016)***	(0.012)	(0.017)***	(0.007)
ΔCPI_M	0.681	1.194	1.841	1.326	0.984	0.178
	(0.207)***	(0.227)***	(0.294)***	(0.357)***	(0.279)***	(0.101)*
ERV_M	0.546	0.994	-0.353	0.629	-1.727	0.605
	(1.076)	(0.788)	(1.383)	(1.598)	(1.549)	(0.584)
FPV_M	0.356	0.075	0.042	0.209	0.066	0.022
	(0.130)***	(0.004)***	(0.317)	(0.222)	(0.631)	(0.106)
IRV_M	0.055	0.018	0.049	0.022	-0.062	-0.014
	(0.043)	(0.026)	(0.056)	(0.057)	(0.052)	(0.017)
RFV_M	0.008	-0.024	-0.015	0.010	0.029	-0.002
	(0.015)	(0.009)***	(0.028)	(0.012)	(0.017)*	(0.005)
Harvest1	-0.015	-0.011	0.023	-0.011	0.009	0.003
	(0.009)*	(0.008)*	(0.013)*	(0.018)	(0.015)	(0.005)
Harvest2	0.015	-0.009	0.024	-0.006	-0.008	-0.001
	(0.013)	(0.009)	(0.012)**	(0.017)	(0.018)	(0.000)***
Planting2	-0.022	-0.008	0.002	-0.029	0.054	-0.003
	(0.011)*	(0.009)	(0.016)	(0.017)*	(0.022)**	(0.005)
b. Sample period: January 2008 – December 2012						
Intercept	0.055	-0.011	-0.050	-0.021	-0.019	0.022
	(0.023)**	(0.019)	(0.028)*	(0.027)	(0.021)	(0.013)*
ΔCPI_M	0.908	0.716	2.606	1.028	0.483	0.326
	(0.235)***	(0.153)***	(0.279)***	(0.304)***	(0.282)*	(0.121)***
ERV_M	-1.415	0.339	1.168	1.439	0.213	1.471
	(1.252)	(0.739)	(0.541)***	(0.294)***	(1.134)	(1.001)
FPV_M	1.249	0.717	0.414	0.241	0.223	0.241
	(0.362)**	(0.309)***	(0.244)**	(0.104)**	(0.124)**	(0.115)**
IRV_M	0.071	0.109	0.069	0.194	0.080	0.062
	(0.106)	(0.051)**	(0.108)	(0.097)**	(0.096)	(0.060)
RFV_M	0.049	0.016	0.022	0.033	-0.015	0.027
	(0.019)**	(0.001)***	(0.010)**	(0.012)***	(0.002)***	(0.008)***
Harvest1	0.023	-0.052	0.032	0.043	0.008	-0.014
	(0.019)	(0.016)***	(0.011)**	(0.012)***	(0.021)	(0.014)
Harvest2	-0.013	-0.001	0.071	0.001	-0.009	-0.016
	(0.020)	(0.018)	(0.019)***	(0.000)*	(0.018)	(0.012)
Planting2	0.021	0.004	0.024	0.023	0.043	0.011
	(0.009)***	(0.002)**	(0.003)**	(0.005)**	(0.020)**	(0.002)**

Note: Robust standard errors into brackets. ***, **, and * denoting significance at 1, 5, and 10%, respectively

Rainfall variability RFV_M is found to be an important determinant of food price volatility, particularly during the second sub-period. This result is recurrent in most studies of price volatility of agricultural commodities in developing countries insofar as the majority of the plots cultivated by farmers are essentially rain-fed (Gilbert and Morgan, 2010; von Braun and Tadesse, 2012; Mirzabaev and Tsegai, 2012). Hence, weather shocks will affect market expectations about end-of-season yield and price levels, fuelling in turn food price volatility.

The hypothesis of seasonality in food price volatility can be verified through the coefficients of *Harvest*1, *Harvest*2, and *Planting*2. In sub-period 1, it appears that volatility was higher for sweet potatoes in the second harvest period compared to the baseline season, whereas it was lower for millet flour in the first harvest period. During the second sub-period, higher price volatilities were associated with the second planting season for all the selected commodities while during the harvest seasons no clear picture emerges from the results. For some commodities (i.e. maize), more volatility occurs during the second harvest period compared to the first planting and harvest seasons, while for the others (i.e. sweet potatoes), the first harvest season appears more volatility than the second one or the first planting season. Similarly to results from GARCH models, price volatility did not seem to follow a seasonal path for the majority of the commodities. Consequently, the seasonality hypothesis of price volatility can only be partially accepted in Uganda, at least for the 6 commodities analyzed in this first essay. Several empirical studies, essentially in agricultural futures markets, have also produced mixed results with regards to the seasonal effect on price volatility (Milonas, 1986; Galloway and Kolb, 1996; Koekebakker and Lien, 2003; Karali and Power, 2013).

We finally check whether the effects of macroeconomic variables vary across different commodities by running restriction tests. The results from the F –tests reported in table 1.9 indicate that, at the 10% significance level, we reject in both sub-periods the hypothesis that each macroeconomic variable has an identical impact on price volatility of the six commodities analyzed. This suggests that, although most macroeconomic variables included in the SUR model present the expected sign, the magnitude of their effects on food price volatility in Uganda has been commodity-specific.

Table 1.9 *F – tests on restrictions across food commodities*

Macroeconomic variables	F - stats	p - value
ΔCPI_M	58.46 (92.97)	.0000 (.0000)
ERV_M	11.74 (74.65)	.0051 (.0000)
FPV_M	30.43 (42.86)	.0012 (.0001)
IRV_M	2.547 (4.95)	.0941 (.0018)
RFV_M	4.741 (15.33)	.0052 (.0001)

Note: The first values concern the sub-period 2000m1-2007m12 while those into parentheses are related to the second sub-period.

1.5 Conclusions

The purpose of the present study was to investigate the time series behavior of food commodity prices in Uganda using monthly price data for six staple foods, namely *matooke*, cassava, maize, sweet potatoes, beans, and millet flour. Results from *unconditional* price volatility analysis revealed that all commodities but beans experienced significant rise in their price volatility. Hence, when we compare two sub-periods (2000-2007 and 2008-2012) in terms of changes in price instability, cassava had the highest increase in mean price volatility (92.9%), followed by millet flour (60%), and sweet potatoes (58.8%). The GARCH (1, 1) estimation results also indicated that the mean *conditional* volatility has increased for half of the commodities analyzed, namely cassava, sweet potatoes, and millet flour. The Exponential GARCH (EGARCH) model, used to capture possible asymmetric and leverage effects in price volatilities, found evidence of *standard* leverage effects only with respect to beans. This suggests that negative shocks would amplify price volatility of that commodity more significantly than positive shocks of the same magnitude. Conversely, *inventory* or *inverse* leverage effects were found in the case of sweet potatoes and millet flour since positive shocks to their price volatilities had more impact than negative shocks.

Results also showed the presence of strong persistence in price volatilities of all commodities but a relatively complex spectrum regarding the nature of spillover effects across food markets. Spillover effects were found to be not only moderate compared to inertia effects but also essentially unidirectional. For instance, shocks to cassava, beans, and millet flour prices spilled unidirectionally over maize prices whereas price shocks to *matooke* and sweet potatoes affected cassava prices.

These results clearly have important policy implications, particularly in terms of price stabilization mechanisms. For instance, they suggest that policymakers should be aware that policies targeting a specific commodity market in the country might also have important repercussions on other markets, thereby either exacerbating or mitigating the levels of their prices and volatilities. Although net sellers might benefit from these high prices through increases of their income, the majority of Ugandan households are either net buyers or purely consumers of marketed foods and consequently will be negatively affected if the implementation of price control mechanisms end up accentuating volatilities. It is therefore crucial to develop and implement measures likely to increase productivity, sustainability and resilience, particularly in the agricultural sector (i.e. improving access of farmers to credits, increasing formal job market opportunities, or promoting risk management practices), and to initiate new transfer programs or improve existing ones so that parts of the gains realized by net sellers from high prices could be distributed to more vulnerable households.

Finally, the study estimated the impacts of macroeconomic factors on observed price volatility in Uganda: monthly volatilities of rainfall, overall inflation, real effective exchange rate, real interest rate, fuel price as well as seasonality effects have been used as potential drivers. Estimating a Seemingly Unrelated Regression (SUR) model for periods of low and high price volatilities, I found that, globally, variables that explained the largest part of observed price volatility included Uganda inflation, rainfall, and fuel price volatilities. The effects of these factors were more pronounced during the second sub-period. The significant and globally positive impact of these variables implies that, beyond actions targeting specifically the agricultural sector such as increased investments in agricultural research and development and downstream services (storage or processing facilities), additional measures would be required to stabilize prices and, ideally, reduce their volatility. Thus, actions such as investments in education, roads, electrification and irrigation projects may play a role in price stabilization in Uganda.

Essay II

Welfare effects of food price changes in Uganda under non-separability

How relevant is the net market position?[15]

2.1 Introduction

To what extent do large food price changes affect household welfare? Who gains and who loses from these price changes? How are these welfare effects distributed across different households? And specifically, what happens when market failures are accounted for? These questions and many others have been at the core of recent debates among development economists, government authorities, NGOs, and the media who fear about the risk of poverty traps, increased vulnerability and food insecurity of the least endowed households on the one hand, and on the other the risk of political turmoil, economic fragility, and social tensions that high food prices might induce (Bellemare, 2015). This concern is particularly germane in developing countries where food consumption accounts for the largest share of households' total expenditures and where the poor often spend disproportionally a large part of their income on food (Mghenyi et al., 2011; Dybczak, et al., 2010; Akson and Hoekman, 2010).

Although Uganda is relatively insulated from international markets due to its landlocked position, the Ugandan price index of food commodities has been steeply rising since March 2008, in sharp contrast with the period before. Indeed, food prices have been relatively stable between 2000 and early 2008, rising annually at 5% (UBoS, 2010). From that period onwards, they have continued to rise due to internal dynamics (rainfall variability, fuel price inflation, exchange rate volatility,…), international food price crisis, and increased demand from neighbor countries (Kenya, DR Congo, and Burundi, among others). Even though high food inflation ceased off between September 2009 and July 2010, prices remained at higher levels and Uganda experienced again high food prices since September 2010, with prices of some commodities like sugar, fish, and milk rising by over 200 percent.

[15] This second essay was written in co-authorship with Gabriella Berloffa.

Several studies have examined the impact of rising food prices in Uganda (Dorosh et al., 2003; Conforti, 2004; Bussolo et al., 2007; Benson et al., 2008; Boysen, 2009; Ulimwengu and Ramadan, 2009; Kaspersen and Føyn, 2010; Silmer, 2010), focusing either on the extent of price transmission between international and domestic prices or on the impacts of soaring global prices on poverty. However, all these studies suffer from two main drawbacks. First, farmers' behavior is modeled assuming that production and consumption decisions are two separable problems, leading to a recursive model (Singh et al., 1986). Notwithstanding its attractiveness, there has been little empirical evidence supporting the recursivity hypothesis, due particularly to imperfections characterizing rural markets in developing countries[16] (Lopez, 1984; Benjamin, 1992; Jacoby, 1993; Skoufias, 1994; Arcand and d'Hombres, 2006). In this study, we explicitly test the separability hypothesis under labor market imperfections. This allows us to identify the role played by virtual or shadow wages in estimating the welfare effects of price changes (Sonoda and Maruyama, 1999). Second, in previous studies, the estimation of direct and substitution welfare effects is done through different simulations applied to data collected before the actual food price shocks occur, and therefore they only identify households potentially vulnerable to rising food prices rather than those with actual welfare losses (Headey and Fan, 2008). Instead, we use three waves among the latest Uganda National Panel Surveys (UNPS) spanning over the years 2005-2011 to estimate the actual welfare effects of increased food prices.

To analyze the welfare changes of Ugandan households consecutive to food price instabilities, this study applied a sequential procedure consisting in three steps. First, virtual and shadow wages of self-employed agricultural households are derived by estimating a stochastic production frontier function following the Battese and Coelli's (1995) Maximum Likelihood-random effects time-varying inefficiency effects model and the Sherlund et al.'s (2002) and Barrett al.'s (2008) approaches. After testing for the separability hypothesis, we then estimate expenditure and price demand elasticities from a food demand system using the Quadratic Almost Ideal Demand System (QUAIDS) model proposed by Banks et al. (1997) and estimated through a Non-linear Seemingly Unrelated Regression (NSUR) model in presence of censoring and endogeneity. To take account of year-specific effects, the heterogeneity of Ugandan households in terms of their food net market position and the impact of labor market frictions, these demand elasticities were estimated for each year and sub-group of households (non-agricultural households, significant net sellers and net

[16] These imperfections include: farmers' preferences towards working on- or off-farm (Huffman, 1980; Lopez, 1986); imperfect substitutability between market-purchased and home-produced food (Imai et al., 2011); missing labor and/or food markets (Singh et al, 1986; de Janvry, Fafchamps, and Sadoulet, 1991, Taylor and Alderman, 2003); presence of fixed and/or variable transaction costs that create a wedge between consumer and producer prices (Key et al., 2000; Henning and Henningsen, 2007)

buyers, and insignificant net sellers and net buyers) for both separable and non-separable models. The final step consists in computing money-metric welfare measures of food price changes with and without the possibility of substitution across commodities.

The remainder of this second essay is organized as follows. In section 2, an agricultural household model is presented and its theoretical predictions are analyzed. Particularly, our conceptual framework seeks to identify potential deviations from the standard household model when labor market imperfections are accounted for and household's net positions in both food and labor markets are incorporated into the analysis. In section 3, we present and discuss the estimation strategy adopted for the computation of welfare effects of price changes. Data descriptions and the construction of some key variables for our econometric estimations (consumer food prices, commodity grouping, and net food market position) are presented in section 4. Section 5 presents and discusses the empirical findings before the conclusion in section 6.

2.2 Theoretical model

In this section, we present a simple theoretical model of the price effects on farmers' welfare with perfect and imperfect labor markets given that labor is, by far, the most important variable input in the production process of Ugandan farmers and the internal labor market, particularly in rural areas, is very thin and generally relies on the family force[17]. Consider a farmer that produces a cash crop Q_c devoted solely to the market and sold at price p_c and a staple food Q_a consumed and/or sold at market price p_a, using family labor L_f^o, hired labor L_h, other variable inputs *V* and quasi-fixed inputs (land and/or capital) *A*. He maximizes his utility by consuming three types of goods: a non-food good (c_n) purchased at market price p_n; food consumption (c_f), either market-purchased (c_f^m) at price p_a or produced on the farm (c_f^a), and leisure c_L. By simplicity, c_f^a and c_f^m are assumed to be perfect substitutes so that $c_f(c_f^m, c_f^a) = c_f^m + c_f^a$. The farmer receives his income from farming activities, off-farm employment L_f^f, and non-labor incomes (*E*). His problem can be formalized as follows:

$$\underset{C}{Max}\, U = U(C; z_u), \qquad C = (c_f, c_n, c_L) \tag{2.1}$$

subject to

[17] These imperfections can result from heterogeneity betwen family and hired labor (Benjamin 1992; Deolalikar and Vijverberg 1983, 1987; Thapa, 2003), the presence of transaction costs (Key et al., 2000), or limited access to employment opportunities (Archand and d'Hombres, 2006; Le, 2012)

$$G\left(Q, X, A; z_q\right) = 0, \qquad Q = \left(Q_a, Q_c\right); X = \left(L_f^o, L_h, V\right) \tag{2.2}$$

$$T - L_f^f - L_f^o - c_L \geq 0 \tag{2.3}$$

$$p_a c_f + p_n c_n + p_v V + g\left(L_h\right) \leq p_a Q_a + p_c Q_c + f\left(L_f^f\right) + E \tag{2.4}$$

In equation (2.1), $U(.)$ is an instantaneous farmer's utility function, assumed monotonically increasing and strictly quasi-concave; z_u is a vector of exogenous shifters in utility. Equation (2.2) gives the technology constraint and relates the farm productions $\left(Q_a, Q_c\right)$ to inputs $\left(L_f^o, L_h, V, A\right)$ through a multi-output, multi-input transformation function $G(.)$, assumed concave and continuous in inputs (Lau, 1976), with z_q, a vector of production shifters. The farmer is also constrained by the time endowment (equation 2.3), where the total time available (*T*) is allocated to on-farm labor, off-farm labor and leisure. The farmer finally faces a budget constraint (equation 2.4) specified in a way that accounts for labor market imperfections. Following Henning and Henningsen (2007) and Glauben et al. (2012), off-farm revenues and hired labor costs are specified as functions $f(L_f^f)$ and $g(L_h)$, respectively. In case of a perfect labor market, both $f(L_f^f)$ and $g(L_h)$ are linear functions $f(L_f^f) = wL_f^f$ and $g(L_h) = wL_h$, respectively. Thus, the marginal revenue of off-farm employment and the marginal cost of hired labor are constant and given by the exogenous market wage rate *w*. Imperfections in the labor market can be captured by modeling $f(L_f^f)$ and $g(L_h)$ as non-linear functions. In particular, off-farm revenues are an increasing and strictly concave function of L_f^f:

$$\frac{\partial f(L_f^f)}{\partial L_f^f} > 0; \frac{\partial^2 f(L_f^f)}{\partial (L_f^f)^2} < 0\,, \tag{2.5}$$

while the costs of hired labor are an increasing and convex function of L_h:

$$\frac{\partial g\left(L_h\right)}{\partial L_h} > 0; \frac{\partial^2 g\left(L_h\right)}{\partial \left(L_h\right)^2} > 0 \tag{2.6}$$

The farmer will choose the levels of consumption goods, on- and off-farm family labor, hired labor, and variable inputs to maximize his utility in (2.1), under the resources and time constraints (2.2) to (2.4).

Let λ, ϕ and μ be the Lagrange multipliers associated with the budget, technology and time constraints, respectively. The FOCs for this problem are:

$$\begin{cases} \frac{\partial U(.)}{\partial c_i} - \lambda p_i = 0 & i \in C = \{c_f, c_n\} \\ \frac{\partial U(.)}{\partial c_L} - \mu = 0 & \\ \phi \frac{\partial G(.)}{\partial Q_i} - \lambda p_i = 0 & i \in Q = \{Q_a, Q_c\} \\ \phi \frac{\partial G(.)}{\partial V} + \lambda p_v = 0 & \\ \phi \frac{\partial G(.)}{\partial L_h} + \lambda \frac{\partial g(.)}{\partial L_n} = 0 & \\ \phi \frac{\partial G(.)}{\partial L_f^o} - \mu = 0 & \\ -\mu + \lambda \frac{\partial f(.)}{\partial L_f^f} = 0 & \\ G(Q, X, A; z_q) = 0 & \\ T - L_f^o - L_f^f - c_L = 0 & \\ p_a c_f + p_n c_n + g(L_h) + p_v V = p_a Q_a + p_c Q_c + f\left(L_f^f\right) + E & \end{cases} \tag{2.7}$$

From the FOCs, we have that: $\frac{\partial U(.)}{\partial c_L} = \phi \frac{\partial G(.)}{\partial L_f^o} = \lambda \frac{\partial f(.)}{\partial L_f^f}$

The shadow wage (i.e. the opportunity cost of time) is therefore given by $w^* = \frac{\mu}{\lambda} = \frac{\partial f(.)}{\partial L_f^f}$. In case of a perfect labor market, the shadow wage is equal to the exogenous market wage w, leading to a separable model, in which the farmer's labor allocation decisions are not affected by consumption preferences, and no tradeoff exists between farm work and leisure (Taylor and Alderman, 2002). If instead, the labor market is imperfect, then $w^* = \frac{\mu}{\lambda} \neq w$. The shadow wage w^* now depends on farmer's preferences through the marginal utilities of wealth (λ) and time (μ). The value of these multipliers will depend on the vector of all exogenous market prices of consumption and production goods $(\mathbf{p} = \{p_a, p_c, p_n, p_v\})$, non-labor incomes, time endowment, consumption and production shifters:

$$w^* = w^*(\mathbf{p}, E, T; z_u, z_q) \tag{2.8}$$

The solution to the farmer's maximization problem leads to a system of output supply $Q_i = Q_i(\mathbf{p}, w^*; z_u, z_q)$ and input demands $X_i = X_i(\mathbf{p}, w^*; z_u, z_q)$, off-farm labor supply $L_f^f = L_f^f(w^*)$, and a consumption system $C_i = C_i(\mathbf{p}, w^*, Y; z_u, z_q)$, where $Y = \Pi^* + w^*(T - c_L) + E$, and $\Pi^* = p_a Q_a + p_c Q_c - p_v V - w^*\left(L_h + L_f^o\right)$.

Hence, a change in market prices will lead to a change in the consumption vectors, output supply, input demands, as well as in the shadow wage. Following the standard non-separable household model (NSM) literature (Singh et al., 1986; Strauss, 1986; de Janvry et al., 1991), this change can be decomposed into two components. Concretely, for a farmer producing a quantity Q_a and consuming c_f of the staple food, the impact of a change in p_a on consumption is given by:

$$\frac{\partial c_f}{\partial p_a} = \left.\frac{\partial c_f}{\partial p_a}\right|_{\Pi^*, w^*} + \left.\frac{\partial c_f}{\partial \Pi^*}\frac{\partial \Pi^*}{\partial p_a}\right|_{w^*} + \frac{\partial c_f}{\partial w^*}\frac{\partial w^*}{\partial p_a} \tag{2.9}$$

which, expressed in terms of elasticities, becomes:

$$E(c_f / p_a) = \underbrace{\left[E(c_f^H / p_a) + \frac{p_a(Q_a - c_f)}{Y}E(c_f / Y)\right]}_{direct\ \ effect} + \underbrace{\left[\left(E(c_f^H / w*) + \frac{w*(L_f - L_h)}{Y}E(c_f / Y)\right)E(w^*/p_a)\right]}_{virtual\ \ effect} \tag{2.10}$$

where $E(i/j)$ represents the elasticity of *i* with respect to *j*, and c_f^H the Hicksian demand of the staple food. The first term in the right-hand side of equation (2.10) represents the direct effect of changes in the exogenous market price on the farmer's consumption, keeping constant the shadow wage. This coincides with the effects of price changes that we would have derived in a separable household model (SM). Indeed, in a separable model, since the virtual effect in (2.10) is equal to zero, an increase of the food price p_a induces a clear negative consumption effect if the household is a net buyer ($Q_a - c_f < 0$) given that both the income and substitution effects are negative. For net sellers, the sign is a priori ambiguous: the effect will be positive if and only if the total income effect outweighs the negative substitution effect.

In the case of non-separability however, we need to consider also the virtual effect, which captures the adjustments of consumption to the changes in the shadow wage ($E(c_f/w^*)$) and due to changes in market prices ($E(w^*/p_a)$) (Strauss, 1986; Sonoda and Maruyama, 1999). Since theoretically the Hicksian elasticity $E(c_f^H/w^*) \geq 0$, the virtual effect will have the sign of the elasticity $E(w^*/p_a)$ if farmers are net sellers of labor (i.e. if family off-farm labor is larger than hired labor, which means that changes in virtual family earnings exceed changes in virtual farm labor costs). In particular, if the increase in p_a increases the shadow wage, and farmers are net buyers of food and net sellers of labor, the elasticity of food consumption to its price will be less negative under non-separability, or even change its sign from negative to positive. In other words, under non-separability, food consumption will decrease less or even increase as the price of food increases. If instead, the increase in p_a reduces the shadow wage, farmers who are net buyers of food and net sellers of labor, will have a larger elasticity (in absolute terms) under non-separability (i.e. food consumption will fall more after an increase in its price).

The reasoning is similar for the other cases, which are summarized in the following table.

Table 2.1 *Theoretical effects of an increase in food prices on food consumption, by net positions in food and labor markets*

	Labor net sellers: $L_f - L_h > 0$		Labor net buyers: $L_f - L_h < 0$	
	$E\left(w^*/p_a\right) > 0$	$E\left(w^*/p_a\right) < 0$	$E\left(w^*/p_a\right) > 0$	$E\left(w^*/p_a\right) < 0$
Food net buyers: $Q_a - c_f < 0$	• (-) direct effect • (+) virtual effect • Total effect in NSM: *less negative or positive*	• (-) direct effect • (-) virtual effect • Total effect in NSM: *more negative*	• (-) direct effect • (-)/(+) virtual effect • Total effect in NSM: *Indeterminate*	• (-) direct effect • (-)/(+) virtual effect • Total effect in NSM: *Indeterminate*
Food net sellers: $Q_a - c_f > 0$	• (-)/(+) direct effect • (+) virtual effect • Total effect in NSM: *less negative or more positive*	• (-)/(+) direct effect • Negative virtual effect • Total effect in NSM: *more negative or less positive*	• (-)/(+) direct effect • (-)/(+) virtual effect • Total effect in NSM: *Indeterminate*	• (-)/(+) direct effect • (-)/(+) virtual effect • Total effect in NSM: *Indeterminate*

Note: (-) and (+) denote negative and positive effects, respectively. NSM: Non-separable household model

Uncovering the sign of the shadow wage elasticity

It is therefore important to derive the expression and sign of shadow wage elasticity $E\left(w^*/p_a\right)$ upon which largely hinge the sign and magnitude of $E\left(c_f / p_a\right)$. By using the expression of the time constraint (equation 2.3) at the optimum ($T - L_f^o(\mathbf{p}, w^*; z_u, z_q) - L_f^f\left(w^*\right) - c_L(\mathbf{p}, w^*, Y; z_u, z_q) = 0$), and applying the implicit function theorem to it (de Janvry et al., 1991; Henning and Henningsen, 2007), we get:

$$\frac{dw^*}{dp_a} = \frac{\left.\frac{\partial L_f^o}{\partial p_a}\right|_{w^*} + \left.\frac{\partial c_L}{\partial p_a}\right|_{w^*}}{-\left.\frac{\partial L_f^o}{\partial w^*}\right|_{p_a} - \left.\frac{\partial L^f}{\partial w^*}\right|_{p_a} - \left.\frac{\partial c_L}{\partial w^*}\right|_{p_a}} \tag{2.11}$$

The numerator in (2.11) represents the direct disequilibrium on the 'household' labor market created by a change in p_a, whereas the denominator captures the indirect disequilibrium created by the change in the shadow wage caused by a change in p_a. In order to get the intuition of how this works, consider the case in which there is no possibility to work off-farm. When p_a increases, the consumption of food decreases and the marginal value of income increases. Therefore a household would like to increase its income, by increasing farm production. This increases on-farm labor demand $\left(\left.\frac{\partial L_f^o}{\partial p_a}\right|_{w^*} > 0 \right)$, but household labor supply may not increase sufficiently $\left(\left.\frac{\partial c_L}{\partial p_a}\right|_{w^*} < 0 \quad \text{and} \quad \left.\frac{\partial L_f^o}{\partial p_a}\right|_{w^*} > -\left.\frac{\partial c_L}{\partial p_a}\right|_{w^*} \right)$. In order to restore the equilibrium on the labor market we would need an increase in the shadow wage if the labor supply is upward sloping $\left(-\left.\frac{\partial c_L}{\partial w^*}\right|_{p_a} > 0 \right)$, or if it is downward sloping $\left(-\left.\frac{\partial c_L}{\partial w^*}\right|_{p_a} < 0 \right)$, but steeper than the labor demand $\left(-\left.\frac{\partial c_L}{\partial w^*}\right|_{p_a} > \left.\frac{\partial L_f^o}{\partial w^*}\right|_{p_a} \right)$. If instead, the labor supply is downward sloping, but flatter than the labor demand, in order to restore the equilibrium we would need a reduction in the shadow wage.

On the contrary, if the direct effect of the increase in p_a is an excess of labor supply, the equilibrium will be restored by a decrease in the shadow wage if the labor supply curve is upward sloping or if it is downward sloping but steeper than the labor demand, and by an increase in the shadow wage if the labor supply is downward sloping, but flatter than the labor demand.

In general, however, under non-separability, it is quite difficult to predict the effect of an increase in p_a on both the shadow wage and food consumption. If the direct effect in equation (2.10) dictates the total effects, then increases in food prices will lead to a reduction of food consumption for net buyers but the effect will remain ambiguous for net sellers. If instead, the degree of labor market imperfections is relatively high such that the indirect component of equation (2.10) is predominant, then the price effect on consumption is theoretically unclear and can potentially lead to abnormal behaviors (de Janvry et al., 1991). As a direct consequence of this ambiguity, we are theoretically unable to determine both the sign and magnitude of the welfare effects of price changes. However, we can derive a money-metric measure for the welfare effect (the compensating variation, CV_{hct}), as a function of the elasticity of the shadow wage to food prices.

Let $e(p,u)$ be the expenditure function associated with the household utility maximization problem, i.e. $e(p,u) = p_a h_f + p_n h_n + w^*(p_a, p_n, ...)h_L$ where h_i is the Hicksian demand for good *i*. The CV is generally defined as: $CV = e(p^1, u^1) - e(p^1, u^0)$, i.e. it measures the net revenues of the planner who must compensate the households. Since in our case income is not exogenous, we have: $e(p^1, u^1) = e(p^0, u^0) + (Y^*(p^1) - Y^*(p^0))$, i.e.:

$$CV = e(p^1, u^1) - e(p^1, u^0) = e(p^0, u^0) - e(p^1, u^0) + \Delta Y^* \tag{2.12}$$

If we take a first-order Taylor series expansion of $e(p^1, u^0)$ and $Y^*(p^1)$, both around p^0, we get:

$$CV \approx (p_a^1 - p_a^0)\left(Q_a - C_f + \left(L_f - L_h\right)\frac{\partial w^*}{\partial p_a}\right) + (p_n^1 - p_n^0)\left(C_n + \left(L_f - L_h\right)\frac{\partial w^*}{\partial p_n}\right) \tag{2.13}$$

where in (2.13) we used the identities:

$$h_a(p^0, u^0) \equiv C_f\left(p^0, Y^*(p^0)\right), \text{ and } h_L(p^0, u^0) \equiv C_L(p^0, Y^*(p^0)) = T - L_f^o - L_f^f$$

Expressed in terms of elasticities, (2.13) becomes:

$$CV \approx \sum_{i=a,n} \frac{\Delta p_i}{p_i}\left(p_i(Q_i - C_i) + w^*\left(L_f - L_h\right)E\left[w^* \mid p_i\right]\right) \tag{2.14}$$

where $E[x \mid y]$ denotes the total elasticity of *x* with respect to *y*.

Note that, when there is no shadow wage effect, (2.14) reduces to the CV capturing only the immediate effect of price changes, as described for example in Vu and Glewwe (2011). The expressions for the short run effect can be derived by taking second order Taylor series expansion of the expenditure function (Friedman and Levinsohn, 2002; Porto, 2010; Vu and Glewwe, 2011). Ignoring the terms involving the product of two elasticities and two changes in prices (or the second order effect of the change in prices on the shadow wage), we have:

$$\begin{aligned} CV \approx & \underbrace{\sum_{i=a,n} \frac{\Delta p_i}{p_i}\left(p_i(Q_i - C_i) + w^*\left(L_f - L_h\right)E\left[w^* \mid p_i\right]\right)}_{first\quad order\quad effects} \\ & + \underbrace{\frac{1}{2}\sum_{i=a,n}\sum_{j=a,n}\left(\frac{\Delta p_i}{p_i}\right)\left(\frac{\Delta p_j}{p_j}\right)\left\{E\left[C_i^H \mid p_j\right] + E\left[C_i^H \mid w^*\right]E\left[w^* \mid p_i\right]\right\}(p_i C_i)}_{substituti\,on\quad effects} \end{aligned} \tag{2.15}$$

where $E\left[C_i^H \mid w^*\right]$ represents the Hicksian compensated elasticity of *x* with respect to *y*.

Whether in non-separable models the compensating variation CV is larger or smaller than in separable models, it depends on both the household positions in the food and labor markets (net buyers or net sellers), and the sign of the elasticity of the shadow wage with respect to food prices.

2.3 Estimation strategy

In this section we present our empirical strategy to estimate econometrically both the separable and non-separable models to assess if and to what extent labor market imperfections influence the sign and magnitude of household welfare effects of price changes. Given the above theoretical framework, the unobservability and endogeneity of the shadow wage w^*, the estimation strategy proceeds in three steps. First, we estimate the shadow price of labor and test for the recursivity hypothesis. Second, given the shadow wage thus obtained, we estimate a Quadratic Almost Ideal Demand System (QUAIDS), and finally compute money-metric welfare measures of price changes under both separability and non-separability.

2.3.1 Estimation of the shadow wage and test of the recursivity hypothesis

One of the common features of the agricultural sector in most developing countries is the predominance of small-scaled farmers that often rely on their family members during planting and harvest seasons. These members are generally unpaid although they benefit from the production outcomes through consumption or distribution of part of the farm profits. Under the hypothesis of perfect labor markets and perfect substitutability between family and hired labor (Deolalikar and Vijverberg, 1987), one can impute the wages for on-farm family labor using the observed market wages for labor of similar requirements. However, farmers may attach subjective values to their on-farm labor that deviate from the market wages or the labor market may simply be missing or incomplete due to different sources of market frictions[18] (de Janvry and Sadoulet, 1991). In this case, the separability hypothesis will break down and one will need to estimate these subjective or shadow prices of on-farm labor. To derive the shadow wages, we build upon Jacoby's (1993) structural labor supply estimation approach, extended by Sherlund et al. (2002) and Barrett et al. (2008) who relax the assumption of allocative efficiency made by Jacoby– equality between the marginal revenue product of labor and market wage.

[18] In many rural areas of developing countries, farmers are generally insulated from local markets due to high transportation costs, are often constrained by liquidity and have very limited access to both formal and informal credits. In this context, hiring labor might represent a significant part of input expenditures that most farmers cannot afford, thereby deciding to employ exclusively family labor in the production process.

The Sherlund et al.'s and Barrett et al.'s approach is a sequential estimation strategy that can be summarized as follows. In the first step, we estimate a stochastic frontier production function on the whole sample of agricultural households following the Battese and Coelli's (1995) approach to derive the marginal product revenue of labor $\left(MRP_L\right)$, using average real market prices of commodities produced. Formally, let Y_{ht} denote the total production (in values)[19] by a farmer *h* in year *t;* X_{ht} be a vector of productive inputs used by farmer *h* at time *t* (such as on-farm family labor L_f^o, hired labor L_h, land size and other variable inputs (fertilizer, seeds, or pesticides); Z_{ht} be the vector of household characteristics (such as household size, education and sex of the household's head, region- and year-specific dummies) and Ω_{ht} be the vector of environmental factors (like labor quality, types of land slope or irrigation). The stochastic production frontier function in the context of panel data is written as follows:

$$Y_{ht} = F\left(X_{ht}, \Omega_{ht}\right) - U_{ht} + V_{ht} \tag{2.16}$$

where $F\left(X_{ht}, \Omega_{ht}\right)$ is the production frontier; U_{ht} is the technical efficiency parameter of production assumed to be function of a set of observable characteristics Z_{ht} (i.e. $U_{ht} = Z_{ht}'\xi + \varepsilon_{ht} \geq 0,$ with the random variable ε_{ht} distributed $N\left(0, \sigma_\varepsilon^2\right)$ and truncated from below at the truncation point $Z_{ht}'\xi$ (Barrett et al., 2008). V_{ht} is the error term assumed independently and identically distributed $N\left(0, \sigma_v^2\right)$. For the empirical analysis, we opt for a flexible translog specification as an approximation to the unknown true production frontier $F\left(X_{ht}, \Omega_{ht}\right)$ (Sherlund et al., 2002):

$$\ln Y_{ht} = \alpha_0 + \sum_{i=1}^{I} \alpha_i \ln\left(X_{iht}\right) + \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{I} \alpha_{ij} \ln\left(X_{iht}\right) \ln\left(X_{jht}\right) + \Omega_{ht}\beta - U_{ht} + V_{th} \tag{2.17}$$

where α_0, α_i, α_{ij} and β are unknown parameters to be estimated.

The Battese and Coelli's panel data estimator is a method of maximum likelihood that simultaneously estimates the parameters of the stochastic production frontier and the technical inefficiency effects. Both the market prices and the estimated parameters from the stochastic frontier are used to derive the estimated marginal product revenue of labor $M\hat{R}P_L$.

The second step consists in estimating the allocative inefficiency scores for the subsample of farmers that supply off-farm labor L_f^f and report a wage w. Using the estimated $M\hat{R}P_L$ and observed

[19] Using values of production instead of physical quantities aims at reflecting the multi-crop nature of most farmers in Uganda and enables the aggregation of different crop productions into a single monetary unit.

market wages w, the allocative inefficiency AI is defined as $AI = \ln\left(w / M\hat{R}P_L\right)$ which is equal to 0 in case of technical efficiency $w = M\hat{R}P_L$ or equivalently $U_{ht} = 0$.

To obtain the estimated shadow wages, we first predict deviations between $M\hat{R}P_L$ and market wages w by regressing the allocative inefficiency on a set of household characteristics excluded in the estimation of the stochastic production frontier equation. These variables include the age (and its squared value), sex, and the level of education of the head, his marital status, the estimated values of livestock owned by the household, regional indicators (dummy variables for each region), and land endowment (land holdings per household member). Second, given the estimated $M\hat{R}P_L$ from the first step and the imputed allocative inefficiency scores $A\hat{I}$ from the second step, the imputed shadow wage $\hat{w}^*$ for households that did not supply labor to the market is computed as follows:

$$\hat{w}^* = \exp\left(A\hat{I}\right) \times M\hat{R}P_L \tag{2.18}$$

Finally, having estimated the shadow wages, a simple separability test can be carried out by checking whether the shadow wage distribution for self-employed agricultural households is significantly identical to the distribution of observed market wages for off- farm workers. The rejection of the null hypothesis of equal distributions between these two sub-groups of agricultural households will thus suggest that the recursivity assumption is not supported by the data in hand.

2.3.2 Food demand system

On the consumption side, the preferences of the household (equation 2.1) are estimated through a Quadratic Almost Ideal Demand System (QUAIDS) model proposed by Banks et al. (1997) which is a flexible functional form that incorporates nonlinear effects and interactions between prices and expenditures in the demand relationships. In terms of budget shares, the QUAIDS model has the following form (Banks et al., 1997):

$$s_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{x}{a(\mathbf{P})}\right] + \frac{\lambda_i}{b(\mathbf{P})}\left\{\ln\left[\frac{x}{a(\mathbf{P})}\right]\right\}^2 \tag{2.19}$$

where x is the total value of food consumption, $s_i = p_i c_i / x$ are consumption shares for each good *i;* p_j are consumer prices of commodity *j* and **P** is a price index; α_i, γ_{ij}, β_i, λ_i are unknown parameters ; and :

$$\ln a(\mathbf{P}) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j, \qquad b(\mathbf{P}) = \prod_{i=1}^{n} p_i^{\beta_i} \tag{2.20}$$

Theoretical restrictions of adding-up, homogeneity and symmetry are imposed to the model in terms of its parameters. Adding-up restriction requires $\sum_{i=1}^{n}\alpha_i = 1, \sum_{i=1}^{n}\beta_i = 0, \sum_{i=1}^{n}\gamma_{ij} = 0, \sum_{i=1}^{n}\lambda_i = 0$. Homogeneity implies $\sum_{i=1}^{n}\gamma_{ij} = 0$ and symmetry requires $\gamma_{ij} = \gamma_{ji}$.

However, the presence of zero values in the consumption of certain commodities and the endogeneity of household total expenditures and shadow wage need to be accounted for to avoid spurious estimations of equation (2.19).

Zero expenditures on certain food items may come from various sources: shortness of the recall period, non-preference, non-affordability, purchase infrequency, non-availability, self-consumption (Boysen, 2012). Since an important proportion of households reported zero consumption in Ugandan surveys, the dependent variable in equation (2.19) becomes censored and estimating the QUAIDS model without controlling for the expenditure censoring will lead to biased estimates. To deal with censored data in the QUAIDS model, we follow the two-step procedure proposed by Shonkwiler and Yen (1999). In the first step, households decide whether to consume a good *i* or not through the estimation of a standard probit model $d_i^* = z_i'\alpha_i + \varphi_i$, where d_i^* is unobserved counterpart of a binary outcome d_i that takes 1 if the household did consume the good *i* and 0 otherwise; *z* is a vector of household demographics and regional dummies for the model identification; φ_i is the error term. Conditional on the decision to consume the good *i*¸ consistent parameters of the QUAIDS are estimated in the following way (Barslund, 2011; Boysen, 2012):

$$s_i^* = \Phi(\hat{\alpha}_i z_i) f(x_i, \beta_i) + \delta_i \phi(\hat{\alpha}_i z_i) + \zeta_i \tag{2.21}$$

where $(\hat{\alpha}_i z_i)$ are estimates from the first step; ϕ and Φ are the standard normal and cumulative density functions, respectively. ζ_i is the error term.

Expenditure endogeneity appears whenever the household expenditure allocation process across products is significantly affected by unobserved factors not captured by explanatory variables included in the estimation of s_i (Bopape, 2006). To test for expenditure endogeneity, we use household income and its square as IVs for total household food expenditure and proceed in two steps. In the first stage, we regress household expenditures on consumer prices, household demographics, and total income (and its squares). In the second stage, the residuals from step 1 ($\hat{\mu}$) are then augmented to the each budget share equation. The null hypothesis of expenditure exogeneity is then tested by checking whether the coefficient of $\hat{\mu}$ is statistically significant. Given potential correlation between the error terms of different budget shares, we also run the endogeneity test using a restricted SUR model (Bopape, 2006) and determine whether the coefficients of $\hat{\mu}$ are jointly significant across all budget share equations. The estimation of the QUAIDS is done by applying a modified version of the Nonlinear Seemingly Unrelated Regression (NSUR) proposed by Poi (2008) to include censoring due to zero expenditures and endogeneity of expenditure and shadow wage.

2.4 Data and descriptive statistics

In this section, we describe the Uganda National Panel Surveys (UNPS), the procedure for constructing the variables used for our empirical analysis, and present their descriptive statistics.

2.4.1 Samples

We use three waves of the Uganda National Panel Surveys (UNPS) collected by the Uganda Bureau of Statistics (UBoS) in 2005/2006 (hereafter UNPS-2006), 2009/2010 (UNPS-2010), and 2010/2011 (UNPS-2011), covering periods of both low and high prices. All the surveys were based on a two-stage stratified random sampling design and therefore allow for comparisons across surveys and aggregation over time. In the first stage, Enumeration Areas[20] (EAs) were selected from the 4 geographical regions of the country and grouped by districts and rural-urban locations (UBoS, 2010). In the second stage, around 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[21]. Among the 3,123 targeted households in UNPS-2006, the UBoS was able to track 2,607 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 UNPS-2010, 2,390 were re-interviewed in the UNPS-2011 with only 2,310 households having complete information in all the three waves. Because our interest is in understanding the welfare consequences of large food price changes in Uganda during the 2005-2011 period, we only keep households with complete information tracked in all the three surveys, giving us a balanced sample of 2,310 observations over three periods[22]. The panel surveys provide

[20] An enumeration area represents "the smallest ground area, mapped with definite boundaries within which a study or interview is carried out" (UBoS, 2012: 32).

[21] In the UNPS-2006, households were first visited between May and October 2005 and then between November 2005 and April 2006. In the UNPS-2010, first visits occurred between September 2009 and January 2010 while the second were conducted between February 2010 and August 2010. For the last wave, first visits were conducted between October 2010 and March 2011, while the second were between April and September 2011.

[22] Given the relatively high attrition rate (26% from 2005 to 2011), we first checked whether attritors and non-attritors were statistically different in terms of household characteristics and consumption patterns. In Appendix B.1 we report the procedure used to test for attrition bias in the data and compute *inverse probability weights* (IPW) to correct for it.

detailed information on household demographics, production (labor[23] and non-labor inputs, outputs harvested and sold), consumption (food and non-food commodities), land holdings and livestock ownership, among others. For each commodity, they list the measurement unit as well as the quantities and values for different types of consumption (household consumption from purchases, consumption away from home, consumption from home production, and consumption of goods received in-kind). Different recall periods were used depending on the nature of the expenditure item: from a seven-day recall period for food consumption to one year for durable, semi-durable and non-consumption expenditures (taxes and duties, pension, social security contribution, remittances, gifts, contribution to funerals...).

2.4.2 Consumer prices, commodity grouping, and consumption shares

Information on consumer prices is given in terms of unit values, obtained by dividing values by quantities. Seen as the highest acceptable price or “subjective price” (Pons, 2011), these unit values might contain measurement errors and reflect both quality and price differences (Deaton, 1988, 1997) and therefore require a correction before being used as a proxy of prices. To that end, we followed the approach proposed by Deaton (1988) whose basic idea is that, insofar as households within the same village (cluster) are usually surveyed within a period of relatively few days, they should normally face the same prices (Boysen, 2012). We first constructed clusters as a combination of EAs and districts, and got 321, 337, and 356 clusters for each panel, respectively. For each commodity in a specific cluster, we generated mean unit values that are then regressed through OLS over household characteristics (households’ physical assets, household composition, education, gender, age of the head...), cluster and other regional dummies. The predicted values for the estimation are then used as imputed consumer prices[24,25].

Furthermore, given the large number of goods consumed by households[26], the estimation of consumption share equations would become cumbersome without prior adjustments. In practice, the solution consists in grouping commodities in order to reduce the number of goods to a relatively

[23] In the surveys, the agricultural modules measure the time spent working on-farm in person-days which reflect both the size of team and the number of days spent. For each plot, the surveys report the number of household members involved and the total person-days. For hired labor, only the total number of person-days per plot is reported for male, female, and children (except in the 2005/6 survey). Hence, to convert these person-days into hours of on-farm (L_f^o) and hired (L_h) labor, we assume that for each day-work, adults (children between 6 and 15 years) work on average 8 (6) hours.

[24] Missing prices were approximated using the average prices at the cluster levels, and if still missing, at the district or regional levels.

[25] We also applied other alternative methods to check for the robustness of our results. For example, Attanasio et al. (2013) propose to use the median unit value at the cluster level as a measure of consumer price. However, this approach gave relatively similar results as the Deaton’s.

[26] The panels collected information on more than 60 different food, beverage and tobacco commodities.

more manageable figure[27]. As an attempt to obtain a reasonable number of parameters and referring to both commodities which are normally close derivatives of one another[28] and previous studies on demand systems in Uganda (Ulimwengu and Ramadan, 2009; Boysen 2012), we constructed 10 food groups plus leisure[29]: *matooke* (k_1), cassava (k_2), potatoes (k_3), maize (k_4), beans (k_5), meat & fish (k_6), fruits & vegetables (k_7), fats & oils[30] (k_8), alcohol & tobacco (k_9), and other foods for the remaining commodities (k_{10}). The prices for each food commodity group were computed as weighted means of commodities in that group, the weights being the mean consumption shares of each item. To approximate the value of leisure time, we use two types of information. In the separable model, we use the reported market wage[31] obtained by those who worked for pay during the last 12 months. For those who did not report any wage, we impute their value using the average market wage at each cluster/district level. In the non-separable model, the shadow wage is used as the opportunity cost of leisure time. To obtain the total value of household food consumption and therefore food consumption shares, consumption from home production has been valued using market prices under the assumption that market-purchased and home-produced goods are perfect substitutes[32,33].

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[27] Theoretically, there exist two alternative approaches for commodity grouping. The first approach -called the composite commodity theorem- asserts that we should group commodities whose prices are moving in parallel. However, since relative prices fluctuate considerably, the applicability of this approach is rather limited. The second approach, known as the separability theorem, states that if preferences are weakly separable, then we can construct independent sub-utility functions for each group and sum them up to get total utility. The weak separability hypothesis can be tested using for instance the *F* and Likelihood ratio version tests. In case of rejecting the null hypothesis of weak separability, the commodity grouping strategy must be guided by both the nature of the problem in hand and previous related studies (Abdulai and Aubert, 2004).

[28] Like cassava flour and grain, maize grain and flour, sweet and Irish potatoes, different types of meat (beef, pork, goat, chicken,…)

[29] The amount of leisure is obtained using the time constraint (equation 2.3) : $c_L = T - L_f^f - L_f^o$. Assuming that each household member aged below (above) 15 years has 12 (16) hours available per day for work/leisure (Henning and Henningsen, 2007; Tiberti and Tiberti 2012), the total annual time available for a household with n_1 members below 15 years and n_2 above 15 years, $T = 365*[(12*n_1)+(16*n_2)]$. L_f^f and L_f^o are the total annual hours for off- and on-farm family labor, respectively.

[30] Cooking oil, margarine, ghee, sugar, salt,…

[31] It is the ratio between the total payments (in cash and in-kind) divided by the total number of hours

[32] This assumption can be tested by computing the shadow price of consumption from home production (Arslan and Taylor, 2008). One can then regress these shadow prices over market prices and other household characteristics and test whether the coefficients associated with market prices are not significantly different from one. However, given the focus of the present study on labor market imperfections rather than missing or imperfect food markets, this assumption was deemed reasonable.

[33] In this study, we prefer the use of “consumption shares” in lieu of “budget shares” and “total value of food consumption” rather than “total food consumption expenditures” given the inclusion of the imputed values of both consumption from home production and leisure time, which are not actual purchases/expenditures.

In table 2.2, we report the percent changes in real consumer prices[34] of food commodity groups between 2005/06 and 2009/10, 2009/10 and 2010/11, and between 2005/06 and 2010/11. Between 2005/06 and 2010/11, most commodity groups were characterized by soaring prices, with cassava, maize, and beans displaying more than 200% increases; potatoes, fruits and vegetables, and other foods more than 100%; *matooke*, meat and fish, and alcohol and tobacco more than 50% increases.

Table 2.2 *Changes in real consumer prices of commodity groups between 2005/6 and 2010/11*

Commodities	Changes in real consumer prices between…		
	…2005/6 and 2009/10	…2009/10 and 2010/11	… 2005/06 and 2010/11
k_1	0.472 (0.299)	0.216 (0.297)	0.745 (0.367)
k_2	1.716 (0.117)	0.569 (0.185)	2.493 (0.540)
k_3	0.915 (0.269)	0.511 (0.493)	1.712 (0.447)
k_4	1.555 (0.289)	0.197 (0.231)	2.296 (0.642)
k_5	0.827 (0.180)	0.413 (0.103)	1.069 (0.341)
k_6	1.63 (0.209)	0.235 (0.169)	2.602 (0.679)
k_7	0.829 (0.105)	0.141 (0.067)	0.953 (0.164)
k_8	0.146 (0.335)	0.327 (0.354)	0.471 (0.416)
k_9	0.514 (0.419)	0.099 (0.090)	0.633 (0.565)
k_{10}	1.23 (0.398)	0.179 (0.210)	1.804 (0.867)
Overall	1.392 (0.152)	0.214 (0.087)	1.467 (0.170)

Note: Item indices k_i : 1: *Matooke*; 2: Cassava; 3: Potatoes; 4: Maize; 5: Beans; 6: Meat and fish; 7: Fruits and vegetables; 8: Fats and oils; 9: Alcohol and tobacco ; and 10: Other foods. Standard deviations into brackets.

Comparing different sub-periods, real consumer prices skyrocketed between 2005/06 and 2009/10. Indeed, the overall percent increase was 139.2% against 21.4% between 2009/10 and 2010/11. During the first two waves, cassava and beans exhibited the highest price increases with 172% and 163%, respectively, while fats and oils and *matooke* displayed the lowest changes in their real prices (14.6% and 47.2%). Compared to the changes between 2005/06 and 2009/10, real price changes, though still positive for all commodity groups, slowed down in 2010/11. Cassava and potatoes presented the highest increases with 56.9% and 51.1% respectively, and alcohol and tobacco and meat and fish the lowest changes with 9.9% and 14.1%.

[34] Real prices were obtained by deflating nominal prices by the UBoS all items' consumer price index (2005/06=100) to take account of potential changes in the purchasing power of Ugandan households. Prices are set at cluster/district level using the Deaton's approach (1988).

Table 2.3 presents both the food consumption shares (excluding leisure) and proportions of zero consumption of commodity groups by panel round for rural and urban areas. What is apparent from these figures are the disparities between rural and urban Ugandan households in the allocation of their budgets to food and non-food items and among food commodities.

Table 2.3 *Food consumption shares and proportion of zero consumption by commodity groups*

	UNPS-2006				UNPS-2010				UNPS-2011			
	Rural		Urban		Rural		Urban		Rural		Urban	
	Mean	Zeros	Mean	Zeros	Mean	Zeros	Mean	Zeros	Mean	Zeros	Mean	Zeros
Food	0.637	-	0.454	-	0.629	-	0.431	-	0.692	-	0.504	-
	(0.198)		(0.204)		(0.217)		(0.199)		(0.203)		(0.214)	
k_1	0.093	0.596	0.099	0.453	0.099	0.575	0.105	0.439	0.111	0.560	0.109	0.389
	(0.151)		(0.127)		(0.153)		(0.130)		(0.167)		(0.128)	
k_2	0.111	0.393	0.044	0.573	0.115	0.340	0.051	0.530	0.085	0.536	0.031	0.715
	(0.151)		(0.089)		(0.146)		(0.090)		(0.134)		(0.077)	
k_3	0.095	0.470	0.046	0.536	0.099	0.412	0.053	0.450	0.028	0.850	0.011	0.923
	(0.143)		(0.084)		(0.140)		(0.089)		(0.092)		(0.052)	
k_4	0.100	0.360	0.078	0.317	0.110	0.376	0.085	0.288	0.086	0.449	0.069	0.334
	(0.094)		(0.109)		(0.157)		(0.120)		(0.139)		(0.103)	
k_5	0.088	0.239	0.066	0.222	0.096	0.243	0.074	0.224	0.117	0.241	0.080	0.212
	(0.099)		(.070)		(0.109)		(0.090)		(0.140)		(0.096)	
k_6	0.149	0.278	0.176	0.195	0.144	0.311	0.173	0.209	0.175	0.286	0.189	0.170
	(0.145)		(0.137)		(0.145)		(0.141)		(0.171)		(0.141)	
k_7	0.101	0.066	0.090	0.076	0.104	0.071	0.096	0.068	0.097	0.084	0.093	0.063
	(0.094)		(0.067)		(0.096)		(.148)		(0.100)		(0.081)	
k_8	0.032	0.030	0.039	0.067	0.032	0.039	0.037	0.053	0.038	0.034	0.041	0.055
	(0.034)		(0.036)		(0.032)		(0.033)		(.067)		(0.037)	
k_9	0.033	0.670	0.033	0.748	0.028	0.722	0.019	0.840	0.036	0.710	0.024	0.830
	(0.075)		(.080)		(0.071)		(.073)		(0.089)		(0.077)	
k_{10}	0.197	0.101	0.329	0.020	0.174	0.122	0.307	0.027	0.225	0.094	0.352	0.028
	(0.187)		(0.237)		(0.184)		(0.067)		(0.213)		(0.234)	
Sample	1818		492		1823		487		1804		506	

Note: Item indices k_i : 1: *Matooke*; 2: Cassava; 3: Potatoes; 4: Maize; 5: Beans; 6: Meat and fish; 7: Fruits and vegetables; 8: Fats and oils; 9: Alcohol and tobacco ; and 10: Other foods. Standard deviations into brackets.

By and large, rural households, predominately agricultural, have allocated to food items 41% more of their budget than urban households whose shares of food consumption in total expenditures counted for around 46%. Between the first and the last surveys, food consumption shares rose for both rural and urban households by 8.6 and 11%, respectively, due particularly to substantial increases between 2009/10 and 2010/11 (10% and 16.9% in rural and urban areas, respectively), while between 2005/6 and 2009/10 food consumption shares slightly decreased for both rural and urban households (1.3% and 5.1%, respectively).

Out of the food consumption, the consumption shares of different food items are relatively close (around or less than 10%), except for meat & fish and other foods which shares are on average greater than 15%. This may suggest that the Ugandan diet is particularly diversified and thus there might be large possibilities of substitution across commodities as a response to food price increases. When we compare the dynamics of these shares during the sample period, beans (32.9% and 21.2% in rural and urban areas, respectively), *matooke* (19.4% and 10.1%), and meat & fish (17.4% and 7.4%) displayed the highest increases in their consumption shares between 2005/6 and 2010/11, while potatoes (-70.5% and -76.1%), cassava (-23.4% and -29.5%), and maize (-14% and -11.5%) had the highest decreases.

When we disaggregate these total changes into the two sub-periods, it appears that for both rural and urban households, most consumption shares showed larger changes (in absolute values) in the first sub-period (2005/6 – 2009/10) than in the second (2009/10- 2010/11) . In the first sub-period, the shares increased on average by 28.9 and 3.5% for rural and urban households, respectively, whereas during the last sub-sample period, they rose in rural areas (+1.4%) but decreased for urban households (-4.6%). Finally, the proportion of zero consumption is relatively high for all food groups, except for fruits & vegetables, fats & oils, and other foods. This underscores the need to explicitly deal with the censoring issue when estimating the food demand systems.

2.4.3 Identification of the household's food market position

In addition to the assumption that the welfare effects of price changes are significantly different under separable and non-separable models, we also assume that these effects are likely to be different across households due to their heterogeneity in terms of food market position. As outlined in our conceptual framework, frictions in the labor markets (whether due to risks, transaction costs, or imperfect substitutability between different types of labor) introduce into the model virtual or shadow effects of food price changes which signs and magnitudes are a priori indeterminate. These additional effects will either over- or under-estimate the expenditure and price elasticities and, consequently, the welfare effects of price changes derived under the recursivity hypothesis, depending on the extent of the household's net positions in both the food and labor markets (see equation 2.15). To take account of this fact, households are first divided into non-agricultural and agricultural households. The former act as pure consumers of staple foods and their welfare effects are theoretically the same in both separable and non-separable models, while the latter produce foods that are either consumed or sold, or both. Second, for each agricultural household, the net market position (or market surplus/deficit) is defined as the difference between the total market value[35] of quantities sold (A_1) and quantities purchased (A_2) of key staple foods consumed and produced by Ugandan households, namely *matooke*, maize, potatoes, cassava, beans, rice, millet, sorghum, fruits & vegetables. Hence, a household is defined as a global net seller (buyer) if $A_1 > (<) A_2$. Moreover, among net sellers, significant net sellers are those with $A_1 \geq 1.5 * A_2$ while insignificant or marginal net sellers are characterized by $A_2 < A_1 < 1.5 * A_2$. A similar subdivision is applied to net buyers. This profiling of the net market status of households using the value definition – instead of weight definition, for example – is particularly suitable in the context of this study as it provides greater insight on households' vulnerability to unexpected price changes by incorporating information on both prices and quantities of staples sold and purchased. Furthermore, this disaggregation will shed light on whether differences in market surplus/deficit led to significant differences in the welfare impacts of price changes as outlined in the theoretical framework.

Summary statistics and descriptions of key variables used in the estimation of different models are reported in table 2.4 by survey round and net market position. The table depicts significant discrepancies among the different types of households in terms of the dynamics of key variables of interest, hence highlighting the need to profile households through their net market position. Unsurprisingly, non-agricultural households (column **A**) present the highest monthly real expenditures per adult equivalent both in terms of food purchases (*vcmarket*) and non-food expenditures (*vnctotal*), with respectively an average over the sample period of 43,400 and 81,500 Uganda Shillings (UShs)[36]. While the total household expenditures (*tothexp2*) excluding non-purchased foods (imputed values of consumption from home production, *vcproduce*, and consumption of food received in-kind or as gifts) have decreased over time by 10.9% between the first and second surveys (henceforth, the first sub-period) and by 32.3% between the second and last surveys (the second sub-period), non-agricultural households increased their expenditures on food items (*vcmarket*), and particularly of staple foods (*vcmarketstaples*) in the first sub-period. Hence, when taken together, food purchases rose by a modest 2.2% during that period, but expenditures on staples soared on average by 66.7%, before declining afterwards by 16.8%. These dynamics provide some insights on the possible reallocation of households' budget between food and non-food items. During periods of high and volatile prices, pure consumers are generally found to decrease their expenditures on non-food items such as health and education to smooth their consumption

[35] To check for the robustness of our results, we also applied different definitions of the net market position, using for example the values of harvest instead of values of sales and the values of consumption instead of purchases (net producers vs net consumers).

[36] Average nominal exchange rate between May 2005 and April 2006 (first survey coverage): 1USD = 1,809.9 Uganda Shillings; between September 2009 and August 2010 (second survey): 1USD = 2,054.4 UShs; and between October 2010 and September 2011 (third survey): 1USD = 2,441.3 UShs (Bank of Uganda, 2013)

(Hoddinott, 2006; Carter et al., 2007). Finally, the table shows that non-agricultural households are likely to have lower family size, younger heads with more years of education and are predominately male-headed.

Significant net sellers (column **B**) logically spent the least on food consumption with a real monthly average per adult equivalent of less than 10,000UShs. However, they followed the same dynamics as non-agricultural households in terms of expenditures of staple foods: first an increase (of 62.5%) between 2005/6 and 2009/10 and then a decrease (of 42.3%) during the second sub-period. This feature is recurrent among other agricultural households, although occurring at different growth rates. Significant net sellers are also characterized by the highest levels of crops harvested and sold which, compared to relatively stable expenditures on variable inputs (*vinputs*: seeds, pesticides, fertilizer, and costs of hired labor), yielded the highest farm profits in each survey round. However, while most indicators present a positive growth rate between the first and second surveys, significant net sellers recorded a striking drop during the second sub-period, particularly in regards to quantities harvested (-56.6%), sold (-55.5%), and farm profits (-64.5%). Several reasons may explain these figures, among them the relatively modest increases in real food prices (21.4% against 139.4% in the first sub-period) that may have incited farmers to engage in alternative activities (non- or off-farm employment) that became more profitable. This can be seen by the decreases in the land size allocated to crops (-36.9%), the number of crops grown (-18.6%), on-farm family labor (-3.7%), and hired labor (-61.1%), but increases in off-farm labor (+67.2) or non-farm income (+58.1%).

At the opposite side of significant net sellers, significant net buyers (column **C**) have the highest levels of food purchases. Although they both have relatively similar levels of total values of food consumption (*vctotal*), and non-food (*vnctotal*), food expenditures of significant net buyers exceed that of significant net sellers on average by 82.4, 74.7, and 87.7% in each survey round, respectively. Further, they harvested and sold the least, yielding the lowest farm profits (even experiencing a net loss in 2010/11). They also cultivated the lowest proportion of land (on average 2.52 acres), grew less crops (around 4), allocated less time to on-farm family labor and much of their time to off-farm labor. Their heads are on average relatively older and the least educated. Put together, these features make significant net buyers particularly at the mercy of instabilities in commodity price markets. As shown in the table, they are selling food crops (*vsalestaples*) even when their harvest might be insufficient to cover their consumption needs. And given that farmgate prices are generally lower than consumer prices due to high transaction in most developing countries, they end up selling at low prices during harvested seasons but buying at high market prices at the lean periods.

Table 2.4 *Household characteristics by year and net market position*

Variable labels	All	A			B			C			D			E		
		2006	2009	2010	2006	2009	2010	2006	2009	2010	2006	2009	2010	2006	2009	2010
vcmarket ([a])	19.4	45.6	46.6	38.4	10.2	9.1	8.1	18.6	15.9	15.2	13.5	12.5	13.1	14.5	15.4	11.7
	(24.3)	(45.9)	(39.9)	(33.8)	(11.4)	(11.2)	(10.5)	(17.9)	(14.9)	(14.4)	(12.1)	(8.3)	(10.9)	(15.8)	(11.6)	(10.9)
vcmarketstaples([a])	9.8	15.7	26.2	21.8	1.6	2.6	1.5	8.8	11.1	9.7	4.4	6.2	4.6	4.9	8.4	5.1
	(12.7)	(13.2)	(20.1)	(19.8)	(2.5)	(4.1)	(2.9)	(10.3)	(10.8)	(10.5)	(4.5)	(4.9)	(4.5)	(5.2)	(7.6)	(5.7)
vcproduce([a])	10.8	-	-	-	19.5	18.2	14.4	11.5	11.6	9.5	17.2	16.4	14.7	16.2	18.7	17.1
	(12.8)				(15.5)	(12.3)	(12.1)	(13.8)	(12.1)	(9.8)	(21.8)	(9.6)	(10.9)	(12.3)	(13.6)	(13.1)
vctotal([a])	32.9	51.1	52.5	44.8	31.3	29.1	25.2	32.1	29.8	26.6	31.9	31.1	33.1	32.1	35.7	30.7
	(26.7)	(45.8)	(42.4)	(33.9)	(20.4)	(17.3)	(16.9)	(25.9)	(19.2)	(17.9)	(27.7)	(17.4)	(37.2)	(23.2)	(19.2)	(32.7)
vnctotal([a])	31.7	105.5	88.1	52.8	22.6	24.6	13.7	22.9	24.1	15.3	28.3	23.7	14.1	26.2	30.1	18.3
	(162.4)	(625.2)	(95.3)	(61.6)	(26.3)	(36.5)	(21.1)	(36.2)	(54.4)	(34.3)	(34.5)	(24.8)	(21.8)	(34.6)	(27.2)	(25.5)
tothexp1([a])	64.7	156.6	140.5	97.6	53.9	53.6	38.9	54.9	53.8	41.9	60.3	54.9	47.1	58.4	65.7	48.9
	(168.8)	(630.9)	(121.4)	(84.5)	(38.9)	(42.9)	(30.3)	(52.5)	(61.1)	(42.3)	(50.1)	(34.3)	(45.1)	(47.4)	(35.8)	(36.7)
tothexp2([a])	51.1	151.1	134.7	91.2	32.7	33.6	21.7	41.5	40.1	30.5	41.8	36.2	27.2	40.8	45.3	30.1
	(168.9)	(631.3)	(120.2)	(85.2)	(32.9)	(41.1)	(26.8)	(47.8)	(60.6)	(41.3)	(42.9)	(29.1)	(27.7)	(43.1)	(32.2)	(32.7)
vharvest([a])	397	-	-	-	1,061	1,009	438.1	318.9	122.6	84.8	898.4	524.8	347.9	699.4	559.9	366.2
	(746)				(1,179)	(1,206)	(449.5)	(519.8)	(319.9)	(233.1)	(1,061)	(468.1)	(394.5)	(778.1)	(542.9)	(519.9)
vharveststaples([a])	306	-	-	-	855.5	815.6	361.6	244.7	67.5	50.1	654.9	437.9	290.4	557.8	424.8	306.7
	(559)				(883.3)	(908.1)	(449.5)	(344.8)	(147.7)	(125.6)	(702.9)	(420.3)	(324.1)	(566.9)	(399.6)	(438.3)
vsales([a])	197	-	-	-	506.9	626.3	278.8	76.5	67.7	45.2	403.1	398.7	215.6	273.3	325.1	172.3
	(421)				(664.7)	(727.2)	(345.2)	(208.7)	(147.7)	(125.4)	(564.4)	(299.6)	(188.1)	(455.4)	(361.6)	(192.9)
vsalestaples([a])	137	-	-	-	385.9	502.3	221.6	28.5	28.1	21.5	240.1	218.9	173.1	164.6	201.4	129.9
	(323)				(534.6)	(604.5)	(267.2)	(68.2)	(61.8)	(58.8)	(355.9)	(223.3)	(164.2)	(261.3)	(164.7)	(157.6)
vinputs([a])	25	-	-	-	101.3	120.9	96.9	42.8	49.9	51.5	130.1	81.1	110.7	76.9	124.3	113.3
	(102)				(262.8)	(215.8)	(181.9)	(242.1)	(162.4)	(107.2)	(372.2)	(134.7)	(214.6)	(188.3)	(195.7)	(251.4)
frprofit([a])	130	-	-	-	398.9	513.1	181.8	29.5	24.3	-6.2	301.5	220.1	104.9	218.8	203.5	59.1
	(386)				(560.3)	(643.9)	(301.8)	(264.9)	(237.7)	(130.4)	(551.9)	(267.9)	(239.6)	(421.8)	(316.6)	(215.6)
land	3.62	-	-	-	3.63	4.33	2.73	1.98	2.95	2.61	3.89	2.64	2.97	2.49	2.89	2.89
	(14.90)				(3.45)	(8.29)	(4.03)	(3.12)	(11.8)	(8.10)	(4.06)	(6.18)	(1.78)	(4.15)	(4.41)	(4.93)
ncrops	4.79	-	-	-	6.56	6.83	5.56	3.64	4.00	4.36	4.95	6.09	6.49	5.03	5.55	6.80
	(3.22)				(2.93)	(3.79)	(3.35)	(2.66)	(3.08)	(2.78)	(2.52)	(3.15)	(3.11)	(2.84)	(2.77)	(3.54)

Table 2.4 (continued)

Variable labels	All	A			B			C			D			E		
		2006	2009	2010	2006	2009	2010	2006	2009	2010	2006	2009	2010	2006	2009	2010
onflabor	3,118	-	-	-	4,221	4,342	4,180	1,862	2,413	3,312	2,712	3,963	3,207	2,747	3,278	3,086
	(5,641)				(3,819)	(13,794)	(5,882)	(2,508)	(3,164)	(3,673)	(3,146)	(5,081)	(2,657)	(2,777)	(3,318)	(3,561)
hlabor	24.72	-	-	-	165	329	128	138	291	124	419	311	143	320	239	66
	(289.61)				(534)	(717)	(356)	(808)	(4,886)	(338)	(1,119)	(1,829)	(365)	(804)	(607)	(183)
offlabor	1,215	-	-	-	1,032	807.8	1,351	1,819	1,315	754.8	1,234	1,214	640.4	2,057	806.7	1,133
	(3,431)				(3,438)	(3,917)	(2,633)	(3,919)	(3,798)	(2,546)	(3,619)	(2,958)	(1,805)	(4,161)	(2,861)	(2,978)
nonfincome([a])	384.1	1,284	300.6	461.5	212.9	200.1	316.3	548.9	215.9	273.9	481.8	277.3	398.5	469.1	218.3	282.1
	(1,058)	(1,872)	(1,076)	(1,248)	(789.7)	(769.4)	(697.5)	(1,235)	(776.5)	(803.5)	(1,322)	(970.1)	(1,217)	(935.1)	(8614)	(586.8)
hhsize	6.55	4.46	5.29	6.23	6.16	7 (3.36)	7.40	5.97	6.77	7.55	6.15	6.73	7.91	6.40	7.01	7.64
	(3.36)	(2.88)	(3.11)	(3.66)	(3.22)		(3.50)	(2.86)	(3.17)	(3.44)	(3.02)	(3.46)	(3.69)	(3.31)	(3.23)	(4.34)
age	45.6	36.9	41.3	42.9	44	47	47.6	44.3	48.32	48.8	42.9	44.2	46.3	41.8	47.7	47.8
	(15.1)	(12.6)	(13.8)	(14.2)	(14.78)	(14.28)	(14.89)	(15.58)	(15.20)	(14.99)	(14.9)	(13.9)	(14.11)	(14.19)	(16.1)	(14.98)
education	5.30	6.86	7.06	7.18	5.34	5.31	5.33	4.58	4.44	4.96	5.47	5.25	5.69	6.09	5.27	5.54
	(4.10)	(4.35)	(4.62)	(4.83)	(3.51)	(3.64)	(3.85)	(3.88)	(3.98)	(4.09)	(3.31)	(3.48)	(3.34)	(3.48)	(3.52)	(3.94)
Gender	70.81	79.01	81.82	79.10	78.8	77.62	77.31	70.40	67.28	65.66	69.27	69.95	65.69	76.47	77.42	72.88
Observations	6,930	423	376	437	552	563	454	1,152	1,201	1,293	81	77	67	102	93	59

Note: ([a]) in ,000's Uganda Shillings (UShs). Standard deviations into brackets. All monetary values are expressed in real terms using UBOS' Consumer price index (2005/6: Base=100). **A** represents non – agricultural households, **B** significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers.

Variable labels: *vcmarket*: real monthly per adult equivalent (r.m.a., henceforth) total food consumption expenditures; *vcmarketstaples*: r.m.a. food consumption expenditures of staples. *vcproduce*: r.m.a. values of food consumption from home production. *vctotal*: r.m.a total values of food consumption (sum of food purchases, consumption from home production, and consumption in-kind or obtained as gifts); *vnctotal*: r.m.a. total household expenditures on non-food items (education, health, durables, non- or semi-durable goods,⋯); *tothexp1* and *tothexp2* denote the r.m.a total household expenditures on food and non-food items, including and excluding consumption from home-production *vcproduce* and food received in-kind or as gifts, respectively; *vharvest* (*vharvestsaples*): total annual values of all crops (staples) harvested; *vsales* (*vsalestaples*): total annual values of all crops (staples) sold; *vinputs:* annual expenditures on variable inputs (seeds, pesticides, fertilizer, hired labor); *frprofit*: farm profit; *land*: land size (in acres); *ncrops*: number of crops grown during the main season; *onflabor*: annual hours of on-farm family labor ; *hlabor*: annual hours of hired labor; *offlabor*: annual hours of off-farm labor; *nonfincome*: real annual non-farm income; *hhsize*: household size; *age*: age of the household head; *education:* number of years of education attained by the household head; and *gender*: proportion of male-headed households.

In this context, if unexpected price increases occur during periods of low storage capacity and with the lack of well-functioning credit and other financial markets, the risk of deterioration of welfare conditions becomes increasingly high.

Between significant net sellers and buyers appear both marginal net sellers and buyers. They both spend relatively similar amount of money on food consumption, higher than significant net sellers but lower than significant net buyers. Their discrepancies become apparent when we look at the production side. Insignificant net sellers (column **D**) produced on average more than insignificant net buyers (+6.3%) only due to the 2005/6's harvest levels (+28.5%). When we only take account of the last two surveys, the picture becomes reversed, with insignificant net buyers (column **E**) producing and selling globally more than insignificant net sellers, although net sellers are still selling more staples than net buyers (+18.8%). Other important differences between these two sub-groups are related to the levels of farm profits, hired labor, or time spent on off-farm employment.

Hence, the above analyses of household characteristics disaggregated by their net position in the food market provide the following key messages that will become apparent in the subsequent sections. First, treating all households as a homogenous group is likely to result in a misleading picture of the dynamics occurring among them. One evidence of this is that food purchases of non-agricultural households are for instance at least 2 times higher than the overall average food expenditures (second column). Second, decomposing agricultural households between net sellers and net buyers still hides important heterogeneity in terms of consumption, production, and other household characteristics. Ideally, given the complexity of agricultural households' behavior (Singh et al., 1986; Strauss, 1986; de Janvry and Sadoulet, 1991; Key et al., 2001), one would need to build as many homogenous sub-groups as data allow. Since different sub-groups of agricultural households will certainly be diversely affected by food price changes, depending on their initial conditions, observable characteristics, and unobserved heterogeneity, group-specific targeted policy interventions are likely to be more effective than uniform policies.

To conclude these data descriptions, we report in table 2.5 the number of agricultural households by their net positions in both food and labor markets. Among the 5,694 total agricultural households, the majority (2,670 or 46.89%) is either self-sufficient ($L_f = L_h > 0$) or autarkic ($L_f = L_h = 0$) in the labor market. Labor net buyers ($L_f - L_h < 0$) slightly outweigh net sellers ($L_f - L_h > 0$) with 28.96 against 24.15%. For all types of agricultural households, around three-quarters are labor net buyers, self-sufficient, or autarkic. Referring to equation (2.10)[37] and table 2.1, this implies that for the majority of the surveyed households, both the price elasticities and compensating variations are theoretically indeterminate in the non-separable model.

Table 2.5 *Decomposition of Ugandan households by their net positions in the food and labor markets*

	Labor net sellers: $L_f - L_h > 0$				Labor net buyers: $L_f - L_h < 0$				Self-sufficient/Autarkic: $L_f = L_h$			
	Total	2005/6	2009/10	2010/11	Total	2005/6	2009/10	2010/11	Total	2005/6	2009/10	2010/11
B	314	116	115	83	543	297	133	113	712	139	315	258
C	946	428	256	262	949	349	245	355	1,751	375	700	676
D	45	18	18	9	40	40	18	22	100	23	41	36
E	70	38	16	16	38	38	30	9	107	26	47	34
Total	1,375	600	405	370	1,649	724	426	499	2,670	563	1,103	1,004

Note: **B** represents significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers.

2.5 Results and discussion

2.5.1 Estimation of shadow wages and separability test

Parameter estimates for both the stochastic production frontier function $F(X_{ht}, \Omega_{ht})$ and technical inefficiency U_{ht} are reported in tables 2.6 and 2.7. The empirical functional form of the production frontier function is represented by a flexible quadratic specification in the productive assets[38]. Although displayed in two distinct tables, both models were estimated simultaneously using the Battese and Coelli's (1995) Maximum Likelihood-random effects time-varying inefficiency effects model. Globally, the estimated coefficients have the expected signs. All labor and non-labor inputs statistically significantly increase the values of crops harvested[39]. For instance, increases in the quantity of on-farm family female labor appear to have more impact on the marketed values of harvests than male labor. Hence, activities such as weeding or transplanting, generally executed by women in Uganda, would tend to be more important to the overall production than for example

[37] For self-sufficient or autarkic households in the labor market, equation (2.10) reduces to:

$$E(c_f / p_a) = \left[E(c_f^H / p_a) + \frac{p_a(Q_a - c_f)}{Y} E(c_f / Y) \right] + \left[E(c_f^H / w^*) E(w^* / p_a) \right]$$

[38] We also used other functional forms of the production frontier $F(X_{ht}, \Omega_{ht})$ such as a generalized Leontief functional form given the preponderance of zero values in input uses. However, only the model presented in this study best fitted the data while others fail to converge or present unrealistic parameter estimates.

[39] For each variable, we run joint tests of the level, quadratic, and interaction terms included in the final empirical specification.

ploughing in which men are predominantly engaged (Jacoby, 1993; Abdulai and Regmi, 2000; Tiberti and Tiberti, 2012).

Table 2.6 *Stochastic production frontier estimates*

Dependent variable: Total value of quantity harvested (in log)		
	Coefficients	Standard errors
Constant	11.805	0.202
land	0.863	0.097***
onfmalelabor	0.181	0.080**
onffemalelabor	0.235	0.061***
onfchildlabor	0.040	0.056
hlabor	0.055	0.024*
varinput	0.193	0.025***
wagehlabor	0.043	0.044
½ $land^2$	-0.227	0.046***
½ $onfmalelabor^2$	0.054	0.030**
½ $onffemalelabor^2$	0.074	0.022**
½ $onfchildlabor^2$	0.037	0.024
½ $hlabor^2$	0.096	0.020***
½ $varinput^2$	0.055	0.004***
½ $ghiredlabor^2$	0.021	0.008***
Land × *onfmalelabor*	0.091	0.034***
Land × *onffemalelabor*	-0.051	0.039
Land × *onfchildlabor*	0.057	0.031*
Land × *hlabor*	-0.005	0.028
Land × *varinput*	0.006	0.010
Land × *wagehlabor*	-0.028	0.011**
onfmalelabor × *onffemalelabor*	-0.086	0.027***
onfmalelabor × *onfchildlabor*	0.017	0.023
onfmalelabor × *hlabor*	-0.080	0.032**
onfmalelabor × *varinput*	0.003	0.008
onfmalelabor × *wagehlabor*	-0.005	0.011
hlabor × *varinput*	-0.004	0.006
hlabor × *wagehlabor*	-0.017	0.007***
LqGood	0.217	0.085**
LqFair	0.062	0.086
LdIr	-0.128	0.177
Yr2009	0.222	0.008***
Yr2010	0.182	0.108*
σ_v	0.343	0.043
σ_u	0.737	0.018
$\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$	0.827	0.015
Observations	5,694	

Note: All continuous variables are reported in log. ***, **, and * denote statistical significance at 1, 5, and 10% levels, respectively.

Variable labels: *land*: land size (in acres); *onfmalelabor*, *onffemalelabor*, and *onfchildlabor* : on-farm family labor (in person-days) by adult males, adult females, and children, respectively; *hlabor*: hired labor (in person-days); *varinput*: total expenditures on seeds, pesticides, and fertilizer used for production; *wagehlabor*: costs of hired labor. *LqGood:* proportion of plots of good quality; *LqFair*: proportion of plots of fair quality; *LdIr*: proportion of irrigated plots; *Yr*2009 and *Yr*2010: dummy variables taking 1 if year=2009 and 2010, respectively.

Table 2.7 *Technical inefficiency estimation results*

	Coefficients	Standard errors
Constant	0.365	0.051***
Gender	0.047	0.003***
Age	-0.006	0.001***
Age^2	0.000	0.000***
Education: Primary level	-0.103	0.008***
Secondary	-0.094	0.010***
University	-0.132	0.030***
Number of crops grown	0.012	0.002***
Number of crops $grown^2$	-0.001	0.000***
Married	0.063	0.007***
Number of children	-0.005	0.001***
adult male	-0.013	0.002***
adult female	-0.021	0.002***
Eastern region	0.047	0.042
Northern region	0.014	0.043
Western region	0.124	0.040***
Ratio Labor/Land	0.006	0.001***
Ratio Adult labor/Total labor	0.109	0.007***
Observations	5,694	

Note: *** and ** denote statistical significance at 1 and 5% levels.

Jointly, family labor is found more productive than hired labor which highlights the possibility of imperfect substitutability between these two types of labor due for instance to the existence of supervision costs or differential work motivations (Deolalikar and Vijverberg 1987). Land characteristics also clearly influence the crop outputs, which values are statistically higher with increases in land size, when cultivated lands are of good or fair quality. The costs of non-labor inputs (seeds, pesticides, and fertilizer) and hired labor positively influenced the output values, though only marginally when compared with the joint effect of family labor. This is probably imputable to their limited usage by Ugandan farmers during the sample period[40].

In terms of technical inefficiency, table 2.7 reveals that its scores are significantly correlated with the gender, level of education of the head and his marital status as well as with household composition, regional effects, and labor-land ratio.

Once we get the estimated parameters from the stochastic production frontier and technical inefficiency, we can derive sequentially the estimated marginal product revenue of labor for the entire sample $M\hat{R}P_L$, compute the allocative inefficiency scores for farmers engaged in both on- and off-farm labor $A\hat{I}$, and finally obtain the estimates of the shadow wages $\hat{w}^*$ for households that did not supply labor to the market. Following the procedure outlined previously (see section 2.3.1), we

[40] For instance, only 3.86, 5.57, and 5.20% of Ugandan farmers use fertilizer (either chemical or organic) in each survey round, respectively. The proportion that purchased pesticides was relatively high, with 11.92, 14.72, and 14.56%, respectively.

summarize in table 2.8 these different values for the full sample, the sub-sample of off-farm workers and self-employed farmers. Theoretically, the allocative inefficiency condition should hold ($M\hat{R}P_L = w$) for agricultural households supplying labor off-farm. Descriptive statistics reported in table 2.8 indeed reveal that the mean observed market wages of farmers working off-farmers only slightly deviate from their estimated marginal product revenue of labor. And as expected, the $M\hat{R}P_L$ of self-employed farmers is on average 22% higher than that of households working off-farm. The consequence of these small deviations between the mean $M\hat{R}P_L$ and observed market wages for farmers supplying labor is that their allocative inefficiency scores will tend to approach small values while they will be higher, in absolute values, for self-employed agricultural households. Negative (positive) $A\hat{I}$ will thereby imply that farmers are undersupplying (oversupplying) on-farm labor relative to off-farm employment (Barrett et al., 2008). As shown in table 2.8, self-employed, contrarily to off-farm workers, tended to undersupply on-farm labor (they reported on average negative estimated $A\hat{I}$ scores). Finding similar results when using data from rice production in Cote d'Ivoire, Barrett et al. (2008) attributed this empirical evidence to labor constraints that impede self-employed agricultural households from working off-farm since they do not have sufficient labor to operate on their own farms.

Table 2.8 *Summary statistics for* w, $M\hat{R}P_L$, $A\hat{I}$, *and* $\hat{w}^*$

	w	$M\hat{R}P_L$	$A\hat{I}$	$\hat{w}^*$	observations
Full sample	-	815.95	-0.16	1,073.14	5,694
		(125.05)	(0.25)	(636.23)	
Off-farm workers	787.31	751.62	0.05	787.31	2,675
	(582.07)	(115.97)	(0.23)	(582.07)	
Self-employed farmers	-	916.19	-0.21	1,520.65	3,019
		(50.56)	(0.20)	(424.27)	

Note: w : Observed real hourly market wage, at the community level ; $M\hat{R}P_L$: Estimated real marginal product revenue of labor; $A\hat{I}$: Estimated allocative inefficiency score; $\hat{w}^*$: Estimated hourly shadow wage. Standard deviations into brackets

Furthermore, table 2.8 indicates that the mean values of estimated shadow wages are clearly larger than observed market wages, as predicted by the non-separable agricultural households' literature. Thus, the observed market wages w serve as lower bounds of the farmers' subjective valuation of their on-farm labor. Finally, as a simple separability test, we performed both the Kolmogorov-Smirnov (K-S) and Epps-Singleton (E-S) tests for equality of shadow wages' distributions between the sub-samples of off-farm workers and self-employed farmers[41]. With both tests reporting *p*-values of zero, we reject the null hypothesis of equal distributions of estimated shadow wages and observed market wages. Otherwise stated, these results suggest that addressing the unobserved wage problem of agricultural households not supplying labor to the market by using observed market wages would underestimate the true, though unknown, cost of on-farm labor and consequently would bias subsequent welfare analyses.

2.5.2 Demand elasticities

Expenditure and Hicksian own-price elasticities[42] are reported in tables 2.9 and 2.10 for both separable[43] and non-separable models to evaluate the extent of virtual or shadow effects on household consumption behavior. All sets of elasticities are computed at the mean values of the predicted consumption shares and controlled for censoring in food consumption. To account for both year-specific effects and households' heterogeneity in regards to their net position in the food market, these elasticities are shown by survey round and net seller/net buyer status.

Conditional expenditure elasticities

As expected, all expenditure elasticities (η_i) are found positive and significant at 1% level, implying that increases in households' overall values of food consumption are accompanied with increases in demand of the individual food items under consideration. In the separable models, meat & fish (η_6) and other foods (η_9) display elasticities greater than one, suggesting that they are luxuries for Ugandan households: as income increases, households will spend proportionally more on the consumption of these food items. Furthermore, compared to food items, estimated elasticities associated with leisure are the lowest, with a 1% increase in household's total expenditure leading to less than 0.6% increase of time allocated to leisure. This could be a reflection of labor constraints faced by Ugandan households, predominately rural and agricultural. The rural labor market is structurally thin and characterized by limited employment opportunities and lower wage rates. In this context, the household's time endowment is often allocated to leisure by default and many

[41] Both the K-S and E-S tests check for dissimilarities between two samples by comparing either their distribution functions (K-S tests) or their empirical characteristic functions (Epps and Singleton, 1986; Goerg and Kaiser, 2009).

[42] Theoretical restrictions of adding-up and symmetry were imposed to the model and the system of share equations in the QUAIDS was estimated using the Non-linear Seemingly Unrelated Regression (NSUR) suggested by Poi (2008). Expenditure endogeneity has been tested and controlled for as well as censoring due to zero purchases using the Shonkwiler and Yen (1999)'s approach. Household composition (number of children, male, and female adults), total time endowment, non-farm incomes, sex, education and age of the head, and consumer prices were used as instruments of the shadow value of leisure in the non-separable model.

[43] See Appendix B.2 for the expressions of demand elasticities from the QUAID model under separability.

households would promptly decrease its share had they received employment offers. In terms of year-specific effects, expenditure elasticities have increased for most food items between 2005/6 and 2009/10 before decreasing in the last survey round. Otherwise stated, periods of higher food price volatilities were characterized by higher sensitivity of Ugandan households to changes in their total expenditures.

When disaggregating households by their food net market status, it appears that differences in estimated expenditure elasticities are particularly striking between significant net sellers and significant net buyers, at least for food items included in the definition of the net seller/net buyer position. Significant net buyers are found to increase the consumption of food items on average by 13% more than their net seller counterparts, with the highest differences related to *matooke* $(\Delta\eta_1 = +31\%)$ and beans $(\Delta\eta_5 = +33\%)$. This is easily understandable since significant net buyers are conceptually in a more urgent need to cover their food deficit than significant net sellers or other agricultural households. By contrast, it is hard to clearly perceive the disparities between insignificant net sellers and net buyers. For most food items, their corresponding estimated expenditure elasticities are remarkably close. Except for *matooke* $(\Delta\eta_1 = +17\%)$ and beans $(\Delta\eta_5 = -14\%)$, their differences barely reach 1%. Non-agricultural households lie somehow between these sub-groups of agricultural households. For example, they are increasing the consumption of most food items more proportionally than significant net sellers but are relatively closer to significant net buyers than to insignificant net sellers or net buyers.

When we relax the assumption of perfect labor markets and impute the value of leisure using shadow wages in lieu of observed market wages, all estimated expenditure elasticities are still positive and significant at 1% level but their magnitude is now reduced for most food items and household sub-groups. Analytically, the discrepancy between separable and non-separable models is attributed to the combined effects of the cross-price elasticities of the shadow wages $E\left(c_i / w^*\right)$ and the elasticities of the shadow wages with respect to expenditures $E\left(w^* / x\right)$[44]. As reported in Appendix B.3, these combined effects were negative for most households which therefore underestimated the elasticities obtained with no labor market failures.

[44] In the non-separable model, $\frac{\partial c_i}{\partial x} = \left.\frac{\partial c_i}{\partial x}\right|_{w^*} + \frac{\partial c_i}{\partial w^*}\frac{\partial w^*}{\partial x} \Rightarrow E(c_i / x) = \left.E(c_i / x)\right|_{w^*} + \left[E\left(w^*/x\right)E\left(c_i/w^*\right)\right]$

Table 2.9 *Expenditure elasticities by survey round, net market position, and (non-) separability*

	2005/6	2009/10	2010/11	Net market position (pooled sample)				
				A	**B**	**C**	**D**	**E**
				a. Separable model (Perfect labor market)				
η_1	0.980	0.995	0.987	0.944	0.777	1.022	0.844	0.989
	(0.023)***	(0.023)***	(0.024)***	(0.027)***	(0.016)***	(0.029)***	(0.016)***	(0.017)***
η_2	0.903	0.953	0.969	0.926	0.954	0.984	0.948	0.942
	(0.021)***	(0.021)***	(0.034)***	(0.060)***	(0.023)***	(0.021)***	(0.024)***	(0.021)***
η_3	0.908	1.001	0.970	1.013	0.892	1.054	0.989	0.985
	(0.022)***	(0.022)***	(0.087)***	(0.022)***	(0.083)***	(0.029)***	(0.023)***	(0.025)***
η_4	0.859	0.880	0.884	0.869	0.783	0.917	0.876	0.875
	(0.022)***	(0.021)***	(0.031)***	(0.028)***	(0.033)***	(0.021)***	(0.025)***	(0.022)***
η_5	0.729	0.756	0.704	0.792	0.588	0.783	0.772	0.663
	(0.019)***	(0.019)***	(0.019)***	(0.016)***	(0.032)***	(0.018)***	(0.017)***	(0.016)***
η_6	1.214	1.342	1.244	1.273	1.236	1.364	1.278	1.297
	(0.015)***	(0.015)***	(0.015)***	(0.016)***	(0.014)***	(0.015)***	(0.012)***	(0.013)***
η_7	0.886	0.892	0.874	0.870	0.873	0.892	0.869	0.888
	(0.014)***	(0.014)***	(0.018)***	(0.017)***	(0.019)***	(0.014)***	(0.017)***	(0.014)***
η_8	0.866	0.873	0.856	0.867	0.850	0.892	0.875	0.874
	(016)***	(0.017)***	(0.017)***	(0.019)***	(0.016)***	(0.016)***	(0.017)***	(0.016)***
η_9	1.234	1.398	1.242	1.412	1.249	1.357	1.248	1.206
	(0.014)***	(0.015)***	(0.014)***	(0.017)***	(0.009)***	(0.016)***	(0.018)***	(0.017)***
η_{10}	0.978	0.917	0.920	0.997	0.917	0.932	0.941	0.944
	(0.036)***	(0.047)***	(0.043)***	(0.044)***	(0.045)***	(0.040)***	(0.018)***	(0.044)***
η_{11}	0.579	0.526	0.551	0.578	0.588	0.536	0.529	0.572
	(009)***	(0.011)***	(0.010)***	(0.011)***	(0.009)***	(0.010)***	(0.010)***	(0.010)***
				b. Non-separable model (imperfect labor market)				
η_1	0.825	0.855	0.841	0.944	0.838	0.841	0.839	0.853
	(0.003)***	(0.002)***	(0.003)***	(0.027)***	(0.002)***	(0.002)***	(0.008)***	(0.011)***
η_2	0.754	0.847	0.777	0.926	0.762	0.802	0.774	0.742
	(0.007)***	(0.005)***	(0.007)***	(0.060)***	(0.007)***	(0.004)***	(0.013)***	(0.019)***
η_3	0.793	0.873	0.833	1.013	0.813	0.829	0.793	0.798
	(0.006)***	(0.005)***	(0.011)***	(0.022)***	(0.006)***	(0.005)***	(0.023)***	(0.024)***
η_4	0.661	0.741	0.674	0.869	0.673	0.699	0.685	0.648
	(0.008)***	(0.009)***	(0.008)***	(0.028)***	(0.009)***	(0.006)***	(0.022)***	(0.023)***
η_5	0.512	0.583	0.538	0.792	0.557	0.549	0.473	0.461
	(0.010)***	(0.009)***	(0.008)***	(0.016)***	(0.010)***	(0.006)***	(0.036)***	(0.029)***
η_6	1.259	1.300	1.289	1.273	1.276	1.295	1.188	1.233
	(0.018)***	(0.019)***	(0.021)***	(0.016)***	(0.021)***	(0.014)***	(0.038)***	(0.033)***
η_7	0.654	0.627	0.663	0.870	0.625	0.657	0.643	0.652
	(0.006)***	(0.006)***	(0.008)***	(0.017)***	(0.009)***	(0.005)***	(0.016)***	(0.018)***
η_8	0.594	0.657	0.619	0.867	0.591	0.641	0.568	0.600
	(0.007)***	(0.007)***	(0.006)***	(0.019)***	(0.009)***	(0.005)***	(0.028)***	(0.020)***
η_9	0.736	1.071	1.037	1.412	1.092	1.071	1.007	1.059
	(0.046)***	(0.061)***	(0.071)***	(0.017)***	(0.076)***	(0.046)***	(0.119)***	(0.078)***
η_{10}	0.794	0.773	0.739	0.997	0.784	0.764	0.781	0.778
	(0.006)***	(0.009)***	(0.007)***	(0.044)***	(0.008)***	(0.005)***	(0.024)***	(0.019)***
η_{11}	0.349	0.314	0.393	0.578	0.326	0.523	0.201	0.135
	(0.018)***	(0.022)***	(0.019)***	(0.011)***	(0.022)***	(0.015)***	(0.056)***	(0.046)***

Note: η_i are conditional expenditure elasticities. Item indices: 1: *Matooke*; 2: Cassava; 3: Potatoes; 4: Maize; 5: Beans; 6: Meat and Fish; 7: Fruits and vegetables; 8: Fats and oils; 9: Other foods; 10: Alcohol and tobacco; and 11: Leisure. The net market position is defined as previously: **A** represents non – agricultural households, **B** significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers. (***) denote significance levels at 1%.

Economically, an increase in the shadow wage, which represents the opportunity cost of leisure time, will have the usual negative substitution effects (leisure becoming virtually more expensive, households substitute towards food items and away from leisure) and an ambiguous income effect. Thus, the above results suggest that either the income effect was also negative (which reinforces the negative substitution effects) or positive but not sufficiently high enough to more than offset the negative substitution effects for most households.

Conditional Hicksian own-price elasticities

With regards to price elasticities, table 2.10 reports the conditional compensated (Hicksian) own-price elasticities evaluated at the means of the data by net market position and labor market regime. All own-price elasticities are negative and statistically significant at 5%, indicating that increases in consumer prices of each commodity group led to reductions in the quantity demanded of the same commodity. Similarly to expenditure elasticities, most price elasticities are less than unity which suggests some rigidities in households' demand responsiveness to price changes. Only livestock products and fish are found price elastic. Own-price elasticities portrayed in table 2.10 can be analyzed either by comparing periods of low (UNPS-2006) and high prices (UNPS-2010 and UNPS-2011) or by contrasting household groups by their net market position and labor market regime.

Starting with the separable models, households became more sensitive to price changes when we move from periods of low and stable prices to those of high instabilities in commodity prices. Particularly, own-price elasticities of *matooke*, maize, and meat & fish increased, in absolute terms, by 13, 17, 22% between 2005/6 and 2009/10 (Tefera et al., 2012). In terms of net position in food markets, non-agricultural households (column **A**) were more sensitive to price changes of maize, potatoes, fish and meat, with the lowest elasticities (in absolute terms) for *matooke* and cassava which are the most important contributive staples to daily caloric intakes in Uganda[45]. Own-price elasticities for agricultural households present a more heterogeneous pattern than expenditure elasticities. Globally, significant net sellers (column **B**) are the least demand-responsive to changes in food prices, particularly for staple foods. They decrease their consumption by 0.55, 0.60, and 0.51% in reaction to a 1% increase in the real prices of *matooke*, potatoes, and beans, respectively. As shown by Finkelshtain and Chalfant (1991), farm income is generally positively correlated with the prices of consumption goods and food production acts as an insurance value that partially protects consumer-farmers from price fluctuations. This stabilizing role will be important the larger

[45] Between 2000 and 2009, *matooke* and cassava were the first and second most important staples in terms of daily caloric intakes with respectively 17% and 13% of the total daily caloric intakes (FAO, 2009).

the food market surplus of a farmer. Hence, since high food prices are often accompanied with higher revenues and consequently increased possibilities for additional consumption, significant net sellers have more room for maintaining or reducing their consumption levels less proportionally than other agricultural households[46].

At the extreme side, significant net buyers (column **C**) were relatively more sensitive to changes in prices of most food items under consideration. In the short run, net buyers behave like pure consumers or non-agricultural households to unexpected changes in food prices given the practical impossibility to adjust or increase their output production and supply. The higher their food market deficit, the more they are likely to react to price changes as non-agricultural households. As shown in table 2.10, except for *matooke* and cassava, own-price Hicksian elasticities of significant net buyers are only slightly different to those of non-agricultural households. Insignificant net sellers (column **D**) and buyers (column **E**) are intrinsically close to each other in terms of sensitivity to price changes. Their food market surplus/deficit is not sufficiently high/lower to benefit/suffer from high food prices as significant net sellers/buyers. Globally, insignificant net sellers (buyers) are found more (less) sensitive than significant net sellers (buyers) to changes in prices of most food items. Similarly to expenditure elasticities, accounting for frictions in the labor markets reduces the magnitude of most price elasticities.

Hence, labor market failures tend to rigidify households' responsiveness in the food markets due to the presence of virtual or shadow effects. These findings are consistent with widespread evidence on agricultural household responses to market incentives when imperfections are accounted for. For instance, studies by de Janvry et al. (1991) and Taylor and Adelman (2002) found significant disparities in households' reactions to price changes in markets with and without frictions, the former generally reporting lower responses than the latter. These results also underscore the risk of biased welfare estimates when we make the assumption of separability between production and consumption decisions of agricultural households and, as a direct consequence, the welfare effects of price increases would probably be over-estimated (at least in the present study) with evident adverse consequences on policy implementations.

[46] However, due to transaction costs more or less important in most developing countries, there is a wedge between producer or farmgate prices and consumer prices. Therefore, income growth rate consecutive to food price increases will generally be lower than growth rates of consumption expenditures.

Table 2.10 *Own-price Hicksian elasticities by net market position*

	2005/6	2009/10	2010/11	Net market position (pooled sample)				
				A	**B**	**C**	**D**	**E**
				a. Separable model (Perfect labor market)				
ε_1	-0.635 (0.040)***	-0.732 (0.038)***	-0.696 (0.035)***	-0.642 (0.042)***	-0.546 (0.027)***	-1.026 (0.046)***	-0.672 (0.027)***	-0.784 (0.029)***
ε_2	-0.684 (0.048)***	-0.702 (0.044)***	-0.678 (0.064)***	-0.516 (0.119)***	-0.632 (0.049)***	-0.978 (0.043)***	-0.598 (0.053)***	-0.637 (0.047)***
ε_3	-0.894 (0.044)***	-0.779 (0.041)***	-0.958 (0.149)***	-0.784 (0.147)***	-0.600 (0.043)***	-0.764 (0.053)***	-0.776 (0.046)***	-0.617 (0.051)***
ε_4	-0.790 (0.062)***	-0.798 (0.055)***	-0.788 (0.072)***	-0.801 (0.129)***	-0.693 (0.075)***	-0.795 (0.054)***	-0.785 (0.068)***	-0.756 (0.061)***
ε_5	-0.514 (0.050)***	-0.500 (0.045)***	-0.537 (0.040)***	-0.427 (0.072)***	-0.508 (0.039)***	-0.621 (0.042)***	-0.515 (0.042)***	-0.531 (0.040)***
ε_6	-1.001 (0.030)***	-1.223 (0.030)***	-1.119 (0.026)***	-1.260 (0.026)***	-1.014 (0.031)***	-1.129 (0.029)***	-1.003 (0.025)***	-1.158 (0.027)***
ε_7	-0.668 (0.027)***	-0.760 (0.025)***	-0.753 (0.028)***	-0.743 (0.030)***	-0.745 (0.030)***	-0.763 (0.024)***	-0.744 (0.030)***	-0.760 (0.025)***
ε_8	-0.596 (0.039)***	-0.626 (0.039)***	-0.328 (0.006)***	-0.350 (0.034)***	-0.365 (0.045)***	-0.305 (0.036)***	-0.258 (0.039)***	-0.257 (0.039)***
ε_9	-0.715 (0.041)***	-0.727 (0.045)***	-0.735 (0.037)***	-0.577 (0.024)***	-0.768 (0.050)***	-0.759 (0.047)***	-0.773 (0.054)***	-0.760 (0.052)***
ε_{10}	-0.750 (0.040)***	-0.700 (0.051)***	-0.751 (0.041)***	-0.734 (0.044)***	-0.711 (0.048)***	-0.747 (0.041)***	-0.740 (0.043)***	-0.708 (0.049)***
ε_{11}	-0.239 (0.009)***	-0.196 (0.011)***	-0.319 (0.009)***	-0.340 (0.011)***	-0.285 (0.009)***	-0.269 (0.010)***	-0.217 (0.011)***	-0.214 (0.011)***
				b. Non-separable model (imperfect labor market)				
ε_1	-0.451 (0.012)***	-0.581 (0.013)***	-0.561 (0.014)***	-0.642 (0.042)***	-0.528 (0.014)***	-0.838 (0.011)***	-0.569 (0.034)***	-0.653 (0.040)***
ε_2	-0.431 (0.011)***	-0.684 (0.010)***	-0.549 (0.014)***	-0.516 (0.119)***	-0.573 (0.013)***	-0.859 (0.008)***	-0.423 (0.030)***	-0.582 (0.039)***
ε_3	-0.669 (0.006)***	-0.671 (0.006)***	-0.697 (0.013)***	-0.784 (0.147)***	-0.699 (0.006)***	-0.680 (0.005)***	-0.691 (0.020)***	-0.703 (0.014)***
ε_4	-0.661 (0.007)***	-0.642 (0.010)***	-0.660 (0.007)***	-0.801 (0.129)***	-0.684 (0.005)***	-0.674 (0.005)***	-0.694 (0.019)***	-0.664 (0.025)***
ε_5	-0.326 (0.029)***	-0.413 (0.017)***	-0.472 (0.015)***	-0.427 (0.072)***	-0.432 (0.037)***	-0.482 (0.011)***	-0.342 (0.066)**	-0.333 (0.053)***
ε_6	-0.763 (0.049)***	-0.773 (0.004)***	-0.778 (0.005)***	-1.260 (0.026)***	-0.775 (0.005)***	-0.782 (0.003)***	-0.763 (0.012)***	-0.783 (0.009)***
ε_7	-0.584 (0.009)***	-0.606 (0.008)***	-0.576 (0.011)***	-0.743 (0.030)***	-0.553 (0.014)***	-0.583 (0.008)***	-0.615 (0.020)***	-0.623 (0.022)***
ε_8	-0.763 (0.049)***	-0.625 (0.045)***	-0.492 (0.039)***	-0.350 (0.034)***	-0.943 (0.055)***	-0.549 (0.030)***	-0.883 (0.180)***	-0.603 (0.114)***
ε_9	-0.708 (0.006)***	-0.723 (0.007)***	-0.787 (0.023)***	-0.577 (0.024)***	-0.798 (0.012)***	-0.769 (0.007)***	-0.873 (0.045)***	-0.757 (0.011)***
ε_{10}	-0.681 (0.013)***	-0.637 (0.021)***	-0.683 (0.015)***	-0.734 (0.044)***	-0.679 (0.017)***	-0.652 (0.013)***	-0.657 (0.040)***	-0.660 (0.046)***
ε_{11}	-0.346 (0.048)***	-0.474 (0.055)***	-0.451 (0.124)***	-0.340 (0.011)***	-0.598 (0.049)***	-0.413 (0.039)***	-0.329 (0.273)***	-0.444 (0.109)***

Note: ε_i are conditional Hicksian own-price elasticities obtained from table A.1. Item indices: 1: *Matooke*; 2: Cassava; 3: Potatoes; 4: Maize; 5: Beans; 6: Meat and fish; 7: Fruits and vegetables; 8: Fats and oils; 9: Other foods; and 10: Alcohol and tobacco; and 11: Leisure.(***) and (**) denote significance level at 1 and 5%, respectively. **A** represents non – agricultural households, **B** significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers.

2.5.3 Welfare effects of price changes

The derivations of both shadow wages and different demand elasticities permit the computation of welfare effects of food prices, using real changes between 2005/6 and 2009/10, and between 2009/10 and 2010/11. In computing these compensating variations, this essay diverges from almost all the previous studies in two different ways. First, instead of applying hypothetical price simulations as it is commonly done in many empirical studies on price shocks, the essay takes advantage of the availability of household panel data collected during periods of stable and high prices which allows to take account of changes that households really experienced. Second, and contrarily to virtually all previous studies, we derive an expression of compensating variations encompassing labor market frictions. We present in this paragraph successively first-order effects and global (first- plus second-order) welfare effects of price changes under both perfect and imperfect labor markets. We are thus able to evaluate the order of magnitude of these frictions. As is standard in empirical literature, these compensating variations are expressed as the percentage of the household real expenditures in the baseline periods (2005/06 for price changes between 2005/06 and 2009/10, and 2009/10 for changes between 2009/10 and 2010/11). These money-metric welfare measures are reported such that positive (negative) values represent welfare losses (gains) due to increases in real food prices. They indicate by what percentage an average Ugandan household would have to increase (decrease) its current total expenditures to achieve the same utility level attained in the corresponding comparison period.

First-order welfare effects of price changes

These first-order or direct effects only consider the immediate welfare consequences of price changes without accounting for potential substitution mechanisms across commodities. What is apparent from the results reported in table 2.11 is that the magnitude of these effects was dependent of the poverty status of households[47], their net position in the food market, and the inclusion or not of labor market frictions. Under separable models, real price increases between 2005/06 and 2009/10 led to an overall welfare gain of 11.1%, implying that a typical Ugandan household needed to decrease its total expenditures by 11.1% in 2009/10 in order to reach the utility level achieved in 2005/06. However, this overall gain hides substantial differences among households. Non-agricultural households are, unsurprisingly, among the biggest losers from price increases. Their direct welfare losses were evaluated at 41.9%, suggesting that they would need to be compensated

[47] Poverty lines were constructed using the Cost-of-basic-needs approach and applying the procedure proposed by Ravallion and Bidani (1993), and Appleton (2001).

by about 42% of their food expenditures in 2009/10 in order to offset the effects of food price increases between 2005/6 and 2009/10.

Table 2.11 *Direct welfare effects of price changes between 2005/6 and 2010/11 under separability (SM) and non-separability (NSM) (CV as a % of initial household expenditures)*

	Model	2005/6-2009/10		2009/10-2010/11	
		Coefficients	Standard errors	Coefficients	Standard errors
All households	SM	-0.111	0.026^{***}	0.094	0.004^{***}
	NSM	0.136	0.058^{**}	0.041	0.004^{***}
Agricultural	SM	-0.271	0.030^{***}	0.079	0.005^{***}
	NSM	0.038	0.069	0.014	0.004^{***}
Non-agricultural	S/NSM	0.419	0.016^{***}	0.155	0.008^{***}
Rural	SM	-0.270	0.031^{***}	0.081	0.005^{***}
	NSM	0.078	0.034^{*}	0.024	0.005^{***}
Urban	SM	0.489	0.034^{***}	0.141	0.007^{***}
	NSM	0.355	0.085^{***}	0.102	0.008^{***}
Poor	SM	0.338	0.051^{***}	0.115	0.004^{***}
	NSM	0.197	0.101^{*}	0.044	0.004^{***}
Non-poor	SM	-0.208	0.031^{***}	-0.090	0.011^{***}
	NSM	0.119	0.063^{*}	0.031	0.012^{*}
Significant net sellers	SM	-0.269	0.053^{***}	-0.149	0.007^{***}
	NSM	-0.087	0.023^{***}	-0.058	0.011
Significant net buyers	SM	0.211	0.032^{***}	0.164	0.004^{***}
	NSM	0.078	0.012^{***}	0.041	0.005^{***}
Insignificant net sellers	SM	-0.103	0.142^{***}	-0.050	0.014^{***}
	NSM	-0.045	0.022^{*}	-0.019	0.008^{***}
Insignificant net buyers	SM	0.061	0.011^{***}	0.139	0.013
	NSM	0.041	0.083	0.016	0.005^{***}

Note: Standard errors are reported into brackets. (***), (**), and (*) denote significant levels at 1, 5, and 10%, respectively.

Indeed, contrarily to agricultural households, these households cannot rely on agricultural revenues to compensate for price increases. Furthermore, consistent with previous studies, poor and urban households also experienced welfare losses of the order of 33.8 and 48.9% (Porto, 2010; Alem, 2011; Tefera et al., 2012). Notwithstanding agricultural households' gains from price increases (27.1% on average), welfare effects were unevenly distributed among them. Both significant and insignificant net buyers suffered the most with respectively 21.1 and 6.1% of welfare losses. By contrast, significant net sellers obtained the highest positive welfare effects (26.9% on average) while, in comparison, insignificant net sellers benefited only marginally from price increases (10.3%). As shown in table 2.4, significant net sellers experienced the highest increases in both crop sales (+23.6%) and farm profits (+33.1%) between 2005/6 and 2009/10, which thereby increased their profit effect and offset the magnitude of price fluctuations. While food prices also increased between 2009/10 and 2010/11, Ugandan households globally lost from price upsurges. On average, they had to increase their expenditures of 2010/11 by 9.4% if they wanted to remain at their 2009/10's welfare level. The reason behind this contrasting picture could reside in the relatively small price increases between 2009/10 and 2010/11 (21.4%) compared to increases in real prices between 2005/6 and 2009/10 (139.2%). Only significant net sellers (14.9%) and to a marginal extent, insignificant net sellers (5%) gained from price increases.

When we allow for imperfections in the labor market, the extent of welfare effects for all households is strikingly reduced. Particularly during the first sub-period, Ugandan households as a whole lost from price increases (13.6%). Although net sellers are still benefiting from food price increases, their welfare gains decline in the first sub-period by 67.7% and 56.3% for significant and insignificant net sellers, respectively, whereas the losses of net buyers are 63.3 % and 32.8% lower for significant and insignificant net buyers, respectively. In the second sub-period, the global welfare loss is now 56.4% lower than that obtained under no labor market frictions. These results are in line with standard non-separable agricultural household models whereby market failures often hamper farmers' responsiveness to price changes or reduce their abilities to respond to price incentives (Singh et al., 1986; de Janvry et al, 1991; Taylor and Adelman, 2003; Löfgren and Robinson, 2002).

Welfare effects of price changes accounting for substitution effects

Although conclusions drawn from the first-order welfare effects provide useful primary insights of price impacts, they have the drawback of ignoring the potential substitution effects of households who generally substitute away from commodities whose relative prices have increased. Thus, they tend to overestimate the negative impacts for welfare losers (non-agricultural households, poor, or net buyers) and underestimate the positive effects for welfare gainers (agricultural and rural households, net sellers). Accordingly, we also report in table 2.12 welfare effects accounting for substitution effects.

Table 2.12 *Total welfare effects of price changes between 2005/6 and 2010/11 under separability (SM) and non-separability (NSM) (CV as a % of initial household expenditures)*

	Model	2005/6-2009/10		2009/10-2010/11	
		Coefficients	Standard errors	Coefficients	Standard errors
All households	SM	-0.154	0.027***	0.042	0.004***
	NSM	0.097	0.057*	0.019	0.003***
Agricultural	SM	-0.299	0.031***	0.029	0.005***
	NSM	-0.009	0.068	-0.001	0.003
Non-agricultural	S/NSM	0.238	0.017***	0.101	0.008***
Rural	SM	-0.397	0.032***	0.031	0.005***
	NSM	0.028	0.069	0.007	0.004*
Urban	SM	0.393	0.036***	0.082	0.008***
	NSM	0.305	0.077***	0.060	0.006***
Poor	SM	0.265	0.052***	0.082	0.011***
	NSM	0.100	0.055*	0.022	0.003***
Non-poor	SM	-0.280	0.031***	-0.123	0.005***
	NSM	0.085	0.019***	0.006	0.010
Significant net sellers	SM	-0.354	0.053***	-0.200	0.007***
	NSM	-0.131	0.023***	-0.068	0.011***
Significant net buyers	SM	0.123	0.032***	0.113	0.005***
	NSM	0.051	0.007***	0.024	0.002***
Insignificant net sellers	SM	-0.177	0.143***	-0.101	0.013***
	NSM	-0.073	0.036**	-0.035	0.009***
Insignificant net buyers	SM	0.035	0.003***	0.086	0.013***
	NSM	0.009	0.012	0.014	0.004***

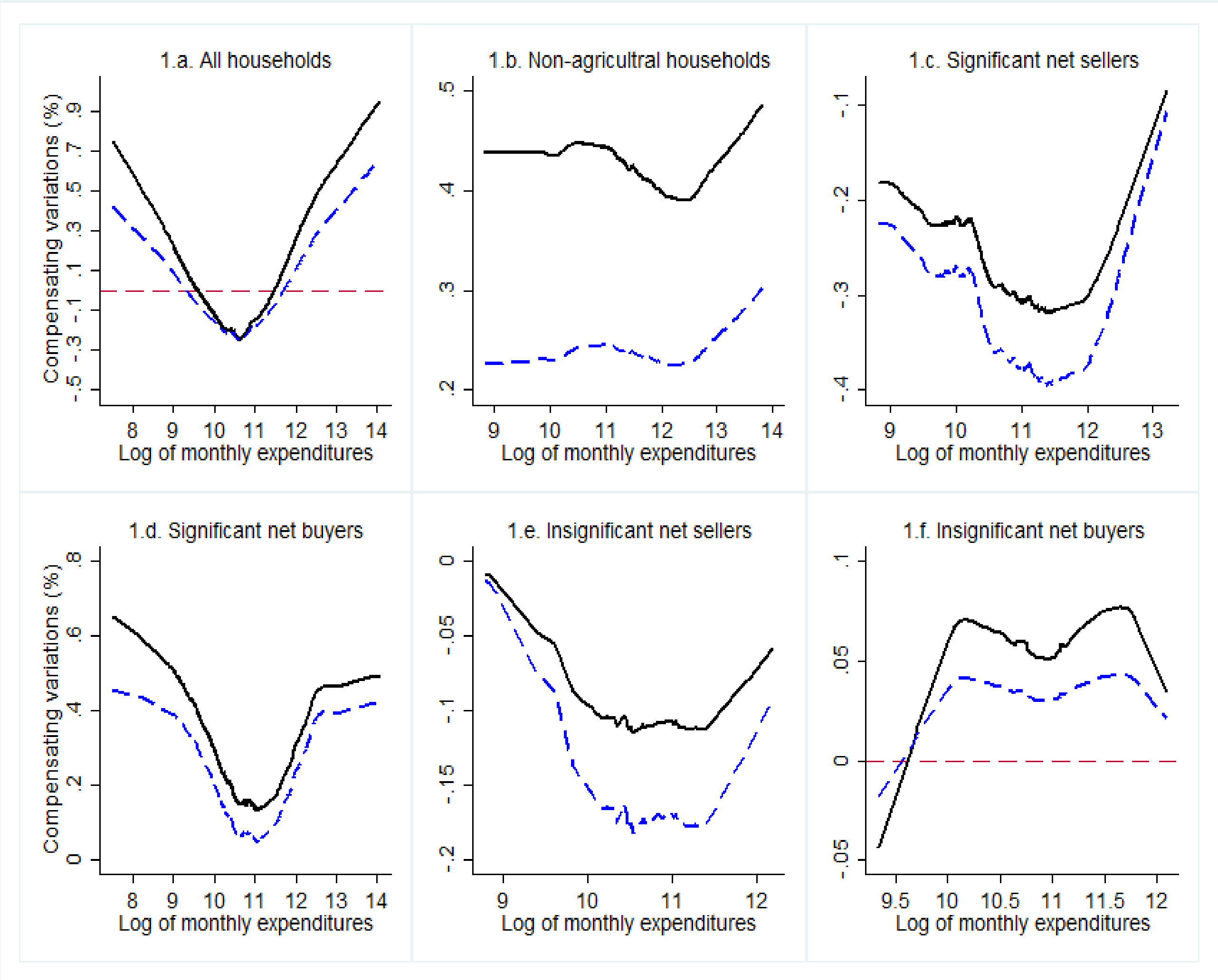
Note: Standard errors are reported into brackets. (***), (**), and (*) denote significant levels at 1, 5, and 10%, respectively.

Between 2005/6 and 2009/10, welfare gains increased on average by 38.7% under separability and welfare losses decreased by 28.6% under non-separability. During the second comparison period, welfare losses declined respectively by 53.7% and 55.3% in models with and without labor market frictions respectively. The fact that these substitution effects are relatively high reflect large possibilities of diet diversification in Uganda where none of the staple foods represents more than 20% of average daily caloric intakes (FAO, 2009a; Benson et al., 2008; Haggblade and Dewina, 2012). Households have therefore a bunch of possibilities to substitute away from expensive commodities. However, not all households have the same improvements in their welfare estimates when allowing for commodity substitution effects. For instance, between 2005/06 and 2009/10, poor households recorded the smallest changes in terms of welfare effects. Their losses only fell by 21.6% against for example an increase of 34.6% for non-poor households under perfect labor markets. Indeed, it is reasonable to think that since the diet of poor households is often made up of cheap commodities, most possibilities of substitution have already been accounted for, hampering the magnitude of their second-order effects. Furthermore, although agricultural households have now gained from price increases in the non-separable models, these welfare effects were too small (-0.9% and -0.1% in both sub-periods, respectively) to be significant. Between 2005/6 and 2009/10, all agricultural households reported large changes in welfare effects due to substitution across commodities under both separability and non-separability. However, during the second sub-period, although second-order effects certainly dampened the extent of adverse welfare impacts of price changes, they were insufficient to countervail them and transform first-order losers to overall gainers.

The estimated welfare effects reported in tables 2.11 and 2.12 indicate the importance of accounting for both labor market frictions and the net seller/buyer status of Ugandan households. These results may also suggest that the estimated compensating variations could vary across the income or expenditure distribution within the same sub-group of households. In order to explore this possibility, we estimated non-parametric locally weighted regressions (LOWESS) using Gaussian kernels. The first-order and total (first- and second-order) welfare effects are regressed on the logarithm of real monthly total expenditures per adult equivalent for non-agricultural households and all sub-groups of agricultural households. Figure 2.1 plots these various welfare effects' distributions of price changes. The solid curves represent first-order effects while the dotted curves display the welfare effects accounting for substitution across commodities. The horizontal dotted line (at 0) gives the threshold below (above) which the welfare effects become positive (negative).

Keeping in mind that negative (positive) values of the compensating variations represent welfare gains (losses), the general shape of the regression function (part 1.a.) seems to indicate that middle-class households suffered the least from food price increases between 2005/6 and 2009/10. By contrast, households located at the extremes of the expenditure distributions (the poorest and the wealthiest households) were the most hit by price changes. While it is easier for rich households to smooth their consumption without jeopardizing their food security or asset holdings, the poorest households do not have large possibilities and may cope with price increases by reducing their livestock or cuting off other household expenditures, such as education or health. On the other hand, a closer look at the different sub-groups helps grasp the differences in welfare distributions across households. Among all sub-groups, non-agricultural households displayed the largest substitution effects while the possibilities of substitution appear small for richer significant net sellers. However, these second-order effects (the differences between the two curves) appeared particularly neutrally distributed for non-agricultural households. At each percentile of expenditure distributions, substitution effects are relatively of equal weight, contrarily for instance to significant (insignificant) net sellers where households at highest (lowest) percentiles have much (less) possibilities of substitution.

Figure 2.1 *Non-parametric estimates of the relationship between compensating variations and household expenditures (2005/6-2009/10) – Separable models*



Dynamics of net market position and welfare effects

As shown in the previous paragraphs, the total welfare impact of price changes will hinge essentially upon the magnitude of these changes, the extent of the market surplus or deficit, and households' sensitivity to price movements. In the case of a marginal deficit, the high consumption cost due to increased food prices may be more than offset by higher income from agricultural activities. This perspective may enhance the possibility to expand production and lead to a shift from subsistence production to cash crop activities (Von Braun and Kennedy, 1994; Govereh et al., 1999; Barrett and Dorosh, 1996) or even a change in the net market position of agricultural households (Porto, 2010; Aksoy et al., 2010). For instance, using Mexican data, Porto (2010) showed that farmers may change their net selling or buying status in case of large substitution effects between crops grown and produced. Aksoy et al. (2010) also noted that between 1993 and 1998, price changes pushed about 21% of Vietnamese households to switch between being net rice seller and net buyer. Among them, 15% net rice buyers in 1993 became net sellers by 1998, while 29% followed the inverse pathway.

Theoretically, in periods of large price increases, switching from a net buying to net selling position would also change the welfare status from loser to gainer. A natural way to address these net market position dynamics is by using transition matrices that depict a household net food position at time *t*-1 and its current position at *t.* Table 2.13 summarizes these dynamics by showing the percent of Ugandan households that shifted from one net market position to another during the first and second sub-periods. The percents in the main diagonals (values in bold) give the proportions of non-movers between *t*-1 and *t* while off-diagonal percents refer to household switchers.

A feature that immediately jumped out of these figures is the prominence of important dynamics. First, in both sub-periods, non-agricultural households and significant net buyers appear trapped in their respective sub-groups, especially in the second-period where around 89% and 77% of non-agricultural households and significant net buyers did not change their net market position. Second, it is revealing that some Ugandan households shifted from non-agricultural households to farmers. This is particularly evident between 2005/6 and 2009/10 where 31.4% of non-agricultural households become farmers, either net sellers (4.3%) or net buyers (27.2%). This proportion dropped to 11% in the second period. A possible reason could be the relative attractiveness of agricultural activities consecutive to food price increases during the sample period. Third, only less than 50% of significant net sellers managed to maintain their status in both sub-periods and around 40% of them even became significant net buyers. Some of them forewent farming activities in 2009/10 (1.1%) and 2010/11 (3.9%). Fourth, in both sub-periods, insignificant net sellers and buyers were the most dynamic. Indeed, 41% and 34% of insignificant net sellers and net buyers in 2005/6 switched to being significant net sellers in 2009/10, whereas in 2010/1, these proportions are reduced to 26% and 30%, respectively. However, the percent of agricultural households that shifted from their initial status to becoming significant net buyers is the most important for all types of farmers. Hence, by and large, it was relatively easier during the sample period for agricultural households to switch to a significant net buyer status than shifting to any other type of household.

Table 2.13 *Dynamics of food net market position between 2005/6 and 2010/11*

				2009/10			
		A	**B**	**C**	**D**	**E**	Total
	A	**68.56**	3.55	25.53	0.71	1.65	423
	B	1.09	**48.01**	39.49	5.80	5.62	552
	C	6.42	1.66	**62.33**	3.04	4.08	1,152
2005/6	**D**	3.70	40.74	45.68	**6.17**	3.70	81
	E	2.64	34.31	55.88	1.96	**4.90**	102
	Total	16.28	24.37	51.99	3.33	4.03	2,310
				2010/11			
		A	**B**	**C**	**D**	**E**	Total
	A	**89.10**	1.33	9.31	0.27	0	376
	B	3.91	**44.23**	40.85	6.39	4.62	563
2009/10	**C**	6.33	12.66	**77.10**	2.00	1.92	1,201
	D	1.30	25.97	61.04	**2.60**	9.09	77
	E	3.23	30.11	59.14	4.30	**3.23**	93
	Total	18.92	19.65	55.97	2.90	2.55	2,310

Note**:** **A** represents non – agricultural households, **B** significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers. The last columns give the total number of observations.

To see how these movements into and out of net seller/net buyer status translated into changes in households' welfare, we report in table 2.14 the average compensating variations of switchers and non-movers from both separable and non-separable models. It is therefore possible to judge of the "rationality" of each switch relative to the status quo. As expected, all households that became significant net sellers gained from food price increases. However, in the first-sub period, the welfare gains of switchers are much less important than those reported by non-mover significant net sellers, whereas in the second period, the magnitudes of their welfare effects only slightly diverge. Furthermore, in the first sub-period, agricultural households that abandoned their farming activities lost more than non-agricultural households that did not switch.

Table 2.14 *Net market position switching movements and welfare effects of price changes*

		2009/10				
		A	**B**	**C**	**D**	**E**
	A	**0.229 [0.229]**	-0.325 [-0.177]	0.082 [0.037]	-0.114 [-0.09]	0.052 [0.034]
	B	0.256 [0.256]	**-0.577 [-0.196]**	0.225 [0.075]	-0.223 [-0.084]	0.042 [0.000]
2005/6	**C**	0.267 [0.267]	-0.299 [-0.184]	**0.226 [0.049]**	-0.136 [-0.177]	0.027 [0.017]
	D	0.287 [0.287]	-0.367 [-0.329]	0.061 [0.024]	**-0.209 [-0.068]**	0.033 [0.012]
	E	0.254 [0.254]	-0.365 [-0.042]	0.257 [0.014]	-0.310 [0.014]	**0.045 [0.031]**
		2010/11				
		A	**B**	**C**	**D**	**E**
	A	**0.097 [0.097]**	-0.184 [-0.057]	0.175 [0.077]	0.017 [-0.008]	-
	B	0.161 [0.161]	**-0.192 [-0.062]**	0.092 [0.019]	-0.087 [-0.018]	0.071 [0.011]
2009/10	**C**	0.104 [0.104]	-0.217 [-0.086]	**0.119 [0.025]**	-0.128 [-0.053]	0.101 [0.020]
	D	-0.004 [-0.004]	-0.222 [-0.063]	0.102 [0.010]	**-0.148 [-0.006]**	0.087 [0.000]
	E	0.052 [0.052]	-0.161 [-0.031]	0.083 [0.013]	-0.079 [-0.103]	**0.035 [0.092]**

Note**:** **A** represents non – agricultural households, **B** significant net sellers, **C** significant net buyers, **D** insignificant net sellers, and **E** insignificant net buyers. In each cell, total welfare effects (first-order plus second-order effects) are reported. Compensating variations from non-separable models are displayed into brackets. (**-**): no observation.

Overall, these figures suggest that it was "rational" during the sample period, at least in the perspective of compensating variations, for non-agricultural households to engage into farming activities, and particularly to become significant net sellers. For these latter, it was not in their interest to change their status or if this happens anyway, they should stay net sellers, though marginally. Significant net buyers would gain by shifting to a significant-net-seller position or if this is impossible, they could minimize their welfare losses by reducing their food market deficit at the levels of insignificant net buyers. Finally, insignificant net sellers would improve their positive welfare effects of price changes by increase their market surplus, whereas insignificant net buyers would rather be net sellers or, as in the second sub-period, drop from farming activities if they cannot sustain their position.

2.6 Conclusions

The motivation behind this second study stemmed from the evidence of soaring food prices that Uganda has been experiencing since 2008 and the lack of updated empirical studies on the potential consequences of price changes on households. To that end, the study made use of a non-recursive agricultural household model under the assumption of labor market imperfections to derive the welfare effects of price surges between 2005/6 and 2010/11. The data came from three of the latest waves of the Uganda National Panel Surveys (UNPS) collected in 2005/6, 2009/10, and 2010/11 and covering each 2,310 households from all the four geographical regions of the country and periods of both stable and volatile food prices.

On the production side, the separability hypothesis has been rejected, suggesting that household's production and consumption decisions were intertwined. On the consumption side, the QUAIDS model specification has been tested and adopted to derive expenditure and price demand elasticities of ten commodities groups, namely *matooke*, cassava, potatoes, maize, beans, meat and fish, fruits and vegetables, fats and oils, other foods, alcohol and tobacco, as well as leisure time. To allow for household's heterogeneous behavior with regards to food price changes, households were divided into five exclusive groups based on their net market position: non-agricultural households, significant net sellers, significant net buyers, insignificant or marginal net sellers and insignificant net buyers.

It appeared that Ugandan households not only reacted differently to price changes but also were differently affected by food price inflation between 2005/6 and 2010/11. Results from the compensating variations revealed that welfare effects of price changes were on average globally lower when labor market imperfections are accounted for, which implies that separable models tend to overstate welfare impacts of price shocks. Further, locally weighted scatterplot smoother (LOWESS) regressions showed that, globally, for most household categories, welfare losses were the highest for the poorest and, surprisingly, richest categories. This provides evidence that not only welfare effects of price changes were unequally distributed both within the same household group and between different household categories, but also that poor households were those who suffered the most from price upsurges, exacerbating the vulnerability to other types of shocks. Finally, the estimation results shed light on important dynamics that occur in the net food market position for most households. In particular, we found that a significant proportion of agricultural households switched from a net seller to net buyer position and the other way around. As consequence, the welfare effects of price changes also reported a similar pattern during the sample period.

Although the above conclusions help understand what happened to Ugandan households between 2005/6 and 2010/11, two important facts should be kept in mind. First, our findings are ultimately anchored to the assumption of a partial equilibrium framework, particularly that all other sources of changes are being held constant. We therefore left out the potential spillover or multiplier effects that food price increases might have induced to the rest of the Ugandan economy (Akson and

Hoekman, 2010). For example, between 2005 and 2011, the Ugandan economy grew annually at an average rate of 7.7% (WDI, 2012), and this could have dampened the negative effects of price shocks through income increases. Allowing for these spillover effects through a general equilibrium model might improve our estimates (de Janvry and Sadoulet, 2006). Second, we estimated direct welfare impacts and allowed for substitution effects across commodities by using only compensating variations and ignoring the risky nature of household activities, most of whom being agricultural. Hence, it is possible to extend the analysis carried in the present study by estimating for example the extent to which Ugandan households would be willing to pay for price stabilization (Bellemare et al., 2013) or by incorporating risk factors both in the consumption and production sides of households.

Essay III

How strongly do agricultural risks and farmers' expectations influence acreage decisions?

Dynamic models of land use in Uganda

3.1 Introduction

Farming is inherently a risky activity. Between the planting and harvest seasons, agro-climatic and economic conditions wherein the farmers operate can change drastically. The consequences of production decisions, generally made well in advance, are thus imperfectly predictable, leading to farm revenues either better or worse than expected (Harwood et al., 1999; Hardaker et al., 2004). There are different types of risks to which a farmer is regularly exposed, among which production/yield and price risks. Production risk originates from supply shocks often related to weather conditions, such as insufficient or excessive rainfall and precipitation, extreme temperature, or from pest infestations. On the other hand, price risks are usually related to fluctuations caused by changes in both demand and supply conditions (Coyle, 1992, 1999; Just and Pope, 2001; Isik, 2002).

Different management tools may help the farmers protect themselves *ex-ante* against production and price uncertainties[48] or mitigate *ex post* their adverse consequences. These strategies range from crop insurance, production or futures options contracts, hedging in futures, to enterprise diversification (Harwood et al., 1999). While many of these options may mitigate the extent of production and price risks, their applicability in developing countries is quite limited due to various institutional and structural constraints, such as poor or absence of well-organized formal insurance and credit markets, the apparent complexity of such coping mechanisms for most farmers, often under-educated, or simply the lack of confidence and interest in those management tools. As an alternative, most farmers in developing countries rely on self-insurance measures to cope with agricultural risks and market fluctuations. They often make different adjustments in the cropping

[48] The terms risk and uncertain are used interchangeably in the study

pattern across both crops and agricultural seasons when they anticipate important changes in weather or market conditions.

Understanding and evaluating the impact of both yield and/or price expectations and their variability on crop choices and acreage allocations have thus become the focus of attention of many applied agricultural economics' studies. These studies, some dating back many decades, have developed both theoretical and empirical models of farmers' responses in presence of price and yield uncertainties. In one of the early attempts to study acreage decisions under multivariate risk, Chavas and Holt (1990) estimated a system of acreage equations for corn and soybean in the United States and found that both risk and wealth variables were significant determinants of corn-soybean acreage allocation decisions. Also, Fafchamps (1992) showed that, in developing countries, crop diversification is generally preferred by small farmers as a response to high price variance in the absence of formal insurance mechanisms. Recently, the swing in commodity prices in 2008, to levels not seen since the early 1970s, led to abundant empirical studies questioning the adjustement of land uses to these price changes (Hausman et al., 2012, and Livingston et al., 2008, 2014 for the United States; Weersink et al., 2010 for Ontario in Canada; Lacroix and Thomas, 2011 for France).

In Sub-Saharan Africa, several studies have been conducted on the determinants of land allocations. Among them, Chibwana et al. (2011) and Mponela et al. (2011) reported that household characteristics (age, education, sex, land ownership, and non-farm incomes) were the main drivers of changes in land distribution patterns in Malawi. Constructing farmers' risk indices from Ethiopian data, Bezabih et al. (2011) found that crop portfolio choice was essentially influenced by rainfall variability and that farmers were likely to choose less risky crops at the expense of high returns. In Uganda, Mwaura (2014) concluded that access to infrastructure, households' stock of education and cultivated area were the key factors that affect land allocations.

Methodologically, different approaches have been applied to estimate acreage response functions. They range from the estimation of structural models of multi-output profit function, input allocations and land use (Carpentier and Letort, 2009; Fezzi and Bateman, 2011; Lacroix and Thomas, 2011; Kaminski et al., 2013) to reduced-form crop choice models (Bezabih et al., 2011; Anderson and Wang, 2012; Allen, 2012).

Built on these studies, this third essay aims at modeling and estimating the responsiveness of agricultural land allocations to changes in agro-climatic and economic conditions, with a particular emphasis on price and yield risks and farmers' expectations of their levels. The study revisits acreage response models based on the theoretical framework of Chavas and Holt (1990), Coyle (1992), and Holt (1999) in order to investigate the main drivers of crop portfolio decisions by farmers in developing countries under risks and unobserved farm and crop heterogeneity. It makes several contributions to the existing empirical studies on farmer's acreage responses.

First, it explores two intertwined dimensions related to acreage decisions that are often emphasized in the literature, namely a multivariate crop selection and the allocation of land area to each potential crop. To take account of this interdependence, farmers' acreage responses are modeled as a two-step procedure. During the first step, farmers determine which crop(s) to grow given their expectations of end-of-season prices and yields, their volatility, and other control variables (weather volatility, farmer and land characteristics…). Conditional on the selected crops, farmers then decide how to share out their land.

Second, while the majority of the previous studies are essentially based on static models and therefore ignore the dynamic nature embodied in agricultural activities, this essay models farmers' decisions as a dynamic process, thereby capturing the possibility of both own and cross state dependencies as well as distinguishing between genuine and spurious state dependencies.

Third, most of the existing studies have centered their attention on aggregated or county-level estimations of land use allocations. Although aggregated data are generally easily accessible and substantially minimize the presence of corner solutions, they present the downside of ignoring farm heterogeneity within counties or regions (Fezzi and Bateman, 2011). In this study, farmers' acreage decisions are modeled and estimated using farm- and plot-level data. These data are often very comprehensive and provide complete information on input uses at plot level, land use allocations, farmers' revenues, costs, and capital likely to improve the empirical analysis of farmers' crop decisions. Furthermore, the panel nature of the data allows to control for unobserved farm heterogeneity which is often a major component in land-use models (Wu et al., 2004; Lacroix and Thomas, 2011).

Fourth, although farm-level data permit direct estimations of acreage share responses to exogenous shocks, the presence of important amount of zero observations in land-use allocations and the bounded nature of the land shares complicate the econometric analysis. To deal with these issues, most studies estimate crop share models using essentially multivariate Tobit specifications. The main drawback of these specifications is that they wrongly treat zero observations as a result of censoring and cannot ensure that the predicted crop shares will lie between 0 and 1 or sum up to 1 for each farmer. As an alternative specification which assures that the above conditions are met, this study uses a multivariate generalization of the fractional regression model[49] proposed by Papke and

[49] In her study of land allocations in Uganda, Mwaura (2014) also used a fractional multinomial logit model. However, the model presented here fundamentally differs from hers in many aspects. First, she only made use of 2 survey rounds (2005/6 and 2009/10) while the present study takes advantage of the last four household surveys in Uganda and therefore generalizes her results and provides much more robust estimates and interpretation. Second, her

Wooldridge (1996, 2008) and recently applied by Sivakumar and Bhat (2002), Mullahy and Robert (2010), Lopez-Garcia and Montero (2010), Wagner (2010), Koch (2010), and Mullahy (2011). The estimation approach is applied to six crops or crop groups (*matooke*, cassava, maize, potatoes, beans, and other cereals) using a four-wave balanced panel of 1,598 agricultural households in Uganda using data collected between 2005 and 2012 by the Uganda Bureau of Statistics (UBoS) as part of the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank.

The results indicate that incorporating past farmers' crop choices and accounting for unobserved heterogeneity significantly improve the predictability performance of the land use models, thereby highlighting the importance of modeling crop choice decisions as a dynamic process. They also shed light on the presence of both strong inertia (positive own state dependence) for all crops but moderate spillover effects (significant cross-state dependence) for most crops. Moreover, farmers are found to be more sensitive to changes in expected yield levels than in expected end-of-season output prices, and yield risks, temperature and rainfall volatility have more impact on crop choices and acreage share allocations than market price risks.

The remainder of the essay proceeds as follows. Section 3.2 presents the conceptual model and its theoretical predictions. Section 3.3 discusses both the empirical implementation of the theoretical model and the related econometric issues. Section 3.4 describes the data used in the estimation of crop choice and acreage share models and further details the construction of some key variables and presents their descriptive statistics. Section 3.5 presents and discusses the main econometric results. Section 3.6 evaluates the prediction performance of the models and finally, section 3.7 gives some concluding remarks.

3.2 Theoretical model

In this section, I outline the theoretical model and the main assumptions made. Some of them are justified by the specificities of the Ugandan agricultural economy and the focus of the present study on price and yield risks, and land allocation constraints, while others mainly respond to the necessity to render the empirical models as tractable as possible and to minimize data requirements (Bonfatti, 2010). To motivate the econometric analysis, I develop a conceptual model in which a representative farmer has land as the only fixed allocation input. That is crops compete for

model is essentially static and does not take account of unobserved heterogeneity among farmers or crops. Last but not least, her analyses leave aside the influence of risks (production, price, and weather risks) in driving farmers' acreage decisions.

allocations of a fixed amount of land, and consequently increases in the land share of one crop in the short run implies inevitably the adjustments in the land allocations of other crops.

Consider a farmer that grows *K* different crops subject to the total land available $\bar{L}$. Furthermore, let $\mathbf{y}$ be a $K \times 1$ vector of end-of-season yields (per acre) for the *K* crops, with elements y_k; $\mathbf{p}$ a $K \times 1$ vector of end-of-season output prices, with elements p_k; $\mathbf{w}$ a $K \times 1$ vector of per-acre production costs, with elements w_k; $\mathbf{a}$ a $K \times 1$ vector of acreages allocated to the *K* crops, with elements a_k; and $\mathbf{s} = (1/\bar{L}) * \mathbf{a}$ a $K \times 1$ vector of acreage shares for the *K* crops, with elements s_k. While production costs are generally known during the planting season, end-of-season outputs and crop prices are unobserved by the farmer at the time the production decisions are made because of various factors generally beyond the farmer's control (rainfall variability, loss of all or part of production due to pest infestations,…) and must therefore be based on farmers' expectations.

Following Coyle (1999), I adopt a mean-variance approach which expressed the utility to be maximized $U(\pi)$ in terms of the first two moments of the farmer's profit (expected profit $E(\Pi)$ and profit risk σ_Π^2). The objective of the farmer is to maximize the expected utility of profit given the fixed land allocable constraint. Under both price and yield risks, the problem can be stated as:

$$\underset{\mathbf{s}}{Max} \quad \bar{L}\sum_{k=1}^{K} s_k E(r_k) - \frac{1}{2}\alpha\left(\bar{L}\right)^2 \left\{\sum_{k=1}^{K} s_k^2 \operatorname{var}(r_k) + 2\sum_{j \neq k}^{K} s_j s_k \operatorname{cov}(r_j, r_k)\right\} \tag{3.1}$$

$$\text{such that} \quad \sum_{k=1}^{K} s_k \leq 1$$

where E is an expectation operator; $r_k = p_k y_k - w_k$ is the per-acre net return of crop *k*. $E(r_k) \equiv r_k^e = p_k^e y_k^e + \operatorname{cov}(p_k, y_k) - w_k$ is the per-acre expected net return of crop *k*, with p_k^e and y_k^e the expected price and per-acre yield of crop *k*; s_k is the acreage share devoted to crop *k*; α is the Arrow-Pratt coefficient of absolute risk aversion which indicates risk-averse, risk-neutral, and risk-seeking attitude if $\alpha > 0$, $\alpha = 0$, and $\alpha < 0$, respectively[50]. Equation (3.1) sheds light on the role of both risks (price and output) and farmer's risk attitude on the acreage allocation process. From equation (3.1), the *K* + 1 first-order conditions to the farmer's optimization problem are given by:

$$\frac{\partial L}{\partial s_k} = r_k^e \bar{L} - \alpha\left(\bar{L}\right)^2 \left[s_k \operatorname{var}(r_k) + \sum_{j \neq k}^{K} s_j \operatorname{cov}(r_j, r_k)\right] - \phi = 0, \quad k = 1,\ldots,K \tag{3.2}$$

[50] Throughout this essay, farmers are assumed to present some degree of risk aversion, as consistently outlined in many empirical studies (Binswanger, 1980 and 1981; Chavas and Holt, 1990; Pope and Just, 1991).

$$\frac{\partial L}{\partial \phi} = 1 - \sum_{k=1}^{K} s_k = 0 \tag{3.3}$$

The solution to these FOCs gives a system of K optimal acreage share equations $\mathbf{s}^*(\mathbf{p}, \mathbf{w}, \Omega_r, \bar{L}, \alpha)$ and the optimal value of the Lagrange multiplier associated with the land constraint $\phi^*(\mathbf{p}, \mathbf{w}, \Omega_r, \bar{L}, \alpha)$, with Ω_r, the variance-covariance matrix of crop returns.

To see how these optimal acreage shares are modified by changes in price or yield risks, let us assume that the farmer only grows two competing crops, j and k[51] and that $\alpha = 1$. Under the above model assumptions, the FOCs can be expressed as follows:

$$\begin{bmatrix} (\bar{L})^2 \operatorname{var}(r_j) & (\bar{L})^2 \operatorname{cov}(r_j, r_k) & 1 \\ (\bar{L})^2 \operatorname{cov}(r_k, r_j) & (\bar{L})^2 \operatorname{var}(r_k) & 1 \\ 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} s_j \\ s_k \\ \phi \end{bmatrix} = \begin{bmatrix} r_j^e \bar{L} \\ r_k^e \bar{L} \\ 1 \end{bmatrix} \tag{3.4}$$

The system of optimal acreage shares and Lagrange multiplier associated with this model is then given by:

$$\begin{bmatrix} s_j^* \\ s_k^* \\ \phi^* \end{bmatrix} = \frac{1}{\bar{L} \operatorname{var}(r_j - r_k)} \begin{bmatrix} (r_j^e - r_k^e) + \bar{L}(\sigma_k^2 - \sigma_{jk}) \\ (r_k^e - r_j^e) + \bar{L}(\sigma_j^2 - \sigma_{jk}) \\ r_k^e (\bar{L})^2 (\sigma_{jk} - \sigma_j^2) + r_j^e (\bar{L})^2 (\sigma_{jk} - \sigma_k^2) + (\bar{L})^2 (\sigma_k^2 \sigma_j^2 - \sigma_{jk}^2) \end{bmatrix} \tag{3.5}$$

where $\operatorname{var}(r_j - r_k) = \sigma_j^2 + \sigma_k^2 - 2\sigma_{jk}$; $\sigma_k^2 = \operatorname{var}(r_k)$; $\sigma_j^2 = \operatorname{var}(r_j)$; $\sigma_{jk} = \operatorname{cov}(r_j, r_k)$

Equation (3.5) reflects implicitly the patterns of both crop substitution and complementarity as it asserts that the optimal acreage share allocated to the first crop will depend on the differential in expected net returns, the total land available and the price and yield risks of each crop (through the variance and covariance of their net returns).

How will the farmer react to a change in each of these variables? For simplicity, consider the case of statistical independence between end-of-season price and yield. In this case, the variance and covariance of the net returns are:

$$\operatorname{var}(r_k) \equiv \operatorname{var}(p_k y_k) = \delta_k^2 \eta_k^2 + (p_k^e)^2 \eta_k^2 + (y_k^e)^2 \delta_k^2 \tag{3.6}$$

and

$$\operatorname{cov}(r_j, r_k) \equiv E(p_j y_j, p_k y_k) = \eta_{jk}(\delta_{jk} + p_j^e p_k^e) + y_j^e y_k^e \delta_{jk} \tag{3.7}$$

where $\delta_k^2 = \operatorname{var}(p_k)$; $\eta_k^2 = \operatorname{var}(y_k)$; $\delta_{jk} = \operatorname{cov}(p_j, p_k)$; $\eta_{jk} = \operatorname{cov}(y_j, y_k)$

The sensitivity of the acreage shares to changes in price and yield risks (δ_j^2, η_j^2) and expected output prices (p_j^e, p_k^e) can then be summarized as follows:

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[51] The analysis can be readily generalized in case of K (>2) competing crops. See Holt (1999).

$$
\begin{cases}
\partial s_j^* / \partial \delta_j^2 = -\left(\overline{L}\right)\left[\eta_j^2 + \left(y_j^e\right)^2\right]\dfrac{N}{D^2} \le 0 \qquad if \quad N \ge 0 & (3.8a) \\
\partial s_j^* / \partial \eta_j^2 = -\left(\overline{L}\right)\left[\delta_j^2 + \left(p_j^e\right)^2\right]\dfrac{N}{D^2} \le 0 \qquad if \quad N \ge 0 & (3.8b) \\
\partial s_j^* / \partial p_j^e = \dfrac{\left[y_j^e - \eta_{jk}\, p_k^e \left(\overline{L}\right)\right] D + 2\left(\overline{L}\right)\left[p_j^e \eta_j^2 - p_k^e \eta_{jk}\right] N}{D^2} \ge 0 \qquad if \quad \eta_{jk} \le 0 \quad \text{and} \quad N \ge 0 & (3.8c) \\
\partial s_j^* / \partial \hat{p}_k^e = \dfrac{\left[-y_k^e + \left(\overline{L}\right)\left(2 p_k^e \eta_k^2 - \eta_{jk}\, p_j^e\right)\right] D - 2\left(\overline{L}\right)\left[p_k^e \eta_k^2 - p_j^e \eta_{jk}\right] N}{D^2} & (3.8d) \\
\partial s_j^* / \partial r_k^e = \partial s_k^* / \partial r_j^e = 1 / D & (3.8e)
\end{cases}
$$

with $D = \overline{L}\,\mathrm{var}(r_j - r_k)$ and $N = \left(r_j^e - r_k^e\right) + \overline{L}\left(\sigma_k^2 - \sigma_{jk}\right)$

In equations (3.8a) – (3.8d), optimal acreage share responses of crop *j* to changes in various exogenous variables are essentially driven by the differential in the expected net returns of the crops, $\left(r_j^e - r_k^e\right)$, the net return variance of the competing crop *k*, and the covariance between the net returns of *j* and *k*. For example, under the model assumptions, relation (3.8a) states that a risk-averse farmer will reduce the acreage allocated to a crop *j* in response to increases in its price variance only if its expected net return exceeds that of crop *k* ($r_j^e > r_k^e$) and the expected net returns of *k* and *j* are either uncorrelated or negatively correlated ($\sigma_{jk} \le 0$) . With regards to crop prices, equations (3.8c) and (3.8d) indicate that the responses of acreage shares to changes in expected prices are not straightforward. Hence, if the farmer anticipates a positive shock to the expected own-price of crop *j*, then the theoretical model predicts that he will allocate more land to that crop only if both yield and net return covariances are zero or negative, and that $r_j^e > r_k^e$. When it comes to the changes in the price of the competing crop, the model fails to predict an unambiguous sign even if one assumes that the expected prices, yields, and net revenues change in opposite directions. The sign will ultimately depend on the relative importance of each component.

Finally, by using the symmetry condition in (3.8e), the relation between price elasticities of acreage shares of *j* and *k* is given by:

$$\varepsilon_{kj}^p = \left(\pi_j^e / \pi_k^e\right)\left(\varepsilon_{jk}^p + \varepsilon_{jk}^y\right) - \varepsilon_{kj}^y \qquad (3.9)$$

where $\varepsilon_{kj}^p = \left(ds_k^* / dp_j^e\right)\left(p_j^e / s_k^*\right)$ and $\varepsilon_{jk}^p = \left(ds_j^* / dp_k^e\right)\left(p_k^e / s_j^*\right)$ are land shares' elasticities of *k* and *j* to changes in expected prices of *j* and *k*; $\varepsilon_{jk}^y = \left(ds_j^* / dy_k^e\right)\left(y_k^e / s_j^*\right)$ is the land share elasticity of *j* to changes in expected yields of *k*; $\pi_j^e = s_j r_j^e \overline{L}$ and $\pi_k^e = s_k r_k^e \overline{L}$ are expected profits of crops *j* and *k*. From (3.9), the cross-price acreage share elasticities of crops *j* and *k* would be equal $\left(\varepsilon_{kj}^p = \varepsilon_{jk}^p\right)$ only when both the crop-specific expected profits are equal $\left(\pi_j^e = \pi_k^e\right)$ and yield elasticities of land shares are equal $\left(\varepsilon_{jk}^y = \varepsilon_{kj}^y\right)$.

3.3 Empirical specification

The empirical specification is guided by the two main objectives of this third essay: on the one hand, understand how farmers decide which crops to grow given agricultural and market-related risks, farmers' expectations, and household characteristics; and on the other, what proportion of land should be optimally allocated to the selected crops. It follows that a farmer's acreage decisions can be modeled as a two-step decision process. Firstly, the participation or selection step during which the farmer chooses the crops to grow. Secondly, the conditional acreage allocation step wherein the farmer derives the optimal acreage share for each selected crop. As pointed out by Lacroix and Thomas (2011: 785), this is a case of multivariate crop selection problem since "(…) unobserved components may affect the choice of several crops by the farmer while influencing the final outcome in terms of land for crop (…)". Each above model allows farmers' land decisions to be determined by both current farm, farmer (un)observed characteristics and past land use decisions, leading to a dynamic crop allocation model. The estimation of these dynamic models seeks to verify a possible state dependence in farm acreage decisions and support for adjustment effects in farmers' land use, i.e. on the one hand, if farmers tend to continue to grow a crop once they have grown it previously or instead support for crop rotational effects; and on the other, if farmers maintain the same land share profile over time.

Referring to the notation used in the previous section, let I_{hkt}^* and s_{hkt}^* denote respectively the latent response variable and latent acreage share corresponding to the *k*th crop in the *h*th farm at time *t*, for $k = 1,...,K; h = 1,...,N,$ and $t = 1,...,T$ *;* let also I_{hkt} and s_{hkt} represent their observable counterparts. The latent dependent variables in the selection and acreage share models associated with each crop *k* at time *t* can be expressed as follows:

$$I_{hkt}^* = \mathbf{V_1}'\boldsymbol{\beta}_\mathbf{k} + \alpha + \kappa_{hkt}, \qquad \forall h,k,t \tag{3.10}$$

$$s_{hkt}^* = \mathbf{V_2}'\boldsymbol{\gamma}_\mathbf{k} + \vartheta + \mu_{hkt}, \qquad \forall h,k,t \tag{3.11}$$

where $\mathbf{V}_1$ and $\mathbf{V_2}$ are vectors of independent variables, sharing some common elements. In $\mathbf{V}_1$ is also included a vector of lagged dependent variables $I_{hk,t-1}$, for $k = 1,..., K$, taking 1 if the farmer *h* grows crop *k* at time *t* – 1 and 0 otherwise. $\mathbf{V}_2$ also contains the vector of lagged acreage shares

$s_{hk,t-1}$, for $k=1,...,K$, which allows current farmers' decisions about a particular crop k to be influenced by previous allocation decisions on all competing crops.

α and ϑ are time-invariant unobserved heterogeneity which may exist at both the household level (for example unobserved farmer's ability) and the crop level (for example, suitability of a particular crop to specific types of land). ε_{hkt} and μ_{hkt} are error terms, assumed identically and independently distributed.

The dynamic structure in both (3.10) and (3.11) creates two theoretical and methodological problems: the initial conditions' problem and the treatment of unobserved heterogeneity. The well-known initial conditions' problem stems from the fact that the start of our observational period may not necessarily coincide with the start of the stochastic process underlying farmers' choices (Heckman, 1981a, b; Wooldridge, 2005a). In other words, crop and acreage decisions at time t = 1 (our first observational time period) depend on farmers' data at time t = 0, unavailable to the econometrician. As suggested by Wooldridge (2005a), one way of preventing estimators from being biased and inconsistent under the initial conditions' problem is to include as an additional regressor the value of the dependent variable at time t = 1 (initial crop choice or initial acreage share, depending on the model). The second problem is related to the treatment of unobserved heterogeneity. A within-transformation procedure cannot be applied to get rid of α or ϑ due to the nonlinearity of the models. Also, introducing $K-1$ dummy variables to estimate the unobserved heterogeneity will result in biased estimation of parameters in (3.10) and (3.11), unless $T \to \infty$, the so-called incidental parameters problem (Wooldridge, 2005a). Following Papke and Wooldridge (2008) and Lacroix and Thomas (2011), I thus apply the Mundlak-Chamberlain approach which consists in writing α and ϑ as a linear function of individual averaged values of time-varying covariates[52]. A similar approach has been applied by Erdem and Sun (2001), Devicienti and Poggi (2007), and Buddelmeyer and Wooden (2008). Taking account of both the initial conditions' and incidental parameters' problems, the unobserved individual heterogeneity in each crop equation k is expressed as follows:

$$\begin{gathered}\Lambda = \upsilon_k + \mathbf{\Delta_{h1}}'\boldsymbol{\upsilon}_{\mathbf{k1}} + \overline{\Gamma}_{\mathbf{hk}}'\boldsymbol{\upsilon}_{k\mathbf{2}} + a_{hk}, \qquad \forall k=1,\dots,K \\ \textit{with} \quad \Lambda = \{\alpha,\vartheta\}, \quad \mathbf{\Delta_{h1}} = \{\mathbf{I_{h1}},\mathbf{s_{h1}}\}, \quad \overline{\Gamma}_{\mathbf{hk}} = \{\overline{\mathbf{V}}_{1,\mathbf{hk}},\overline{\mathbf{V}}_{2,\mathbf{hk}}\} \quad \forall k=1,\dots,K\end{gathered} \tag{3.12}$$

[52] The Mundlak-Chamberlain approach relies on the assumption that α and ϑ are normally distributed. Although this seems restrictive, it is easier to implement. To allow for a more flexible functional form, a non-parametric strategy, similar to that of Heckman and Singer (1984) could be adopted. However, the flexibility it allows comes at cost, like the non-convergence of the estimator or the impossibility to inverse the Hessian to get standard errors (Bigsten et al., 2006).

where Λ are individual random effects, assumed to be K-variate normal with variances $\sigma^2_{\Lambda k}$ and covariance between k and j given by $\sigma_{\Lambda k}\sigma_{\Lambda j}\rho_{jk}$. $\mathbf{I_{h1}}$ and $\mathbf{s_{h1}}$ are the vector of first observations of farm choice and acreage shares in farm h, respectively; $\overline{\Gamma}_{\mathbf{hk}} = \frac{1}{T}\sum_{t=1}^{T}\Gamma_{\mathbf{hkt}}$; $\Gamma_{\mathbf{hk}} = \{\mathbf{V_{1,hk}}, \mathbf{V_{2,hk}}\}$. a_{hk} is a random component assumed distributed $N(0, \sigma^2_{akt})$.

These models are estimated for six main crops or crop groups: *matooke* ($k=1$), cassava ($k=2$), maize ($k=3$), potatoes[53] ($k=4$), beans ($k=5$), other cereals[54] ($k=6$), and a residual category defined as "other"[55] ($k=7$). In what follows, I describe more in detail the estimating equations for the selection and acreage share models and the econometric issues they raise.

3.3.1 Dynamic multivariate selection model

In this model, farmers are not restricted to choosing only one crop among the K possible alternatives[56]. Indeed, farmers in developing countries are often poorly insured against agricultural and market-related risks (price and yield variability, weather shocks…). To cope with such risks, they generally engage in crop diversification (Fafchamps, 1992; Kurosaki and Fafchamps, 2001; Mukherjee, 2010) by adopting a multi-cropping system with the hope that crops with relatively stable prices will compensate revenue variability caused by crops with more volatile prices. Furthermore, due to potential complementarity or substitutability between the crops to grow, it is most likely that the error terms in each crop selection model will be correlated with one another, advocating therefore for a simultaneous estimation of farmers' crop selection decisions. To allow for a possible multi-cropping strategy among farmers and the presence of both unobserved heterogeneity and state dependency, I estimate the multivariate selection model using a dynamic multivariate probit (Dynamic-MVP) regression:

$$I^*_{hkt} = \upsilon_k + \mathbf{Z}'\boldsymbol{\beta}_\mathbf{k} + \sum_{j=1}^{K}\eta_{jk}I_{hj,t-1} + \sum_{j=1}^{K}\upsilon_{jk}I_{hj1} + \overline{\mathbf{Z}}_\mathbf{h}'\boldsymbol{\upsilon}_{k\mathbf{2}} + \kappa_{hkt}, \qquad \forall h,k,t \tag{3.13}$$

with

$$I_{hkt} = 1\left(I^*_{hkt} > 0, \qquad \forall h = 1,\ldots,N; k = 1,\ldots,K; t = 1,\ldots,T\right)$$

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[53] Irish and sweet potatoes

[54] Rice, millet, and sorghum

[55] Crops and/or land uses included in this « other » category are farm-specific. They include crops such as groundnuts, wheat, or soybeans.

[56] It is theoretically possible to ensure that alternatives will be mutually exclusive even when the farmer can choose more than one crop (Train, 2003). However, when K is large, there is $2^K - 1$ possible crop combinations (excluding the one where no crop is grown) which represents 63 alternatives in a 6-crop choice model, as in this study (See Appendix C.1).

The error terms κ_{hkt} jointly follow a *K*-variate normal distribution with zero conditional mean and variance of 1, and a symmetric $K \times K$ covariance matrix $\mathbf{\Sigma}$. In this dynamic setting, true state dependence effects are captured through the dummies of the lagged dependent variables. The model also helps test for the presence of dynamic spillover effects in farmers' decisions by including cross-lagged values.

Let $\mathbf{\Omega}_{hkt}^{M}$ denote the vector of all right-hand side (RHS) variables in the dynamic multivariate crop selection model and $\mathbf{\theta}^{M}$ be the vector of all parameters to be estimated. To derive marginal probabilities, let $w_j = c_j\left(\mathbf{\Omega}_j^{M}{}'\mathbf{\theta}^{M}\right)$ and $c_j = \left(2I_j - 1\right)$, for $k = 1,\ldots,K$, where the subscripts *h* and *t* have been suppressed for convenience. In this case, the probability of observing a particular crop choice *j* among all possible combinations is given by (Cappellari and Jenkins, 2003):

$$\begin{aligned} &\Pr\left(I_1 = 0,\ldots,I_j = 1,\ldots,I_K = 0 \quad \middle| w_1,\ldots,w_j,\ldots,w_K\right) = \Phi_K\left(w_1,\ldots,w_j,\ldots,w_K;\bar{\Sigma}_j\right) \\ &= \int_{-\infty}^{-\left(\mathbf{\Omega}_1^{M}{}'\mathbf{\theta}^{M}\right)} \cdots \int_{-\infty}^{\left(\mathbf{\Omega}_j^{M}{}'\mathbf{\theta}^{M}\right)} \cdots \int_{-\infty}^{-\left(\mathbf{\Omega}_K^{M}{}'\mathbf{\theta}^{M}\right)} \phi_K\left(\kappa_1,\ldots,\kappa_j,\ldots,\kappa_K;\bar{\Sigma}_j\right) d\kappa_1 .. d\kappa_j .. d\kappa_K \end{aligned} \tag{3.14}$$

where $\Phi_K(.)$ and $\phi_K(.)$ are *K*-variate normal density and probability distribution functions, respectively. $\bar{\Sigma}_j = R_j \Sigma R_j$ with R_j is a *K* x *K* diagonal matrix with diagonal elements c_j et zeros elsewhere. In this *K*-variate probit model, it is straightforward to show that the log-likelihood function is (Greene, 2003):

$$\ln L = \sum_{h=1}^{N}\sum_{k=1}^{K-1}\sum_{t=1}^{T} I_{h,k,t} \ln \Phi_K\left(w_1,\ldots,w_j,\ldots,w_K;\bar{\Sigma}_j\right) \tag{3.15}$$

The estimation of this dynamic-MVP model was done using the Simulated Maximum Likelihood (SML) method with the Geweke-Hajivassiliou-Keane (GHK) simulator. The dynamic-MVP regression framework has previously been applied in various studies, including Seo and Mendelsohn (2007) for a multi-country analysis of African farmers' livestock choice under climate change scenarios, Oparinde and Hodge (2011) for households' adoption of coping strategies against health shocks in rural Nigeria, or Fleming (2014) for the adoption of management practices among Maryland farmers.

3.3.2 Dynamic acreage share model

An important aspect in farming activities consists usually in deciding how much of the available land to allocate to different crops. As discussed early, this decision can be affected by both current and past allocation decisions. Otherwise stated, I seek to evaluate the expected value of s_{hkt}^{*}, given the covariate vector $\mathbf{X_{hkt}}$, unobserved farm- and crop-specific effects ϑ, and past acreage shares $s_{hk,t-1}$, $\forall k = 1,...,K.$

To deal with potential sample selection in a multivariate setting, I apply a generalization of the Heckman two-step method proposed by Tauchmann (2005, 2010). The main virtue of this approach is that rather than restricting the estimation procedure to the subsample of farmers with positive crop selection as is commonly done, each element of the RHS is weighted by I_{hkt} so that the estimation is based on the full sample and conditioned on I_{hkt}.[57] Therefore, the second-step estimation of (3.11) is based on the conditional expectation:

$$E\left(s_{hkt}\middle|\mathbf{X_{hkt}}, \vartheta_{hk}, I_{hkt}\right) = I_{hkt}\mathbf{X'_{hkt}}\ \boldsymbol{\beta_k} + I_{hkt}\vartheta_{hk} + I_{hkt}\chi_k\lambda_k\left(\mathbf{Z'}\boldsymbol{\gamma_k} + \overline{\mathbf{Z}}'_{\mathbf{hk}}\ \boldsymbol{\zeta_k}\right),\ \forall h,k,t \quad (3.16)$$

In each equation k, the inverse Mills ratio $\lambda_k\left(\mathbf{Z'}\boldsymbol{\gamma_k} + \overline{\mathbf{Z}}'_{\mathbf{hk}}\ \boldsymbol{\zeta_k}\right)$ from the first-step multivariate crop selection model is included as an additional covariate with χ_k, its parameter to be estimated.

Given equation (3.11) and the procedure in (3.16), the dynamic crop acreage model has the following form:

$$s_{hkt} = \begin{cases} \upsilon_{0,k} + \mathbf{X'}\boldsymbol{\gamma}_k + \sum_{j=1}^{K}\psi_{jk}s_{hj,t-1} + \sum_{j=1}^{K}\upsilon_{j1}s_{hj1} + \overline{\mathbf{X}}_{\mathbf{hk}}'\boldsymbol{\upsilon}_{\mathbf{2,k}} + \chi_k\lambda_k + \mu_{hkt} & if\ I_{hkt} = 1 \\ 0 & if\ I_{hkt} = 0 \end{cases},\ \forall k,h,t \quad (3.17)$$

In (3.17), the coefficients $\psi_{jk}, \forall k = 1,..,K$ capture own- and cross-true state dependence effects. Hence, the acreage share of crop k at time t s_{hkt} is assumed to depend on both its previous acreage share ($s_{hk,t-1}$) and acreage shares allocated to alternative crops $s_{hj,t-1}$, $\forall j \neq k$. This enables to test for the present of dynamic spillover effects in farmers' crop decisions.

In estimating equation (3.17), we need to take account of the fact that the dependent variables (acreage crop shares) and their predicted values have two-corner outcomes, 0 and 1, with non-trivial probabilities and continuous values between 0 and 1. This relates to fractional dependent variables (Papke and Wooldridge, 1996, 2008) and implies that $s_{hk,t} = 0$ if $s^*_{hkt} \le 0$; $s_{hk,t} = s^*_{hk,t}$ if $0 < s^*_{hkt} < 1$; and $s_{hk,t} = 1$ if $s^*_{hkt} \ge 1$.

There is a long tradition in econometrics of estimating share or fractional models. Their applications include modeling time use, optimal portfolio shares, consumer budgets, or land use allocations. Various estimation strategies have been proposed in the literature to account for the bounded nature

[57] See Tauchmann (2005, Appendix A) for details. The estimation of the second step on the subsample of farmers for which $I_{hkt} = 1$ would lead to severerly unbalanced panel. Hence, this approach is particularly useful in the present study since the Woodridge's method of handling the initial observations' problem requires a balanced panel.

of the dependent variables. Early econometric attempts were applied in demand analysis for the estimation of systems of food consumption under censoring (Christensen et al., 1975; Deaton and Muellbauer, 1980; Banks et al., 1997; Yen et al., 2003). Recently, Fezzi and Bateman (2011) and Lacroix and Thomas (2011) estimate land use shares using a system of two-limit Tobit models via quasi-maximum likelihood. Despite the widespread use of uni- or multivariate Tobit models on fractional data among researchers, the estimated results do not guarantee that the fitted values will lie between 0 and 1[58]. In their seminal paper, Papke and Wooldridge (1996) develop a robust Quasi-Maximum Likelihood (QML) model, as in Gouriéroux, Monfort and Trognon (1984) for the estimation of a univariate fractional regression model through a Bernoulli log-likelihood function. Papke and Wooldridge (2008) extend their previous model to panel data and develop a QML estimation method to account for endogeneity. Several generalizations of Papke and Wooldridge works to the multivariate setting have been recently proposed to model various issues, from commodity flows (Sivakumar and Bhat, 2002) to transportation time (Ye and Pendyala, 2005), expenditure shares (Koch, 2010), household time use (Mullahy and Robert, 2010), financial asset portfolio (Mullahy, 2011), corporate capital structure choices (Ramalho, Ramalho, and Murteira, 2013) and education tests (Nam, 2012).

Along the lines of Mullahy and Robert (2010), and Mullahy (2011), I use a dynamic multivariate fractional logit (dynamic-MVFL) model to estimate equation (3.17). Indeed, one way of ensuring that the conditional mean $E\left(s_{hkt}\middle|\mathbf{\Omega}^{\mathbf{S}}\right)\in(0,1)$ and that $\sum_{k=1}^{K}E\left(s_{hkt}\middle|\mathbf{\Omega}^{S}\right)=1$ is to use a multinomial logit functional form:

$$E\left(s_{hkt}\middle|\mathbf{\Omega}^{S};\boldsymbol{\theta}_k^S\right)=Q\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_k^S\right)=\frac{\exp\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_k^S\right)}{\sum_{l=1}^{K}\exp\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_l^S\right)},\qquad l=1,\ldots,K \tag{3.18a}$$

$$=Q_k\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_k^S\right)=\frac{\exp\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_k^S\right)}{1+\sum_{l=1}^{K-1}\exp\left(\mathbf{\Omega}^{S}{}'\boldsymbol{\theta}_l^S\right)},\qquad \forall k\neq K \tag{3.18b}$$

where $\mathbf{\Omega}^{S}$ denote the vector of all RHS variables in the dynamic-MVFL model and $\boldsymbol{\theta}_k^S$ the vector of all parameters to be estimated in the *k*th equation. Similarly to standard multinomial logit models, identification of the multivariate fractional logit requires the normalization of one of the parameters. In this essay, I chose the share of "other crops" (k = 7) (equation (3.18b), implying that $\theta_K^S=\theta_7^S=0$.

[58] Another reason of the inappropriateness of the use of Tobit models is simply because the dependent variables are not actually censored since values outside the 0-1 interval are not feasible (Baum, 2008).

Assuming that the functional form in (3.18a) is correct and given the identification assumption in (3.18b), the multivariate fractional likelihood log-function is given by:

$$\ln L = \sum_{h=1}^{N}\sum_{k=1}^{K-1}\sum_{t=1}^{T} s_{h,k,t} \ln Q_k\left(\mathbf{\Omega}^{S}{}'\mathbf{\theta}^{S}\right) \tag{3.19}$$

The estimated parameters are then obtained from the first order conditions applied to (3.19)[59]. As is well known in any two-step estimation procedure, second-stage standard errors of parameter estimates will be incorrect because they are derived from the first-stage participation model. In the empirical estimation, I rely on bootstrapping methods[60]. However, the normalization required by the adding-up restriction renders difficult the interpretation of point estimates derived from the maximization of (3.19). To obtain results that are invariant with the type of normalization selected, the estimates of interest are acreage elasticities computed at sample average, and defined as the relative effect of a covariate x_j on the expected conditional means $E\left(s_{h,k,t}|\mathbf{X_{hkt}}\right)$. For continuous and discrete exogenous variables, these effects are given respectively by equations (3.20a) and (3.20b) (Mullahy and Robert, 2010):

$$\hat{\varepsilon}_{k,j} = \frac{\partial E\left(\hat{s}_{h,k,t}|\mathbf{X_{hkt}}\right)}{\partial x_j}\frac{x_j}{E\left(\hat{s}_{h,k,t}|\mathbf{X_{hkt}}\right)} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} x_{ijt}\left(\hat{\gamma}_{kj} - \sum_{l=1}^{K-1}\hat{\gamma}_{lj}Q_l\right) \tag{3.20a}$$

$$= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} x_{ijt}\left[Q_K\left(X_{ht,-j}\hat{\gamma}_{k,-j} + \hat{\gamma}_{kj}\right) - Q_K\left(X_{ht,-j}\hat{\gamma}_{k,-j}\right)\right] \tag{3.20b}$$

where $\hat{\varepsilon}_{k,j}$ stands for the estimated expected acreage elasticity of crop k with respect to changes in the covariate x_j. Due to the adding-up restriction, $\sum_{j=1}^{K}\hat{\varepsilon}_{k,j} = 0$, which implies that the effect of a covariate will lead to a reallocation of land across crop alternatives. $\hat{\gamma}$ is the estimated parameter; $\hat{s}_{h,k,t}$ is the estimated share of land allocated to crop k by household h in year t. $X_{ht,-j}$ is the covariate vector for the h-th observation, excluded the j-th element.

To investigate the causal factors of both multivariate crop choices and crop acreage shares, I include in $\boldsymbol{X_{hkt}}$ and $\mathbf{Z_{hkt}}$ six categories of explanatory variables, namely expected output prices (p_{kt}^{e}) and

[59] The estimation of the multivariate fractional logit model was done using a Quasi-maximum likelihood function programmed in Stata's Mata language written by John Mullahy who kindly provided the author with the codes. Although his approach was primarily intended for cross-sectional data, it can be readily extended to the panel data case by appealing to the Correlated Random Effects approach to estimation (Chamberlain, 1980 and Mundlak, 1978) and specifying the conditional mean of the unobserved effect as a parametric function of the time-averages of the independent variables as in (3.12).

[60] The number of replications used was chosen following the approach proposed by Andrews and Buchinsky (2000). Each crop share was estimated separately to derive the optimal number of bootstrap replications which were then averaged out in the multivariate fractional logit estimation.

yields (y^e_{kt}), their respective risk measures (vp^e_{kt} and vy^e_{kt}), farm or land characteristics, climatic variables, and farmer's characteristics. Referring to land characteristics, I control for total land size (tld), land quality (ldq), type of land irrigation ($tdir$), and the nature of land slope ($ldsp$). ldq measures the proportion of fertile plots (land of good quality) in the total plots cultivated by the farmer; $ldir$, the proportion of rain-fed plots, and $ldsp$, the proportion of plots with flat or gentile slopes. Climatic variables include the average expected monthly rainfall (mar), its coefficient of variation ($marcv$), the temperature deviation (dmt)[61] and its coefficient of variation ($dmtcv$). Farmer's characteristics contain the years of education ($educ$), age (age), and gender (sex) of the household head, as well as the household size (hsz). I impose exclusion restrictions by including in $\mathbf{Z_{hkt}}$ adult ratio (adr)[62], non-farm income (nfi), and regional dummies variables.

3.4 Data and construction of variables

The implementation of the acreage allocation model described in the previous section requires a substantial amount of data regarding crop choices, farmers' expectations of output prices and yields, farm and farmer characteristics, and climatic variables. Data on crop choices, land use and size, variable input prices and quantities (labor, seeds, pesticides, fertilizer,…), farm and household characteristics are obtained from a four-wave panel dataset of the Uganda National Panel Surveys (UNPS) conducted in 2005/6, 2009/10, 2010/11, and 2011/2012[63] by the Uganda Bureau of Statistics (UBoS). For this study, each wave contains information on 1,598 balanced agricultural households, located in all the geographical regions of the country. Pooling these time series and cross-sectional data gives 6,392 observations for the crop choice and acreage allocation models (1,598 farmers x 4 years).

3.4.1 Plot size

The surveys report two measures of land size: GPS measures and farmer's own estimation. However, while area measures from farmers' own assessments are available for almost all plots, GPS-based area measures suffer from important missing values due to various constraints such as

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[61] The difference between monthly maximum and minimum temperatures (in degrees Celsius).

[62] Defined as the ratio between the number of household members above 18 and the total household size

[63] The first wave (2005/6) collected agricultural information for the second cropping season of 2004 (July-December 2004) and first cropping season of 2005 (January-June 2005). The remaining waves gathered information for the two cropping seasons (January-June and July-December) of 2009, 2010, and 2011, respectively. Hence, to avoid confusion from the reader between the timing of the surveys and the periods they actually covered for the agricultural module, I will subsequently refer to the panels in terms of waves 1 to 4.

"[…] reducing survey costs, […] keeping household interview durations within reasonable limits, and […] the difficulty of asking respondents to accompany enumerators to agricultural plots that are situated far from dwelling locations […]" (Kilic at al., 2013: 3). To deal with these missing GPS-based data, I apply a multiple imputation approach initiated by Rubin (1987).[64] Hence, in all the subsequent analyses, land size will refer to multiply imputed land areas.

The persistent or transitory nature of distributional land patterns can be analyzed using transition matrices for successive panel waves[65]. Results presented in table 3.1 indicate unequal land dynamics during the sample period.

***Table 3.1** Bivariate transition matrices of changes in the distribution of total land holdings*

		Land size in 2011/12 (acres)						
		]0 ; .6[	[.6 ; 1.25[	[1.25 ; 2.5[	[2.5 ; 7[	[7 ; 10[	>=10	N. obs.
	]0 ; .6[	**46**	23.9	17.2	10	1.4	1.5	402
Land size in	[.6 ; 1.25[	19.2	**26.1**	25.8	25.3	1.5	2.1	395
2005/6	[1.25 ; 2.5[	8.1	15.7	**29.4**	36.5	6.1	4.2	394
(acres)	[2.5 ; 7[	6	7.3	19.3	**49.1**	8.5	9.8	316
	[7 ; 10[	2.9	5.7	0	57.1	**17.1**	17.2	35
	>=10	3.8	8.9	12.5	26.8	7.1	**41.1**	56
		Land size in 2009/10						
		]0 ; .6[	[.6 ; 1.25[	[1.25 ; 2.5[	[2.5 ; 7[	[7 ; 10[	>=10	N. obs.
	]0 ; .6[	**60.2**	22.4	10.2	5.7	0	1.8	402
Land size in	[.6 ; 1.25[	24.1	**40.8**	22.8	9.9	1.5	.9	395
2005/6	[1.25 ; 2.5[	8.9	28.4	**36.3**	21.3	2	3.1	394
	[2.5 ; 7[	7.6	11.4	22.2	**44.9**	5.1	8.8	316
	[7 ; 10[	2.9	14.3	8.6	45.7	**11.4**	17.1	35
	>=10	5.4	8.9	8.9	25	8.9	**42.9**	56
		Land size in 2010/11						
		]0 ; .6[	[.6 ; 1.25[	[1.25 ; 2.5[	[2.5 ; 7[	[7 ; 10[	>=10	N. obs.
	]0 ; .6[	**55.3**	25	11.8	5.8	.8	1.5	400
Land size in	[.6 ; 1.25[	16.6	**32**	29.6	17.6	.7	3.5	409
2009/10	[1.25 ; 2.5[	5.1	19.6	**35.5**	32.7	3.4	3.7	352
	[2.5 ; 7[	3.5	5.3	18.2	**54.1**	7.9	11	318
	[7 ; 10[	2.6	2.6	5.1	33.3	**25.6**	30.8	39
	>=10	8.8	1.3	7.5	22.5	8.8	**51.3**	80
		Land size in 2011/12						
		]0 ; .6[	[.6 ; 1.25[	[1.25 ; 2.5[	[2.5 ; 7[	[7 ; 10[	>=10	N. obs.
	]0 ; .6[	**54.6**	19.9	13.8	8.9	1.2	1.6	326
Land size in	[.6 ; 1.25[	23.2	**40.4**	23.5	10.7	1.6	.6	319
2010/11	[1.25 ; 2.5[	10.9	15.3	**39**	31.5	1.9	1.4	359
	[2.5 ; 7[	3.9	8.7	17.4	**58.1**	7.3	4.6	413
	[7 ; 10[	1.7	3.3	15	36.7	**26.7**	16.7	60
	>=10	5.8	5	11.6	29.8	8.3	**39.7**	121

Note: Each cell gives the row percentage.

[64] The Stata's `mi impute` command has been used to impute these missing values. (See Appendices C.2 – C.4).

[65] The intervals were constructed from the pooled distribution of land sizes. Farms were divided into 2 broad categories: small farms (<10 acres) and large farms (>=10 acres). Small farms were then subdivided into 4 groups using respectively the 25th percentile, the median, the mean, and the 75th percentile as bounds. For each survey, extreme or outlier values were defined as those beyond the 99th percentile and replaced by values observed at that percentile.

Between the first and last wave (part one of the table), important transitions are observed but state persistence is relatively mitigated: for example, only 46% of farms with less than 0.6 acres remained in the same state in the last wave and 1.5% increased their land size up to more than 10 acres. However, between successive waves, the table uncovers very high persistence, particularly for states 1 and 4. For example, although there is a significant decrease over time in the persistence rate within state 1 (from 60.2 to 55.3 and 54.6%), persistence in state 4 shows instead a significant increase (from 44.9 to 54.1 and 58.1%), suggesting that likelihood of moving from state 1 (very small farms) to other states (medium or large farm sizes) increased over time.

3.4.2 Representation of price expectations and risks

At the time production decisions are made, a farmer ignores what will be the end-of-season output prices. The empirical implementation of crop choice and acreage share models thus requires a statement on how farmers form their expectations about future prices and their related risks. There is no consensus as to how variables representing riskiness in prices should be formulated in econometric models. Various models of price expectations tested for agricultural commodities include: naive expectations (Houck and Gallagher, 1976; Shumway and Chang, 1980; Chavas and Holt, 1990), adaptive expectations (Nerlove, 1958), rational expectations (Muth, 1961; Goodwin and Sheffrin, 1983; Shonkwiler and Emerson, 1982; Beach et al., 1995, among others), futures prices (Schroeder and Goodwin, 1991), or a combination of the previous models (Lopez, 1986; Tada, 1990). The *naive* expectations model states that today's price is simply the most recently observed (or previous) price; the *adaptive* expectations model argues that the expected price is the weighted average of the previous price and the previous expected price, with geometrically declining weights; the *rational* expectations model assumes that expectations are formed based on the relevant structure of the economic system given all relevant information available to the farmers when planting decisions are made. Finally, the *composite* expectations model considers the expected price as a weighted average of prices based on adaptive and rational expectations.

These expected prices were computed using monthly real food prices[66] from time series' prices collected by the Foodnet market price information project of the International Institute of Tropical Agriculture (IITA). The Foodnet dataset consists of weekly wholesale price series for 23 Ugandan

[66] For each series, nominal prices were deflated by the UBoS all items' consumer price index (2005/06=100) to take account of potential changes in the purchasing power of Ugandan households.

markets[67] and more than 20 staple foods from September 1999, week 40 to December 2012, week 52[68].

Let $p_{M,t}$ be the market price of crop *i* at time *t* and $p^e_{N,t}$, $p^e_{A,t}$, $p^e_{R,t}$, and $p^e_{MX,t}$ denote its expected value derived from the naive, adaptive, rational, and composite expectations models, respectively. Following Chavas et al. (1983), Chavas and Holt (1990), and Tada (1990), $p^e_{N,t}$ and $p^e_{A,t}$ can be written as:

$$p^e_{N,t} = p_{M,t-1} \tag{3.21a}$$

$$p^e_{A,t} = p^e_{A,t-1} + \beta\left(p_{M,t-1} - p^e_{A,t-1}\right) = \sum_{n=1}^{\infty} \beta(1-\beta)^{n-1} p_{M,t-n} \approx \sum_{j=1}^{J} \omega_j E_{t-j-1}\left(p_{M,t-j}\right) \tag{3.21b}$$

where E_{t-j-1} is the expectation, when crop *i* is planted at time $t - j$, of the end-of-season price in year $t - j$ and $E_{t-j-1}\left(p_{t-j}\right) = p_{M,t-j-1}$. ω_j are declining weights as we go back in time and are expressed as $\omega_j = \frac{2(J+1-j)}{J(J+1)}$, with *J* the number of lags (Hommes, 1998). For simplicity, I only consider the case where *J* = 3 (i.e the past three observed market prices)[69]. Given $p^e_{N,t}$ and $p^e_{A,t}$, the expected price variances are defined as a weighted sum of the squared deviations of the past 3 market prices from their respective expected values. Formally, the expected price variance of crop *k*, δ^2_{kt}, and expected price covariance of crops *j* and *k* in time *t*, δ_{jkt}, are expressed as follows:

$$\delta^2_{kt} = \sum_{i=1}^{3} \omega_i \left(p_{k,t-i} - p^e_{\Delta,k,t-i-1}\right)^2 \tag{3.22a}$$

$$\delta_{jkt} = \sum_{i=1}^{3} \omega_i \left(p_{j,t-i} - p^e_{\Delta,j,t-i-1}\right) \times \left(p_{k,t-i} - p^e_{\Delta,k,t-i-1}\right), \quad \text{with} \quad p^e_{\Delta,t-i-1} = \left\{p^e_{N,t-i-1}, p^e_{A,t-i-1}\right\} \tag{3.22b}$$

In regards to the rationally expected prices $p^e_{R,t}$, I draw on the work of Feige and Pearce (1976) and Nerlove et al (1979) who have shown that rational expectations can fundamentally be approximated using ARIMA specifications. I test the order of integration of each price series allowing for the

[67] Arua, Gulu, Kitgum and Lira in the Northern region; Luwero, Masaka, Rakai, Kiboga, and Kampala (Kisenyi, Owino, Nakawa, Kalerwe) in the Central region; Iganga, Mbale, Jinja, Soroti, and Tororo in the Eastern region; and Jinja, Kabale, Kibale, Kasese, Hoima, and Mbarara in the Western region

[68] The use of market-level data to derive price expectations of economic agents is not exempt from criticisms. Overall, the main criticism is the assumption of homogenous information set for all market participants (Pesaran, 1987). Therefore, in the absence of data on farmer-level expectations over output prices, the analysis carried out in this third essay should be considered as an indirect approach of deriving price formation in Uganda.

[69] In this case, the weights are given by $\omega_1 = .5$, $\omega_2 = .33$, and $\omega_3 = .17$

possibility of structural breaks using Bai and Perron (2003) tests[70]. Appendix C.5 reports the ARIMA estimates for the selected price series[71]. The same procedure is applied to derive expected price variances of each price series.

Knowing $p^e_{R,t}$, the composite expected price is given by $p^e_{MX,t} = \lambda * p^e_{A,t} + (1-\lambda) * p^e_{R,t}$, where $0 \leq \lambda \leq 1$[72]. Crop price risks ($vp^e_{N,i}, vp^e_{A,i}, vp^e_{R,i}, vp^e_{MX,i}$) are thus defined as the square root of the expected price variances derived from different expectations models.

To identify which expectations model best describes the price formation process, I use a simple unbiasedness test from the estimation of the following relationship:

$$p_{M,t} = \alpha + \beta * p^e_{\Delta,t} + \mu_t \text{, with } p^e_{\Delta,t} = \left\{ p^e_{N,t}, p^e_{A,t}, p^e_{R,t}, p^e_{MX,t} \right\} \quad (3.23)$$

In order for price forecasts to be consistent with observed prices, they should be unbiased predictors of the actual market prices. This implies that the intercept $\alpha = 0$ and the slope $\beta = 1$ at 5% significant level (Beach et al., 1995). Appendix A.6 contains the results of the unbiasedness tests. They suggest that the null hypothesis of unbiasedness is rejected for all commodities in the naive (except for other cereals), adaptive, and rational (except for maize) expectations models. However, when we combine the adaptive and rational expectations models using the λ values that offer the best statistical fits (Adjusted R – squared)[73] for the price expectation model (3.23), we fail to reject the null hypothesis of unbiasedness for all selected commodities. In other words, at the market level, the estimated results advocate for a mixed expectations model rather than a pure naive, adaptive, or ARIMA models. Consequently, all expected prices and price risks used in the crop choice and acreage share estimations will refer to the composite expectations model. Lopez (1986), Tada (1991), and Chembezi (1994) have also demonstrated the high capacity of the composite models in explaining price expectations behavior.

3.4.3 Expected yields and yield risks

To obtain the expected yields (y^e_k), we need to identify the set of weather variables likely to influence the level of end-of-season yields. It is well-established for example that the levels of

[70] In the case of structural breaks or shifting trends in price series, the standard Augmented Dickey-Fuller (1981), Phillips-Perron (1988) unit root tests become biased because of their potential confusion of structural breaks in the series as evidence of non-stationarity (Ghoshray, Kejriwal, and Wohar (2012). See essay I, section 1.4.1.

[71] Results of the unit root tests (not presented here) indicated that all price series were I (1). Hence, in the $\text{ARIMA}(p,d,q)$ estimation results, the price series were first-differenced (*d* = 1).

[72] In the extreme case where $\lambda = 0$, producers are assumed to form their expectations based solely on the ARIMA specification. On the opposite side $\lambda = 1$ implies price expectations according to the adaptive model. Finall, when $0 < \lambda < 1$, both adaptive and rational models are accounted for in farmers' price expectations.

[73] 0.3 for cassava and beans; 0.4 for *matooke* and potatoes; 0.5 for maize and 0.6 for other cereals.

rainfall, precipitation, and temperature are important factors in determining crop yields (Mitchell et al., 1990; Porter and Semenov, 2005; Lobell et al., 2007). To derive farmers' expected yields, I follow the specification proposed by Chavas and Holt (1990) and applied in numerous empirical studies (see, for example, Lin and Dismukes, 2007; Weersink, et al., 2010; Liang et al., 2011):

$$y_{hkdt} = \mathbf{W}_{dt}'\alpha + \beta_{dt}t + \theta_{kd} + \varepsilon_{hkdt} \tag{3.24}$$

where y_{hkdt} is the current yield of crop *k* for a farmer *h* living in cluster/district *d* at time *t*. $\mathbf{W}$ is a vector of weather variables[74] in district *d* at time *t* (expected monthly rainfall mar and deviation in temperature dmt and their coefficients of variation $marcv$ and $dmtcv$) and their quadratic terms to allow for non-linear effects of weather factors (Porter and Semenov, 2005); θ_{kd} is district-level fixed effect, and *t* denotes a linear time trend. Equation (3.24) was then estimated separately for each crop *k*.

Given that data on yields are left-censored at 0, I used a panel Tobit regression and take out the predicted values as expected yields. Crop yield risk (vy^e_{kt}) was then measured as the standard deviation of the estimated residuals from the Tobit model.

Appendix C.7 defines key variables and presents their descriptive statistics.

3.5 Empirical results

3.5.1 Dynamic multivariate crop selection model

The estimated coefficients of the dynamic multivariate crop selection model reported in table 3.2 are derived from the empirical specification elaborated in equation (3.13). The model was estimated using the Simulated Maximum Likelihood (SML) method and the GHK simulator, with initial conditions *a la* Wooldridge. As suggested by Cappellari and Jenkins (2003), I choose the

[74] I obtain data on climatic characteristics from various annual issues of the Statistical Abstracts of the UBoS. These data contain monthly information on temperature (degree Celsius) and rainfall (mm). Although yield data are at farm level, data on temperature and rainfall were only available for 12 meteorological stations covering all the geographical regions of the country: Arua, Gulu, and Lira in the Northern region; Entebbe and Kampala in the Central region; Jinja, Soroti, and Tororo in the Eastern region; and Kabale, Kasese, and Mbarara in the Western region. These data were then merged with farm survey data for the respective years. Similarly to Coyle (1999), mean and variance of weather variables in station *s* at time *t* were first computed as: $\bar{\tau}_{st} = \tau_{s,t-1}$ and $\mathrm{var}(\tau_{st}) = \sum_{i=1}^{3} \omega_i \left(\tau_{s,t-i} - \bar{\tau}_{s,t-i}\right)^2$, with the weights ω_i being defined as in (3.22). For each region, these means and variances were then averaged over their respective stations.

number of draws (100)[75] greater than the square root of the sample size (80) to reduce the simulation bias. I also derived starting values from univariate random-effects probit regressions (Cappellari and Jenkins, 2006; Fezzi and Bateman, 2011) and dropped from the final model variables that presented a high collinearity, particularly covariances between expected prices.

We first note that all coefficients of pairwise correlations between error terms (ρ_{ij}) are statistically significant, supporting the hypothesis of interdependence of farmers' crop choices and the appropriateness of a joint estimation of the crop selection equations. Moreover, the likelihood ratio test rejects at a high significance level the hypothesis that all pairwise correlations of error terms are simultaneously zero. The model prediction also appears satisfactory since the marginal predicted probabilities of success for each crop choice $\Pr(I_k = 1)$ are in all cases greater than 50%.

Globally, the signs of the explanatory variables are in line with our predictions and most variables of interest are significant at least at 5% level. The coefficients of lagged dependent variables highlight the existence of a great degree of true state dependence in crop choices. Put differently, after controlling for observed and unobserved heterogeneity, past crop choices significantly and positively influence current farmers' decisions. This crop persistence over time may be explained by both farmers' preferences and specific constraints. For example, the costs of transitioning from one crop to another may be sufficiently high due to differences in input requirements or agronomic constraints that a farmer may simply decide to maintain this past land allocation pattern.

In addition, there is evidence of cross-persistence in farmers' choices for most crops, as suggested by the coefficients of lagged variables of alternative crops. Most of these coefficients are negative, implying crop rotational effects. Indeed, it is well documented that growing the same crop year after year on the same plot may result in low yields and high costs, while cultivating a sequence of different crops over several planting seasons could ultimately increase land profitability (Choi and Sohngen, 2003; Livingston et al., 2008). Alternatively, changes in profitability due to expected changes in relative prices of different crops may convince a farmer to adjust his future land allocations. Similarly to lagged variables, own initial observations significantly increase the chances of growing crops, contrarily to most initial values of competing crops.

With respect to price expectations, all estimated coefficients of own-expected prices are not only significant but also have the expected signs: farmers' anticipations of an increase in expected market prices positively affect the likelihood of selecting and growing crops. Conversely, the more volatile the expected crop prices, the lower the likelihood of crop selection, as implied by the negative and significant sign of all expected own price risks.

[75] I also tried alternative numbers of draws (150, 200, and 500) but final results did not significantly improve.

Table 3.2 *Coefficient estimates-Dynamic Multivariate Probit model*

	Coefficient estimates					
	matooke	cassava	maize	potatoes	beans	Ot. cereals
State dependence variables						
$I_{1,t-1}$	**1.261 (0.073)*** **	-0.068 (0.069)	-0.164 (0.065)**	-0.033 (0.065)	0.203 (0.069)***	-0.154 (0.066)**
$I_{2,t-1}$	-0.017 (0.063)	**0.755 (0.057)*** **	0.045 (0.056)	0.157 (0.057)***	-0.051 (0.066)	-0.239 (0.061)***
$I_{3,t-1}$	-0.025 (0.065)	0.066 (0.055)	**0.499 (0.056)*** **	0.021 (0..053)	0.050 (0.057)	-0.006 (0.054)
$I_{4,t-1}$	-0.146 (0.057)**	0.108 (0.055)**	-0.038 (0.055)	**0.569 (0.052)*** **	-0.065 (0.054)	-0.044 (0.052)
$I_{5,t-1}$	0.266 (0.071)***	-0.107 (0.065)*	0.212 (0.061)***	-0.005 (0.058)	**0.717 (0.061)*** **	-0.188 (0.061)***
$I_{6,t-1}$	-0.187 (0.064)***	-0.083 (0.038)**	-0.112 (0.056)**	-0.053 (0.056)	-0.145 (0.059)**	**0.813 (0.057)*** **
Initial observations						
$I_{1,1}$	**0.372 (0.072)*** **	-0.119 (0.073)*	0.026 (0.073)	0.105 (0.064)*	0.206 (0.076)***	-0.113 (0.054)*
$I_{2,1}$	-0.060 (0.065)	**0.527 (0.055)*** **	-0.024 (0.061)	0.037 (0.055)	-0.037 (0.063)	-0.018 (0.063)
$I_{3,1}$	0.145 (0.073)**	-0.047 (0.063)	**0.398 (0.058)*** **	0.008 (0.058)	-0.045 (0.065)	-0.096 (0.062)
$I_{4,1}$	0.035 (0.064)	0.040 (0.056)	0.075 (0.057)	**0.303 (0.051)*** **	-0.026 (0.059)	0.025 (0.059)
$I_{5,1}$	0.266 (0.073)***	-0.002 (0.068)	-0.171 (0.065)***	-0.071 (0.029)***	**0.460 (0.063)*** **	-0.099 (0.053)*
$I_{6,1}$	-0.133 (0.067)**	-0.139 (0.060)**	-0.078 (0.056)	0.022 (0.054)	-0.197 (0.062)***	**0.561 (0.059)*** **
Expected output prices and price risks						
p_1^e	**0.413 (0.024)*** **	-0.066 (0.030)**	-0.016 (0.030)	-0.036 (0.029)	-0.043 (0.039)	-0.016 (0.029)
p_2^e	-0.008 (0.009)	**0.328 (0.011)*** **	0.016 (0.007)**	0.001 (0.007)	0.015 (0.011)	0.007 (0.008)
p_3^e	-0.002 (0.001)*	-0.001 (0.002)	**0.429 (0.004)*** **	0.004 (0.003)	-0.001 (0.002)	0.002 (0.000)***
p_4^e	-0.018 (0.018)	0.026 (0.023)	0.025 (0.019)	**0.071 (0.035)***	-0.066 (0.029)**	-0.039 (0.021)*
p_5^e	-0.020 (0.001)***	0.008 (0.019)	-0.032 (0.022)	-0.031 (0.023)	**0.151 (0.030)*** **	-0.056 (0.021)***
p_6^e	-0.038 (0.037)	0.063 (0.035)*	0.028 (0.049)	-0.024 (0.056)	-0.129 (0.050)***	**0.202 (0.112)***
vp_1^e	**-0.355 (0.049)*** **	-0.001 (0.037)	0.077 (0.035)**	-0.033 (0.033)	0.049 (0.045)	0.006 (0.035)
vp_2^e	-0.048 (0.052)	**-0.469 (0.075)*** **	-0.106 (0.043)**	-0.047 (0.043)	0.009 (0.051)	-0.040 (0.043)
vp_3^e	0.046 (0.055)	-0.037 (0.048)	**-0.513 (0.131)*** **	0.071 (0.035)*	0.021 (0.063)	-0.041 (0.049)
vp_4^e	-0.013 (0.060)	-0.108 (0.057)*	0.012 (0.052)	**-0.571 (0.091)*** **	-0.015 (0.056)	0.054 (0.052)
vp_5^e	0.093 (0.051)*	0.022 (0.045)	0.027 (0.044)	-0.008 (0.040)	**-0.291 (0.066)*** **	-0.067 (0.038)*
vp_6^e	0.004 (0.040)	-0.021 (0.039)	-0.051 (0.041)	0.013 (0.038)	-0.014 (0.044)	**-0.083 (0.042)***
Expected yields and yield risks						
y_1^e	**1.005(0.173)*** **	-0.149 (0.105)	0.067 (0.011)***	0.085 (0.109)	-0.190 (0.112)*	0.098 (0.057)*
y_2^e	-0.160(0.068)**	**0.613 (0.025)** **	-0.004 (0.024)	0.039 (0.031)	-0.044 (0.025)*	0.083 (0.062)
y_3^e	0.107 (0.097)	0.015 (0.169)	**0.624 (0.011)*** **	0.109 (0.045)**	-0.007 (0.009)	0.203 (0.108)*
y_4^e	0.063 (0.151)	0.152 (0.152)	0.138 (0.149)	**0.259 (0.154)***	- 0.056 (0.149)	0.229 (0.159)
y_5^e	-0.193 (0.208)	-0.297 (0.213)	-0.318 (0.211)	-0.342 (0.212)*	**0.475 (0.021)*** **	0.099 (0.237)
y_6^e	0.109 (0.173)	0.088 (0.006)***	0.278 (0.171)*	0.176 (0.196)	0.104 (0.198)	**0.583 (0.240)** **
vy_1^e	**-0.589(0.266)** **	-0.630(0.466)	-0.557(0.462)	-0.505(0.463)	-0.630(0.464)	-0.703(0.507)
vy_2^e	-1.314(0.339)***	**-1.210(0.330)*** **	-1.241(0.322)***	-1.289(0.330)***	-1.174(0.330)***	-0.956(0.437)**
vy_3^e	-0.532(0.332)*	-0.604(0.306)**	**-0.684(0.299)** **	-0.611(0.309)**	-0.675(0.299)**	-0.096(0.452)
vy_4^e	0.478(0.721)	0.019(0.701)	0.109(0.699)	**-0.411(0.179)*** **	0.189(0.703)	-0.095(0.726)

Table 3.2 (continued)

	matooke	cassava	maize	potatoes	beans	Ot. cereals
vy_5^e	0.547(0.688)	0.048(0.679)	0.009(0.684)	0.066(0.688)	**-0.470(0.027)****	-0.159(0.698)
vy_6^e	-0.486(0.296)*	-0.440(0.266)*	-0.484(0.273)	-0.411(0.279)	-0.495(0.282)*	**-0.323(0.150)****
Climatic variables						
mar	-0.073 (0.004)***	-0.014 (0.005)***	-0.010 (0.005)**	-0.029 (0.004)***	-0.063 (0.005)***	-0.031 (0.006)***
$marcv$	-1.230 (0.438)***	-1.386 (0.423)***	-0.446 (0.042)***	-0.629 (0.057)***	-1.036 (0.413)***	-0.417 (0.048)***
dmt	-0.416 (0.102)***	-0.381 (0.102)***	-0.045 (0.011)***	-0.327 (0.094)***	-0.033 (0.104)	-0.212 (0.092)**
$dmtcv$	-1.530 (0.494)***	-1.897(0.805)**	-0.308 (0.076)***	-1.758 (0.988)***	-0.101 (0.008)***	-0.431 (0.079)***
Land characteristics						
tld	0.142 (0.040)***	0.085 (0.033)**	0.120 (0.035)***	0.081 (0.032)***	0.179 (0.039)***	0.147 (0.034)***
ldq	0.143 (0.017)***	0.064 (0.015)***	0.290 (0.140)**	0.060 (0.032)*	0.011 (0.006)***	0.061 (0.006)***
$ldir$	0.013 (0.068)	0.041 (0.059)	0.031(0.053)	0.051 (0.131)	0.004 (0.147)	0.042 (0.163)
$ldsp$	-0.225 (0.117)*	-0.055 (0.093)	0.082 (0.092)	-0.223 (0.092)**	0.031 (0.103)	-0.191 (0.096)**
Household characteristics						
$educ$	0.087 (0.001)***	0.148 (0.076)**	0.082 (0.048)**	0.090 (0.039)**	0.034 (0.013)***	0.023 (0.016)*
age	0.719 (0.278)**	-0.031 (0.317)	0.281 (0.0259)	-0.103 (0.284)	-0.493 (0.317)	0.026 (0.304)
sex	0.112 (0.060)**	0.056 (0.054)	0.011 (0.053)	-0.023 (0.049)	-0.042 (0.058)	0.031 (0.056)
hsz	0.278 (0.112)**	0.162 (0.096)*	0.101 (0.012)***	0.089 (0.048)**	0.123 (0.069)**	0.131 (0.002)***
adr	0.163 (0.153)	-0.030 (0.131)	-0.255 (0.131)*	-0.124 (0.121)	0.020 (0.144)	-0.354 (0.138)***
nfi	0.008 (0.005)*	-0.000 (0.004)	-0.011 (0.004)***	-0.003 (0.004)	0.001 (0.004)	-0.004 (0.004)
Ctl	0.234 (0.092)***	-0.063 (0.784)	0.347 (0.693)	-0.128 (0.707)	0.658 (0.418)**	-0.619 (0.004)***
$East$	-0.027 (0.339)	0.121 (0.083)***	0.648 (0.282)***	0.471 (0.133)***	0.029 (0.352)	-0.899 (0.067)***
$West$	0.092 (0.033)***	0.024 (0.002)***	0.529 (0.312)*	0.208 (0.035)***	0.886 (0.397)**	0.064 (0.007)***
Cons	3.791 (2.135)*	6.598 (1.937)***	0.960 (2.083)	6.296 (2.101)***	5.854 (2.369)**	5.453 (3.147)*
ρ_{ij}						
ρ_{1j}	1	0.066 (0.038)*	-0.048 (0.006)***	0.042 (0.005)***	0.087 (0.041)**	-0.145 (0.038)***
ρ_{2j}		1	0.038 (0.002)***	0.277 (0.029)***	0.036 (0.016)**	-0.106 (0.031)***
ρ_{3j}			1	0.107 (0.029)***	0.297 (0.032)***	-0.025 (0.000)***
ρ_{4j}				1	0.152 (0.033)***	0.041 (0.010)***
ρ_{5j}					1	-0.059 (0.034)*
ρ_{6j}						1
$\Pr(I_k = 1)$	0.692	0.713	0.720	0.591	0.721	0.609

Note: Robust standard errors into parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively. ρ_{ij} stands for the coefficient of the correlation between error term of crops *i* and *j*.

Likelihood of all $\rho_{ij} = 0, \forall i \neq j : \chi^2_{33} = 2{,}587.021, \quad p-value = 0.0000$

This suggests that higher but more volatile expected prices of a specific crop may dissuade a farmer from growing it in favor of more stable crops in terms of prices, implying a price risk-averse attitude. Similarly to output prices, the estimated coefficients of expected yields are found to be positive and significant while increases in own yield risks are detrimental to crop selection.

In terms of climatic variables, increases in expected monthly rainfall only have a very marginal effect on crop selection while changes in its volatility (measured by changes in coefficient of variation) significantly and negatively affect current land decisions. Analogously, it is changes in volatility of temperature spreads (difference between average monthly maximum and minimum temperatures) rather than in their mean values that influence the most farmers' crop choices. These results are consistent with findings by Wu et al. (2004) and Weersinsk et al. (2010).

Land characteristics also diversely influence farmers' crop selection decisions. Whereas increases in the total agricultural land size and the proportion of good-quality plots positively increase farmers' crop participation, the proportion of both rain-fed and flatted plots appears irrelevant in explaining farmers' crop choices, probably because most agricultural plots (more than 90%) were only rain-fed or had flatted/gentile slopes (around 85%).

In addition, most demographic variables do not significantly influence crop choices. Exceptions are household size and the level of education of the head. Household size increases the likelihood of growing all selected crops. This result is in accordance with the characteristics of the agricultural sector in most developing countries where not only agriculture is primarily of subsistence but also a large share of labor involves self-employment. In this context, increasing family size constrains the household to either increase farm production (through more land areas to cultivate or improved productivity) or seek off-farm labor opportunities. In all equations, the level of education attained by the farmer appears to have a positive and significant impact on crop selection. Finally, the estimated coefficients of most regional dummies variables are significant, suggesting important cluster and geographical effects due probably to agro-climatic specificities[76].

3.5.2 Dynamic acreage share model

The second model is the selectivity-corrected ***dynamic acreage share model*** which specifies the factors affecting land area allocations by Ugandan farmers. Appendix C.8 presents the estimation results of the dynamic multivariate fractional logit models with (Model I) and without (Model II) unobserved heterogeneity accounted for. I discarded from the final results covariates with high collinearity, particularly covariances of expected prices and yields as well as some time-averaged variables from the Mundlak-Chamberlain transformation.

Let us first take heed to the variables related to state dependence ($s_{hj,t-1}$) and initial conditions (s_{hj1}). At first glance, all crops exhibit significant own state dependence, whether I allow for individual heterogeneity or not. The share of each crop in the current period s_{hkt} depends positively on the acreage share previously allocated to that crop $s_{hk,t-1}$. The results further show that the initial land

[76] For example, *matooke* is generally consumed in western, central, and southern parts of the country. cassava is generally grown in northern, northwestern and eastern regions of Uganda.

allocation s_{hk1} is an important determinant of current acreage decisions, which suggests, according to the empirical framework, a significant correlation between farmers' "pre-sample" and current characteristics. The results also reveal the presence of significant dynamic spillover effects among the acreage equations, implying a strong cross state dependence. These estimated effects are negative and consequently the share of each crop in the current period is negatively influenced by the shares of alternative crops in the previous period. Thus, for a fixed, allocatable land size in a multicrop system, the acreage model reveals a competition among crops for area shares. It can also be noted that the coefficients of lagged dependent variables are mostly larger (in absolute values) in models II, where unobserved heterogeneity has been ignored, resulting in an overestimation of the effects of state dependence. This feature is however expected because the effect of the uncontrolled unobserved heterogeneity is partly included in the coefficients of lagged outcome terms (Divicienti and Poggi, 2007).

To check whether the addition of lagged dependent variables improves acreage model performance, I also estimated a static-MVFL (models without state dependency and initial observations problem). The comparison of the estimated coefficients (presented in Appendices C.8 and C.9) indicates that the magnitude of most coefficients tend to decrease (in absolute values) when we go from the static to dynamic models. These differential impacts can be attributed to the fact that the variables in the static models are absorbing parts of the effects otherwise captured by state dependency.

However, these parameter estimates are not *per se* informative of the marginal effects of the covariates on the acreage shares. To analyze their partial effects, tables 3.3-3.5 show the expected acreage elasticities using equations (3.20a) and (3.20b) for both the static and dynamic models with unobserved heterogeneity.

Table 3.3 reports the estimated results of crop share elasticities with respect to expected prices and yields and their respective risk measures. The first result that is worth noting is that all own-price elasticities (values in bold) are positive and highly significant. For all the selected crops, the expected price effects are inelastic. For example, one percent increase to the expected prices of *matooke*, maize, and beans increases the expected land acreage shares of these crops by respectively 0.35 (0.32%), 0.44 (0.38%), 0.37 (0.31%) in the static (dynamic) model. The cross-price elasticities are also significant at 1 percent level, all negative, and in most cases smaller than the own-price acreage responses, implying crop substitution among Ugandan farmers concerning crop land allocations.

Table 3.3 *Acreage elasticities of expected prices and yields and their related risks- Static vs Dynamic models*

	Matooke		Cassava		Maize		Potatoes		Beans		Other cereals	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
Expected prices												
p_1	**0.354*****	**0.322*****	-0.043***	-0.036***	-0.059***	-0.047***	-0.042***	-0.036***	-0.055***	-0.047***	-0.021***	-0.012***
p_2	-0.042***	-0.037***	**0.378*****	**0.359*****	-0.079***	-0.068***	-0.048***	-0.043***	-0.068***	-0.056***	-0.049***	-0.037***
p_3	-0.047***	-0.039***	-0.068***	-0.072***	**0.439*****	**0.382*****	-0.042***	-0.046***	-0.075***	-0.066***	-0.035***	-0.033***
p_4	-0.042***	-0.036***	-0.043***	-0.042***	-0.046***	-0.042***	**0.276*****	**0.224*****	-0.048***	-0.036***	-0.021***	-0.018***
p_5	-0.071***	-0.096***	-0.062***	-0.062***	-0.010***	-0.068***	-0.040***	-0.048***	**0.368*****	**0.308*****	-0.028***	-0.027***
p_6	-0.024***	-0.021***	-0.056***	-0.049***	-0.053***	-0.042***	-0.024***	-0.028***	-0.048***	-0.035***	**0.219*****	**0.198*****
Expected yields												
y_1	**0.524*****	**0.505*****	-0.180***	-0.092***	-0.206***	-0.137***	-0.139***	-0.121***	-0.162***	-0.138***	-0.178***	-0.103***
y_2	-0.236	-0.198	**0.698*****	**0.469*****	-0.148***	-0.104***	-0.108***	-0.088***	-0.155***	-0.069***	-0.125***	-0.116***
y_3	-0.184	-0.115	-0.094***	-0.059***	**1.037*****	**0.723*****	-0.181***	-0.138***	-0.180***	-0.168***	-0.075***	-0.068***
y_4	-0.177***	-0.150*	-0.108***	-0.077***	-0.128***	-0.101***	**0.584*****	**0.449*****	-0.074***	-0.067***	-0.151***	-0.147***
y_5	-0.183	-0.146*	-0.140***	-0.119***	-0.185***	-0.104***	-0.090***	-0.046***	**0.876*****	**0.659*****	-0.108***	-0.096***
y_6	-0.140***	-0.064*	-0.073***	-0.055*	-0.051***	-0.045**	-0.045***	-0.037**	-0.098***	-0.046*	**0.756*****	**0.640****
Price risks												
vp_1	**-0.007*****	**-0.025*****	-0.012***	-0.025***	-0.007***	-0.005***	-0.003***	-0.005***	-0.007***	-0.015***	-0.005***	-0.005***
vp_2	-0.011***	-0.089***	**-0.011*****	**-0.045*****	-0.012***	-0.044***	-0.011***	-0.049***	-0.013***	-0.041***	-0.013***	-0.013***
vp_3	-0.006***	-0.030***	-0.005	-0.025***	**-0.020*****	**-0.010*****	-0.004	-0.020***	-0.006***	-0.030***	-0.007***	-0.035***
vp_4	-0.011***	-0.049***	-0.026***	-0.059***	-0.021***	-0.095***	**-0.008*****	**-0.036*****	-0.021***	-0.095***	-0.012***	-0.055***
vp_5	-0.001***	-0.005	-0.001***	-0.004	-0.006***	-0.029	-0.001	-0.004	**-0.005*****	**-0.024****	-0.009***	-0.043
vp_6	-0.011***	-0.028	-0.015***	-0.026	-0.008***	-0.041	-0.010***	-0.026	-0.010***	-0.025	**-0.009*****	**-0.023***
Yield risks												
vy_1	**-0.087*****	**-0.102*****	-0.052***	-0.094***	-0.050***	-0.074***	-0.042***	-0.077**	-0.044***	-0.073***	-0.023***	-0.056**
vy_2	-0.098***	-0.115***	**-0.047*****	**-0.063*****	-0.048***	-0.058***	-0.325***	-0.053*	-0.029***	-0.014*	-0.027***	-0.073*
vy_3	-0.123**	-0.133*	-0.190***	-0.129*	**-0.176*****	**-0.162*****	-0.134***	-0.107*	-0.155***	-0.090*	-0.080***	-0.060
vy_4	-0.150*	-0.150**	0.047***	-0.134***	-0.045***	-0.109*	**-0.039*****	**-0.137*****	0.037***	0.036*	0.022***	0.050*
vy_5	-0.020**	-0.050***	-0.050***	-0.039*	-0.019*	-0.019*	0.020	-0.019*	**-0.024****	**-0.048*****	-0.025*	-0.014*
vy_6	0.045***	-0.015*	0.072	-0.026*	-0.046***	-0.051***	-0.053***	-0.020*	-0.069***	-0.010*	**-0.047****	**-0.020*****

Note: ***, **, and * indicate coefficients statistically significant at 1, 5, and 10% levels, respectively.

This inelastic reaction of acreage shares to expected prices may be partially explained by crop-specific agronomic constraints (Wu at al., 2004), crop interdependence since changes in the prices of one crop also affect acreage decisions of other crops (Lacroix and Thomas, 2011), or market failures (de Janvry et al., 1991).

Second, the impact of own expected yields on acreage shares is both positive and in all cases higher than the corresponding price elasticities. Similar to price elasticities, maize displays the largest coefficient (0.72), followed respectively by beans (0.66) and other cereals (0.64) in the dynamic model. Cross-yield elasticities are all negative, confirming the substitutability nature of the selected crops. These result patterns are consistent with the findings by Weersink et al. (2010) for Canadian farmers who showed that expected yields had much higher effects on land acreage than expected prices. The larger impact of yield expectations may be explained by the fact that most agricultural households in Uganda are subsistence farmers or net buyers (Benson et al., 2008; see essay II). Therefore, they place greater value on yields as large yields imply higher production and subsequently more room for home consumption, while increases in the expected end-of-season output prices are essentially more meaningful to farmers participating into food markets.

Third, price and yield risks also appear to be relevant determinants of land allocation decisions: the more volatile the expected output prices or yields, the smaller the proportion of land the farmer will be willing to share out between the selected competing crops. And similarly to the case of expected values, farmers appear more sensitive to changes in yield risks than in price risks for all crops, regardless of the model specification. Estimated elasticities associated with price risks are in most cases less than 0.05% while yield risk elasticities are around 0.10%, reaching the highest levels for maize (-0.18 and -0.16% in the static and dynamic models, respectively). Similar patterns were found by Lin and Dismukes (2007), Weersink et al. (2010), Hung and Khanna (2010), and Liang et al. (2011).

These various own- and cross- acreage elasticities can be further illustrated by simulating the effects of simultaneous shocks to the expected prices and yields and their volatility across all crops. Table 3.4 shows these equiproportional elasticities computed by vertically summing the statistically significant own- and cross- elasticities in table 3.3. The table reveals that a positive shock to all the expected prices would increase the acreage shares of all selected crops in both the static and dynamic specifications, although the effects are relatively larger in the static models. When the simulated shocks originate from expected yields, the impacts are globally amplified. For instance, the acreage shares towards maize would increase by 2.32% and 1.15% in case of a 10% positive shock to the expected yields and prices of all crops, respectively. However, if a covariate shock would simultaneously increase the volatility of both prices and yields, it would become unattractive to maintain previous cropping patterns given the shrinkage of the expected gross revenues. Consequently, the estimated results suggest that farmers would allocate away from all the selected crops.

Table 3.4 *Equiproportional elasticities* **-** *Static vs Dynamic models*

	Matooke		Cassava		Maize		Potatoes		Beans		Other cereals	
	S	D	S	D	S	D	S	D	S	D	S	D
p^e	0.128	0.093	0.106	0.098	0.192	0.115	0.080	0.023	0.074	0.068	0.065	0.071
y^e	0.207	0.145	0.103	0.067	0.319	0.232	0.021	0.019	0.207	0.171	0.119	0.110
vp^e	-0.047	-0.193	-0.065	-0.154	-0.074	-0.154	-0.032	-0.110	-0.062	-0.250	-0.055	-0.131
vy^e	-0.433	-0.565	-0.292	-0.483	-0.384	-0.473	-0.593	-0.413	-0.284	-0.199	-0.180	-0.113

Note: The letters S and D stand for the static and dynamic acreage share models, respectively. p^e and y^e represent the equiproportional price and yield elasticities, while vp^e and vy^e are their risk elasticity counterparts.

In addition to expected prices and yields, climatic characteristics also play a key role in defining crop acreage allocations. As suggested by the first part of table 3.5, the effects of changes in average rainfall and temperature are mixed. Increases in average monthly rainfall positively affect the shares of maize, potatoes and beans, while extreme temperatures are significantly detrimental for all selected crops. The results further emphasize that it is the changes in the volatility rather than in the mean values of the climatic variables that are more influential for land allocations. Indeed, the impact of increased volatility in rainfall and temperature is significant at 1% for all crops. Whereas the average temperature displays for instance a marginal effect in the dynamic model, its volatility reduces expected crop shares by 0.09% for both cassava and other cereals and 0.16% for beans. These results are in line with findings by Arriagada (2005), Kurukulasuriya and Mendelsohn (2008), Seo and Mendelsohn (2007, 2008) and Kaminski et al. (2013) who reported that changes in climatic conditions push farmers to substitute away from agricultural activities. In regards to land characteristics, the second part of table 3.5 indicates that only changes in total land available and the proportion of good quality land positively and significantly influence the shares to be allocated to different crops. The largest (smallest) impact of land size concerns cassava (maize) with 0.14% (0.06%) and 0.11% (0.01%) in the dynamic and static models, respectively. Finally, farmers' characteristics have a negligible impact on acreage shares.

Table 3.5 *Effects of agro-climatic variables and farmer's characteristics*

	Matooke		**Cassava**		**Maize**		**Potatoes**		**Beans**		**Other cereals**	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
Climatic characteristics												
mar	-0.108	-0.089	-0.023***	-0.014**	0.023***	0.018**	0.024***	0.020*	0.018***	0.015**	-0.014	-0.011
$marcv$	-0.061***	-0.049***	-0.062***	-0.066***	-0.042***	-0.090***	-0.026***	-0.079***	-0.022***	-0.006***	-0.094***	-0.045***
dmt	-0.025*	-0.024*	-0.012*	-0.011*	-0.024*	-0.180*	-0.096*	-0.068**	-0.035***	-0.027**	-0.039*	-0.034*
$dmtcv$	-0.197***	-0.142	-0.138***	-0.089***	-0.179***	-0.103***	-0.189***	-0.157***	-0.158***	-0.160***	-0.087***	-0.089***
Farm characteristics												
tld	0.108***	0.082***	0.113***	0.135***	0.007	0.058***	0.102***	0.068***	0.054***	0.087***	0.055	0.077***
ldq	0.008***	0.005*	0.033***	0.006*	0.058***	0.002**	0.034***	0.056*	0.039***	0.010**	0.055***	0.011*
$ldir$	0.049	0.095	0.030	0.038	0.022	0.019	0.034	0.039	0.023	0.067	-0.099	-0.011
$ldsp$	-0.017	-0.008	0.039	0.027	0.051	0.028	-0.011	-0.036	0.054	0.018	0.011	-0.027
Farmer's characteristics												
$educ$	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.001	0.000	0.000
age	-0.014	-0.021*	0.013	-0.005	-0.006	-0.019	0.014	0.006	0.014	0.001	0.019	0.009
sex	0.014	0.011	0.003	-0.004	-0.001	-0.004	-0.003	-0.009	0.000	-0.006	0.003	-0.004
hsz	0.015***	0.070*	0.019***	0.020*	0.002***	0.070*	0.007***	0.009**	0.010***	0.010*	0.011***	0.013*

Note: ***, **, and * indicate coefficients statistically significant at 1% , 5%, and 10% levels, respectively.

3.6 Predictability performance

To assess the quality of the estimation results and their predictability performance, I compare for each farmer the actual and predicted crop shares obtained from acreage share models and test for the significance of these differences. Table 3.6 shows a comparison between observed s_k and predicted $\hat{s}_k$ acreage shares.

Table 3.6 *Observed versus predicted acreage shares*

		Static model					Dynamic model			
		s_k	$\hat{s}_k$	Δs_k	Δs_k / $\hat{s}_k$	Equality test	$\hat{s}_k$	Δs_k	Δs_k / $\hat{s}_k$	Equality test
	k_1	0.118	0.146	0.028	0.192	4.729	0.120	0.002	0.017	0.367
		(0.195)	(0.135)	(0.128)		[0.006]***	(0.158)	(0.112)		[0.006)]
	k_2	0.165	0.186	0.021	0.113	3.427	0.171	0.006	0.035	0.901
		(0.213)	(0.127)	(0.150)		[0.005]***	(0.152)	(0.142)		[0.007]
	k_3	0.144	0.157	0.012	0.076	2.264	0.149	0.006	0.040	0.963
2009/10		(0.186)	(0.113)	(0.129)		[0.005]**	(0.135)	(0.119)		[0.006]
	k_4	0.092	0.114	0.021	0.184	5.067	0.096	0.004	0.041	0.935
		(0.142)	(0.090)	(0.101)		[0.004]***	(0.104)	(0.095)		[0.004]
	k_5	0.134	0.147	0.013	0.088	2.803	0.138	0.004	0.029	0.787
		(0.163)	(0.100)	(0.115)		[0.005]***	(0.119)	(0.109)		[0.005]
	k_6	0.100	0.128	0.027	0.211	5.179	0.104	0.004	0.038	0.672
		(0.175)	(0.122)	(0.114)		[0.005]***	(0.143)	(0.108)		[0.006]
	k_1	0.122	0.152	0.030	0.197	5.140	0.125	0.003	0.024	0.449
		(0.193)	(0.133)	(0.131)		[0.006]***	(0.153)	(0.121)		[0.006]
	k_2	0.164	0.196	0.031	0.158	5.147	0.174	0.008	0.046	1.341
		(0.201)	(0.129)	(0.144)		[0.006]***	(0.147)	(0.144)		[0.006]*
	k_3	0.113	0.136	0.023	0.169	5.053	0.121	0.009	0.074	1.816
2010/11		(0.157)	(0.099)	(0.116)		[0.005]***	(0.114)	(0.109)		[0.005]*
	k_4	0.083	0.108	0.025	0.231	6.550	0.088	0.005	0.057	1.371
		(0.125)	(0.085)	(0.088)		[0.004]***	(0.094)	(0.086)		[0.004]*
	k_5	0.123	0.147	0.024	0.163	5.245	0.128	0.005	0.038	1.001
		(0.152)	(0.097)	(0.112)		[0.005]***	(0.108)	(0.108)		[0.005]
	k_6	0.075	0.112	0.036	0.245	7.726	0.079	0.003	0.039	0.692
		(0.151)	(0.112)	(0.103)		[0.005]***	(0.124)	(0.093)		[0.005]
	k_1	0.120	0.150	0.030	0.200	5.430	0.122	0.002	0.016	0.407
		(0.182)	(0.126)	(0.121)		[0.006]***	(0.149)	(0.114)		[0.006]
	k_2	0.130	0.158	0.028	0.177	5.550	0.138	0.008	0.058	1.466
		(0.172)	(0.107)	(0.122)		[0.005]***	(0.125)	(0.122)		[0.005]*
	k_3	0.121	0.139	0.017	0.122	3.726	0.128	0.007	0.055	1.346
2011/12		(0.155)	(0.100)	(0.112)		[0.005]***	(0.117)	(0.104)		[0.005]*
	k_4	0.084	0.108	0.024	0.222	6.651	0.086	0.003	0.037	0.672
		(0.121)	(0.084)	(0.083)		[0.004]***	(0.095)	(0.082)		[0.004]
	k_5	0.132	0.149	0.017	0.114	3.779	0.136	0.005	0.035	0.989
		(0.152)	(0.093)	(0.112)		[0.004]***	(0.111)	(0.110)		[0.005]
	k_6	0.074	0105	0.031	0.295	6.947	0.076	0.003	0.039	0.692
		(0.144)	(0.108)	(0.096)		[0.005]***	(0.122)	(0.088)		[0.005]

Note: k_1, k_2, k_3, k_4, k_5, and k_6 refer respectively to *matooke*¸ cassava, maize, potatoes, beans, and other cereals. The equality test is a *t*-test with unequal variances checking whether the mean predicted shares are significantly different from the mean observed shares. $\Delta s_k = \hat{s}_k - s_k$. Standard deviations and standard errors are reported into parentheses and into brackets, respectively. ***, **, and * indicate coefficients statistically significant at 1% , 5%, and 10% levels, respectively.

The columns Δs_k and $\Delta s_k / \hat{s}_k$ give the absolute and relative differences between the two sets of acreage shares for panel waves 2009/10, 2010/11, and 2011/12.

The first conclusion is that the static share model performs poorly in terms of prediction of the acreages to allocate to different crops. All the expected shares are significantly overstated for each crop and in each panel wave. The mis-prediction occurs mostly with regards to potatoes and other cereals. For example, in 2009/10, the differences were the smallest for maize (7.6%) and beans (8.8%) but very large for other cereals (21.1%) and potatoes (18.4%). Second, when past crop choices and initial conditions are accounted for, the predictability performance of the model is significantly improved. Indeed, in the dynamic model, the acreage shares are remarkably well predicted with the deviations from the actual shares being on average of less than 5% and globally not significant. In general, the dynamic share model appears more accurate for *matooke* and beans.

The second performance test consists in analyzing how well the estimated results predict the optimal crop choice. To that end, I define for each farmer in a given year the optimal crop choice as the crop yielding the highest expected profit using the predicted shares. However, in the surveys, data on input values and quantities are collected at the plot/parcel level, with no details on how they are allocated to different crops. To obtain crop-specific input allocations, I follow the behavioral approach proposed by Just et al. (1990) to estimate input allocations in multicrop farms. It consists in estimating a system of input allocation equations as a function of crop acreage shares, regional and time dummies. More specifically, I estimate the following linear model with Seemingly Unrelated Regression (SUR):

$$x_{iht} = \sum_{k=1}^{K} \alpha_{hkt} s_{hkt} + \boldsymbol{\beta}_{\mathbf{1}}'\mathbf{D}_{\mathbf{1}} + \boldsymbol{\beta}_{\mathbf{2}}'\mathbf{D}_{\mathbf{2}} + \boldsymbol{\gamma}'\mathbf{Z} + \varepsilon_{iht}, \qquad \forall i = i,\ldots,I, \tag{3.25}$$

where x_{iht} is the total expenditure on variable input $i, \forall i = 1,\ldots,I$ by farmer *h* at time *t*. x_{iht} contains farmers' real expendiures on hired labor, seeds, fertilizer, and pesticides. s_{hkt} is the acreage share allocated to crop *k*; $\mathbf{D}_{\mathbf{1}}$ and $\mathbf{D}_2$ are vectors of regional and time dummies; $\mathbf{Z}$ is a vector of farmers' characteristics (such as age, sex, and education of the household's head). $\alpha_{hkt}, \boldsymbol{\beta}_{\mathbf{1}}, \boldsymbol{\beta}_2$, and $\boldsymbol{\gamma}$ are unknown parameters to be estimated; ε_{iht} is the error term assumed normally and identically distributed. The estimated parameters $\hat{\alpha}_{hkt}$ are then multiplied by the land allocated by the farmer to each crop $s_{hkt} * \overline{L}_{ht}$ to get crop-specific allocation of input *i*.

In table 3.7, the third column ("obs.") gives for each crop the number of farmers whose optimal crop choice is actually $k_i, \quad \forall i = 1,\ldots,6$. Each cell in the static and dynamic models provides the percent of (in)correct predictions, with the main diagonals (values in bold) showing the proportion of correct predictions. For example, in 2009/10, among the 167 farmers whose *matooke* (k_1) was actually the optimal crop choice, the static share model correctly identifies 25.7% of them (43 farmers) and erroneously predicts that 43.7, 10.8, and 19.8% of them will have maize, potatoes, and beans as optimal choices.

***Table 3.7** Comparison between predicted and observed optimal crop choice*

	Observed optimal crop		Predicted optimal crop choice											
			Static model						Dynamic model					
	crop	Obs.	k_1	k_2	k_3	k_4	k_5	k_6	k_1	k_2	k_3	k_4	k_5	k_6
2009/10	k_1	*167*	**0.257**	0.000	0.437	0.108	0.198	0.000	**0.431**	0.012	0.323	0.048	0.186	0.000
	k_2	256	0.004	**0.379**	0.527	0.070	0.016	0.004	0.000	**0.508**	0.379	0.066	0.047	0.000
	k_3	598	0.000	0.002	**0.987**	0.010	0.000	0.002	0.012	0.003	**0.968**	0.007	0.010	0.000
	k_4	242	0.008	0.020	0.446	**0.512**	0.012	0.000	0.049	0.033	0.306	**0.591**	0.020	0.000
	k_5	276	0.011	0.011	0.536	0.101	**0.341**	0.000	0.029	0.014	0.377	0.065	**0.511**	0.004
	k_6	52	0.000	0.058	0.481	0.250	0.115	**0.096**	0.019	0.058	0.327	0.135	0.173	**0.288**
2010/11	k_1	56	**0.036**	0.071	0.732	0.107	0.054	0.000	**0.643**	0.054	0.107	0.107	0.089	0.000
	k_2	406	0.000	**0.527**	0.461	0.002	0.010	0.000	0.000	**0.613**	0.352	0.005	0.029	0.000
	k_3	696	0.000	0.007	**0.993**	0.000	0.000	0.000	0.000	0.013	**0.980**	0.001	0.006	0.000
	k_4	140	0.000	0.086	0.550	**0.264**	0.100	0.000	0.007	0.107	0.343	**0.543**	0.000	0.000
	k_5	279	0.000	0.122	0.452	0.011	**0.416**	0.000	0.000	0.082	0.330	0.025	**0.563**	0.000
	k_6	18	0.000	0.778	0.222	0.000	0.000	**0.000**	0.000	0.111	0.278	0.000	0.000	**0.611**
2011/12	k_1	62	**0.032**	0.032	0.290	0.048	0.597	0.000	**0.629**	0.065	0.065	0.249	0.000	0.000
	k_2	322	0.000	**0.422**	0.466	0.022	0.090	0.000	0.000	**0.612**	0.298	0.012	0.078	0.000
	k_3	648	0.002	0.009	**0.969**	0.005	0.015	0.000	0.000	0.009	**0.971**	0.003	0.017	0.000
	k_4	169	0.000	0.047	0.485	**0.207**	0.260	0.000	0.000	0.041	0.266	**0.692**	0.000	0.000
	k_5	365	0.000	0.019	0.384	0.005	**0.592**	0.000	0.000	0.044	0.285	0.011	**0.660**	0.000
	k_6	27	0.000	0.148	0.786	0.000	0.036	**0.000**	0.000	0.000	0.222	0.000	0.000	**0.778**

Note: k_1, k_2, k_3, k_4, k_5, and k_6 refer respectively to *matooke*¸ casssava, maize, potatoes, beans, and other cereals

From table 3.7, it appears that the overall predictive power of the static model is relatively weak. The model performs exceptionally well only with respect to maize (k_3) with nearly 100% of correct predictions. For the remaining crops, the proportions of exact predictions are globally low. In 2010/11 and 2011/12, the static model even falls to correctly identify a single farmer concerning the choice of other cereals. In contrast, the dynamic model presents a relatively improved prediction power for all crops. On average, its predictions are accurate in more than 50% of cases and are greater than those from the static model. The differences between these two models are particularly striking with respect to *matooke* and other cereals (in 2010/11 and 2011/12).

3.7 Conclusions

This study has used farm- and crop-level data of Ugandan agricultural households to understand the relative importance of perceived agricultural and market risks on farmers' crop choices and acreage decisions. It proposes a theoretical model in which a representative farmer optimally chooses the land shares to allocate to different crops in order to maximize the expected utility of profit. The underpinning theoretical model is then translated into two related specifications of farmers' crop decisions: a multivariate selection model and an acreage share model. The former describes how the farmer decides which crop(s) to grow while the latter models how he allocates his land area to different crops conditional on crop selection. All these models take account of two important facets of the farmer's behavior: the possibility of state dependence and spillover (or rotational) effects through the incorporation of past crop choices and land allocations, and the presence of unobserved heterogeneity in the farmer's decision process. The models are applied to a balanced panel of 1,598 farmers, first interviewed in 2005/6 by the Uganda Bureau of Statistics (UBoS) and then followed successively in 2009/10, 2010/11 and 2011/12.

The results provide evidence of both strong state dependence and significant spillover effects in farmers' crop choices and area allocations. This means that, although Ugandan farmers tend to reproduce their previous land distributional patterns (positive own state dependence), they are also likely to adjust their choices to take advantages of rotational effects (negative cross-state dependence) or changes in relative crop profitability. In terms of risks and expectations, both the multivariate crop selection and acreage share models agree on the crucial role played by farmers' expectations of market prices, yield levels and their variability (captured by price and yield risks), on the one hand, and rainfall and temperature variability, on the other. They suggest that expected own prices and yields positively influence the likelihood of crop selection and land shares while their variability stresses a risk-averse behavior from Ugandan farmers. They finally show that changes in weather variability (in terms of coefficients of variation of rainfall and temperature) are likely to impact more on crop selection and land allocations than changes in their average values.

Essay IV

Welfare growth, poverty traps, and differential exposure to food price shocks

Evidence from Uganda

4.1 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 in order 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 last essay 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. In the analysis, the emphasis is put on household consumption and assets, rather than on income, which generally suffers from important measurement errors, particularly in developing countries, and is more prone to stochastic movements and sensitive to transitory disturbances likely to generate false positives and false negatives in regards to poverty traps (Barrett et al., 2006). This choice has also the advantage of enriching welfare analyses by decomposing poor into subgroups of stochastically and structurally poor - depending on the levels of household assets and their consumption levels - and by investigating whether these two groups are significantly different in their likelihood of being trapped into poverty.

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[77], 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. The next section presents a brief literature review on the links between shocks, welfare dynamics and poverty traps. Section 3 summarizes existing empirical evidence pertaining to micro-level poverty traps. In Section 4, a modified consumption growth model is presented and its theoretical implications are discussed. Section 5 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 6, different estimation methods are discussed and empirical results are presented. Section 7 concludes the study.

4.2 Literature review: shocks, welfare dynamics, and poverty traps

In recent years, the analysis of welfare dynamics over time has gained prominence in development economics' circles. The heed has been particularly put on the reasons why some individuals or households manage to lift themselves permanently out of poverty, while others still remain mired into poverty for an extended period of time. Of particular interest is the vulnerability of individuals or households to idiosyncratic and covariate shocks. Indeed, researchers have explored the mechanisms through which the occurrence of such shocks may induce a profound modification of

[77] The Uganda's GPD grew from 5.9 percent in 2009/10 to 6.7 percent in 2010/11 (UBOS, 2012), while that of Sub-Saharan Africa decreased from 5.2 to 3.9% during the same period.

the welfare accumulation dynamics (in terms for example of income, consumption, or assets) and potentially lead to poverty persistence and poverty traps. For example, climate shocks, associated with extreme weather conditions (e.g., droughts, floods, cyclones) may overnight bring households' assets to a level below which accumulation growth becomes impossible without a substantial external push (Giesbert and Schindler, 2012). In rural areas of many developing countries, weather-related disasters (insufficient rainfall, extreme temperatures, droughts, etc) may have catastrophic consequences on crop production and therefore on farm revenues. For example, Carter et al. (2007) found evidence that short-term asset shocks (hurricane in Honduras) and long-term income shocks (drought in Ethiopia) were responsible of people being trapped into poverty.

The concept of poverty traps originates from macro-economic literature on growth dynamics through three hypotheses. The first is the idea of *unconditional convergence* according to which all households will follow the same welfare equilibrium path and will ultimately converge to a unique living standard and asset stock. In this Solow-type growth model, any shock will only temporarily modify the welfare dynamics, without preventing the convergence towards the equilibrium to occur (Geromini et al., 2006). Under the *conditional convergence* hypothesis, dating back to Baumol (1986) and DeLong (1988), there are as many welfare pathways as there are groups or clubs of individuals sharing some intrinsic characteristics (agro-ecological conditions, natural resource endowments, ethnic diversity, innate abilities and skills, etc). Depending on their characteristics, some groups will face a low-level equilibrium from which they cannot escape and move to a higher equilibrium level. The last hypothesis posits the prevalence of *multiple equilibria*, with at least one associated with a poor standard of living and another with a high level of well-being (Carter and Barrett, 2006). In this context, poverty trap is characterized by the existence of critical thresholds, with at least one threshold, once crossed, leads to poverty exit and welfare accumulation and below which depletion occurs (Barrett et al., 2007; Kraay and McKenzie, 2014).

Theoretically, the economics literature identifies at least three structural causes of multiple equilibrium poverty traps, playing at different scales: "big push" theories of development, originated from Rosenstein-Rodan (1943); physical work capacity theories (Dasgupta 1993, 1997); and incomplete and missing markets (Barrett and Carter, 2013)

The first theoretical argument for poverty traps stems from the concept of "big push" that emphasizes the necessity of coordinated investments as a basis to industrialization. When many different sectors of an economy simultaneously adopt increasing returns technologies or when the economy allocates most of its resources to the increasing returns sectors, then wages will be high in all sectors, creating more income and demand for goods which in turn will enlarge the market, leading to industrialization. Conversely, the allocation of resources to constant returns sectors will result in low wage levels across sectors and demand reductions (Kraay and McKenzie, 2014). On the other hand, the "big push" model can also be associated with coordination failures between firms wherein agents only mimic the economic behavior of their peers by deciding whether to invest or not depending on their expectations of what other agents will do. In this case, poverty trap occurs when all agents fail to invest in the efficient technology.

The second widely developed cause of poverty trap assumes a non-linear relationship between individual physical work capacity and his nutritional or food intake status. In this model, labor productivity and wage depend solely on consumption and income is entirely derived from labor market (Van Campehnout and Dercon, 2012). The underlying idea is that poverty will beget poverty or be self-reinforcing insofar as poor households will not have enough resources to increase the quantity and quality of their food intake. They will become too undernourished to either participate productively into the labor market (from which they are thus rationed) or earn enough (and therefore consume enough) to help them climb out of nutritional poverty traps. As long as consumption will be below a certain threshold, the worker will remain unproductive and will thus be trapped into poverty.

Finally, uninsured risks and incomplete credit and other financial markets can give rise to poverty traps' mechanisms, particularly in developing countries where households often have limited access to capital and insurance markets. From this perspective, shocks can have disproportionally permanent consequences on welfare accumulation, trigger irreversible mechanisms for individuals already close to the poverty line, and keep poor households from climbing out of poverty (McPeak and Barrett, 2001; Dercon, 2005; Krishna, 2006). *Ex ante* management strategies to risk exposure and *ex post* mitigation mechanisms may also lead to poverty traps. To manage risk exposure, poor households may choose a diversified portfolio comprised of low-risk activities but at the expense of asset returns, reinforcing the likelihood of being trapped into poverty. For example, Bezabih et al. (2011) found that in Ethiopia crop portfolio choice was essentially influenced by rainfall variability and that farmers were likely to choose less risky crops at the expense of high returns. *Ex post*, empirical evidence indicates that poor households often sell out their meager assets, principally livestock, to cope with shocks and smooth their consumption, thereby exacerbating their already-unsustainable welfare conditions. In some other circumstances, empirical findings suggest that poor may instead opt for asset smoothing by reducing their consumption or healthcare expenditures or withdrawing children from school, resulting in health and education deficiencies and potential intergenerational transmission of poverty (Hoddinott, 2006; Carter et al., 2007; Amare and Waibel, 2013).

4.3 Empirical evidence on poverty traps

Over the last two decades, empirical research that has concentrated on the identification of poverty traps and the existence of single or multiple welfare equilibria has obtained mixed results. For example, using a six-year panel of income from rural Chinese provinces, Jalan and Ravallion (2002) find evidence of a geographical poverty trap, implying that well-endowed areas enjoy consumption levels rising over time, while households trapped into geographic poverty are stuck into a lower standard of living. Lokshin and Ravallion (2004) analyze nonlinearities of household income in the presence of endogenous attrition using a four-year household panel from Russia and a six-year panel from Hungary. By means of a semi-parametric Full Information Maximum Likelihood (FIML), they find evidence of nonlinearities in income dynamics but fail to find a dynamic poverty trap.

Lybbert et al. (2004) use 17-year cattle herd histories collected among pastoralists in southern Ethiopia to study stochastic livestock dynamics. They apply a Nadaraya-Watson estimator of bivariate case using Epanechnikov kernel with an arbitrary bandwidth of 1.5 and find evidence of multiple dynamic wealth equilibria among pastoralists. Particularly, they find that households with herd size less than 15 heads fall into a sedentarisation zone, while households with more than 15 head converge to an upper equilibrium of about 75. Above this level, accumulation becomes too costly to be sustainable.

Adato et al. (2006), Carter and Barrett (2006); Barrett et al. (2006), Quisumbing and Baulch (2009) Naschold (2009; 2013), Giesbert and Schindler (2012), Amare and Waibel (2013) all look at poverty trap from an asset-based perspective and derive asset-based wellbeing indices through either a regression of expenditure/income on the household's productive assets or a factor analysis. Specifically, Carter and Barrett (2006) argue that an asset-based approach to poverty trap enables the researcher to distinguish persistent or structural poverty from stochastic poverty. Using a livelihood-weighted approach to compute an asset index, Adato et al. (2006) and Amare and Waibel (2013) find an S-shaped asset accumulation process and evidence of poverty traps in South-Africa and rural Vietnam, respectively. Barrett et al. (2006) study welfare dynamics in rural Kenya and Madagascar. They use qualitative and quantitative evidence to see what causes persistent poverty. They find evidence of S-shaped asset dynamics using both non-parametric regressions and a fourth order polynomial regression. On the other hand, Naschold (2009, 2013), Quisumbing and Baulch

(2009), Giesbert and Schindler (2012), have not found evidence for multiple equilibria but rather a single stable state at a low level of well-being around the poverty line towards which everyone converges.

Van Campenhout and Dercon (2012) explore the existence of livestock asset poverty traps in Ethiopia using the Ethiopia Rural Household Survey (ERHS) from round 1 to round 6. Using a GMM estimation and Threshold Auto-Regression model proposed by Hansen (1999; 2000), they find nonlinearities in the dynamics of Tropical Livestock Units (TLUs) and multiple equilibria of TLUs. When estimating the speed of convergence towards the low and high equilibria, they find that the convergence to the former was almost twice as fast as convergence towards the latter.

Kwak and Smith (2010) and Dutta (2014) test for the existence of both single and simultaneous poverty traps in Ethiopia and India, respectively. Using a range of econometric (parametric, non- and semi-parametric) methods to the Ethiopia Rural Household Survey (ERHS) from 1994 to 2004, Kwak and Smith (2010) identify only a single stable welfare equilibrium when using the full panel sample but two equilibria when they split the data into two time intervals (1994-1999 and 1999-2004). Moreover, their results suggest that households with chronic undernourishment and illiteracy are trapped into lower equilibria while richer households enjoy high level of asset equilibrium. Finally, Dutta (2014) uses the local polynomial regression with Epanechnikov kernel weights to test the existence of multiple equilibria in asset poverty dynamics and a partial linear mixed model to investigate the impact of under-nutrition and illiteracy on asset accumulation process in India. He finds evidence of a single dynamic asset equilibrium across rural households but multiple traps (asset, under-nutrition and illiteracy traps) in most depraved States.

4.4 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 $U(c;\theta^f)=u(c)+\nu(c|z(\theta^f))$, where $u(c)$ is an intrinsic consumption utility and $\nu(c|z(\theta^f))$ is the utility gap or "gain-loss utility" function due to the realization of θ_{ht}^{f}. The utility-gap function is given by $\nu(c|z(\theta^f))=\nu[u(c)-u(c|z(\theta^f))]$, with $\nu(c|z(\theta^f=1))=0$, 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:

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

subject to (4.1)

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

$$k_0 \text{ given}$$

where $\mathbf{E}_0(\bullet)$ is the conditional expectation $\mathbf{E}_0(\bullet|\Psi_0)$ 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:

$$V\left(t, k_t \middle| \Omega_{\theta_t}\right) = \underset{c_s}{Max} \quad \mathbf{E}_t \left\{ \sum_{s=t}^{\infty} \beta^s \left[u(c_s) + \nu\left(u(c_s) - u\left(c_s \middle| z\left(\theta_s^f\right)\right)\right)\right] \right\} \quad s.t \quad k_{t+1} = \theta_t^k \left[f(k_t) + (1-\delta)k_t \right] - c_t \tag{4.2}$$

The Bellman's principle of optimality associated with the value function in (4.2) for each t = 0, 1,2,… gives the following result:

$$V\left(t, k_t \middle| \Omega_{\theta_t}\right) = \underset{c_t}{Max} \left\{ \beta^t \left[u(c_t) + \nu\left(u(c_t) - u\left(c_t \middle| z\left(\theta_t^f\right)\right)\right)\right] + \mathbf{E}_t V\left[t+1, \theta_t^k \left[f(k_t) + (1-\delta)k_t \right] - c_t\right] \right\} \tag{4.3}$$

It is straightforward to show that the first order conditions derived from the stochastic Bellman equation in (4.3) give the following Euler equation[78]:

$$\begin{aligned} &\mathbf{E}_t \left\{ \theta_{t+1}^k \beta^{t+1} \left[f'(k_{t+1}) + (1-\delta) \right] \times \left[u'(c_{t+1}) + \nu'\left[g\left(c_{t+1}; \theta_{t+1}^f\right)\right] \times \left(u'(c_{t+1}) - u'\left(c_{t+1} \middle| z\left(\theta_{t+1}^f\right)\right)\right)\right] \right\} \\ &= \beta^t \left\{ u'(c_t) + \nu'\left[g\left(c_t; \theta_t^f\right)\right] \times \left(u'(c_t) - u'\left(c_t \middle| z\left(\theta_t^f\right)\right)\right)\right\} \end{aligned} \tag{4.4}$$

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* (4.4) 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 (4.4) can be rearranged to give:

$$\frac{U'\left(c_t; \theta_t^f\right)}{\beta \mathbf{E}_t U'\left(c_{t+1}; \theta_{t+1}^f\right)} = \theta_{t+1}^k \left[f'(k_{t+1}) + (1-\delta) \right] \tag{4.5}$$

where

$$U'\left(c_t; \theta_t^f\right) = u'(c_t) + \nu'\left[g\left(c_t; \theta_t^f\right)\right] \times \left(u'(c_t) - u'\left(c_t \middle| z\left(\theta_t^f\right)\right)\right) \tag{4.6}$$

and

$$U'\left(c_{t+1}; \theta_{t+1}^f\right) = u'(c_{t+1}) + \nu'\left[g\left(c_{t+1}; \theta_{t+1}^f\right)\right] \times \left(u'(c_{t+1}) - u'\left(c_{t+1} \middle| z\left(\theta_{t+1}^f\right)\right)\right) \tag{4.7}$$

[78] This equation is obtained using the following Bellman-type equation obtained by maximizing (4.3): $\mathbf{E}_t \left(\tau_{k,t+1} - \frac{\tau_{c,t+1}}{\varsigma_{c,t+1}} \bullet \varsigma_{k,t+1} \right) = -\frac{\tau_{c,t}}{\varsigma_{c,t}}$, where the subscripts k and c denote partial derivatives, and $\tau(.) = \beta^t \left[u(c_t) + \nu\left(u(c_t) - u\left(c_t \middle| z\left(\theta_t^f\right)\right)\right)\right]$, and $\varsigma(.) = \theta_t^k \left[f(k_t) + (1-\delta)k_t \right] - c_t$

The left-hand side of (4.5) 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 (4.5) 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, $g(c_t;\theta_t^f)=0 \rightarrow u(c_t)=u(c_t|z(\theta_t^f)), \forall t$, $U'(c_t;\theta_t^f)=u'(c_t), \forall t$), and assets are not affected by shocks ($\theta^k=1$), the left-hand side of equation (4.5) reduces to a standard Euler equation.

Second, if instead $u(c_t)\neq u(c_t|z(\theta_t^f)), \forall t$, 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:

$$U'(c_t;\theta_t^f)=u'(c_t)\{1+v'[g(c_t;\theta_t^f)]\}-u'(c_t|z(\theta_t^f))\{v'[g(c_t;\theta_t^f)]\}\neq u'(c_t), \forall t \tag{4.8}$$

Hence, from equation (4.8), it is possible to get for some households $c_t|z(\theta_t^f)<c_t$ while for others $c_t|z(\theta_t^f)>c_t$, depending on their initial characteristics, attitude towards risk, preferences, or expectations about the future. Particularly, when $c_t|z(\theta_t^f)<c_t$, 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 $(\theta^k<1)$, 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 $U(c_t;\theta_t^f)=u\left((\theta_t^f)^{\pi} c_t\right)$, 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: $u(c)=\frac{c^{1-\rho}}{1-\rho}$ 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 (4.5) 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:

$$\Delta\ln c_t \equiv \ln\left(\frac{c_t}{c_{t-1}}\right)=\pi\left(\frac{1-\rho}{\rho}\right)\ln\left(\frac{\theta_t^f}{\theta_{t-1}^f}\right)+\frac{1}{\rho}\ln\left(\theta_t^k\right)+\frac{1}{\rho}\ln\left(\frac{1}{\beta}\right)+\frac{1}{\rho}\ln\left[f'(k_t)+(1-\delta)\right] \quad (4.9)$$

Equation (4.9), 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 4.9) 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 (4.9) leads to the following specification:

$$\Delta\ln c_{ht} \equiv \ln\left(\frac{c_{ht}}{c_{ht-1}}\right)=\sigma_0+\sigma_1 Z_{ht}+\sigma_2\Delta\ln\theta_{ht}^f(X,Z)+\sigma_3\ln\left(\theta_t^k\right)+\sigma_4 X_{ht}+\sigma_5 X_h+\eta_h+\mu_{ht} \quad (4.10)$$

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 the 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.

4.5 Data

This last essay 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 essay, the final sample of each survey contains information on 2,173 balanced households[79], 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[80] (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[81]. The panel surveys provide detailed information on household demographics, production (quantities and values of both inputs and outputs), consumption (food and non-food commodities), landholdings and livestock ownership, types of shocks and coping strategies, among others. Different recall periods were used depending on the nature of the expenditure items: they go from a seven-day recall period for food consumption to one year for durable, semi-durable and non-consumption expenditures (taxes and duties, pension, social security contribution, remittances, gifts, contribution to funerals,...).

4.5.1 Construction of a food price shock variable

A key challenge in estimating equation (4.10) 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 datasets I are using 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, thereby leaving the researcher to surmise on the likelihood of exposure to price shocks. Second, price changes affect households differently depending on their tastes, preferences, composition, or their

[79] To test for a potential attrition bias, I apply 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 is then done through the *inverse probability weighting* (IPW) procedure (Fitzgerald et al, 1998; Wooldridge, 2002). See Appendix B.1.

[80] An enumeration area represents "the smallest ground area, mapped with definite boundaries within which a study or interview is carried out" (UBoS, 2012: 32).

[81] In the UNPS-2006, households were first visited between May and October 2005 and then between November 2005 and April 2006. In the UNPS-2010, first visits occurred between September 2009 and January 2010 while the second were conducted between February 2010 and August 2010. In the third wave, first visits were conducted between October 2010 and March 2011, while the second were between April and September 2011. For the last survey, first occurred between November 2011 and April 2012 and second between May 2012 and December 2012.

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[82] of the commodity *i*¸ then CPI_{hct}, based on price levels in period 0 (in this essay, 2005/6), can be computed as a modified *Laspeyres* formula:

$$CPI_{hct} = \sum_{i=1}^{I} s_{hct}^{i} \left(\frac{p_{ct}^{i}}{p_{c0}^{i}} \right) \tag{4.11}$$

where the basket of goods in equation (4.11) is made up of 7 food commodities or commodity groups considered as the most important in the Ugandan diet: *matooke*[83], 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), the use of food consumption shares s_{hct}^{i} 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:

[82] I include the imputed values of consumption from self-produced goods

[83] *Matooke* refers to starchy bananas that are cooked and consumed as staple (Haggblade and Dewina, 2010) and represents one of the most important staple foods in the Ugandan diet.

$$\Delta CPI_{hct} = \alpha_0 + \alpha_1 CPI_{hct-1} + \alpha_2 t + \kappa + \varepsilon_{hct}; \qquad t = 1,...,T \tag{4.12}$$

The residuals from equation (4.12), $\hat{\varepsilon}_{hct}$, 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 essay 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 (4.12) 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. The prominence of positive shocks over 2009-2011 is not surprising since this period corresponds to the recent global food price crisis but also has seen sharp increases in domestic food prices in Uganda[84].

Table 4.1 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 on the extent of their exposure to price shocks: *high* if the normalized $\hat{\varepsilon}_{hct}$ exceeds the 75th 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.

Different features emerge from table 4.1. 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.

[84] See Essay II.

Table 4.1 *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	0.27	0.24	0.23	0.35	0.38	0.05	0.02	0.03	0.01	0.36	0.35	0.71
% of agr. households	0.83	0.34	0.26	0.19	0.34	0.38	0.05	0.29	0.05	0.02	0.03	0.31	0.76
% of net sellers**	0.27	0.28	0.22	0.07	0.35	0.41	0.03	0.03	0.05	0.01	0.34	0.32	0.85
% of net buyers**	0.55	0.29	0.27	0.26	0.37	0.38	0.06	0.02	0.04	0.02	0.32	0.31	0.66
% of poor households *	0.28	0.32	0.24	0.18	0.31	0.37	0.04	0.02	0.05	0.01	0.34	0.22	0.78

Note: * Poor households are defined using the official absolute poverty line of 1 USD PPP per capita/ per day converted into Uganda Shillings (UShs). A household is then poor if its real consumption (food and non-food) per adult equivalent lies below the poverty line. ** 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

By and large, the lower the degree of exposure to food price shocks, the more important the 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 2%, compared to an average of 25% and 26% 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.

4.5.2 Asset index

Household wellbeing can be analyzed through different measurement indicators, ranging from consumption to income and aggregate asset indices. In developing countries, consumption levels have always been preferred to income due to its potential measurement errors and acute volatility. 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), Adato et al. (2006), Carter and Barrett (2006), McKay and Perge (2013), Naschold (2013), and Kwak and Smith (2014), among others, 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)[85] where a livelihood indicator, in this study real monthly values of consumption per adult equivalent divided by the official poverty line, is regressed over a bundle of assets

[85] Another approach to construct an asset index is to use principal components or factor analyses. As indicated by Naschold (2013: 939), "[n]either method of constructing the asset index is inherently superior but one can be a useful validation for the results of the other".

(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):

$$\lambda_{ht} = \beta_0 + \sum_{i=1}^{I} \beta_i A_{ht}^i + \sum_{j,k}^{I} \beta_{jk} A_{ht}^j A_{ht}^k + \mathbf{Z'\alpha} + \mathbf{D'\omega} + \vartheta_h + \varepsilon_{ht} \tag{4.13}$$

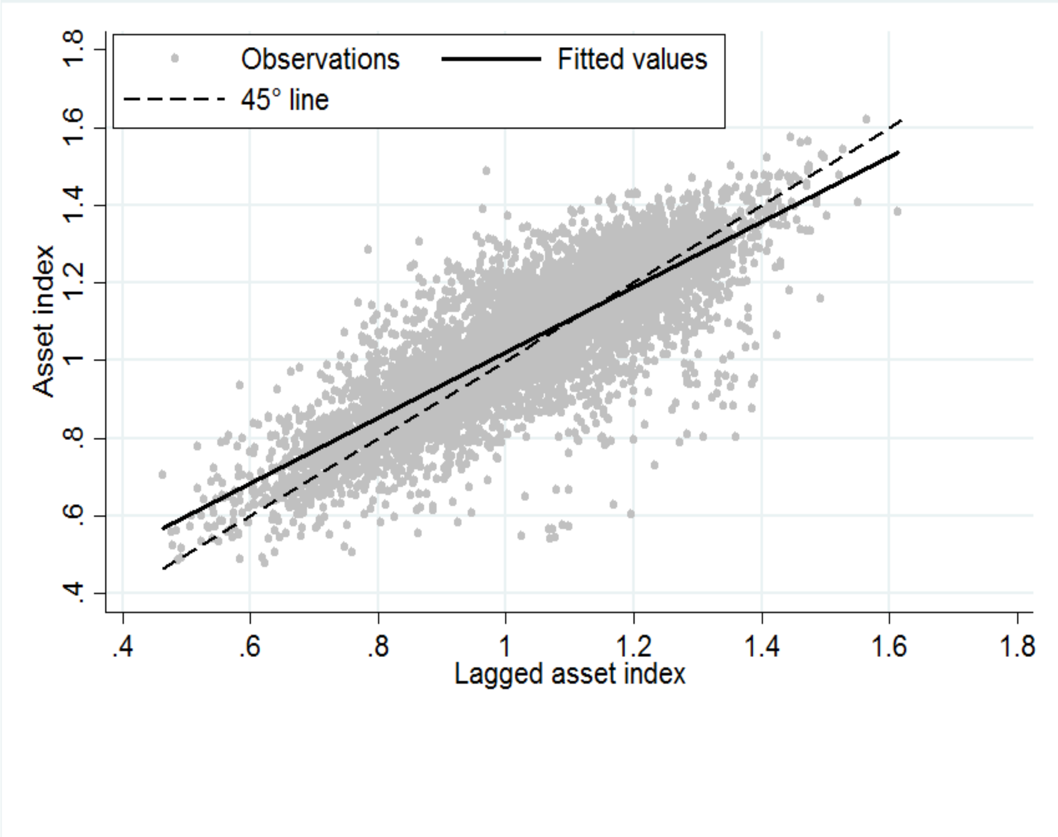
where the dependent variable $\lambda_{ht} = \frac{c_{ht}}{P_t}$ is the real monthly values of consumption per adult equivalent c_{ht} expressed at a percent of the official poverty line[86] P_t at time *t*. A_{ht}^i, A_{ht}^j, and A_{ht}^k are the amounts of physical or productive assets *i,j,* and *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 (4.13) 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 4.1, I plot the asset index a_{ht} at current period against its one period lagged value. The scatterplot portrays interesting features of households' assets accumulation. First, there seems to be 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

[86] 1 USD PPP per capita/ per day converted into Uganda Shillings (UShs)

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 4.1 *Scatterplot of asset index*



4.5.3 Descriptive statistics

Table 4.2 presents summary statistics of key variables used in this study. Household total consumption expenditures (food and non-food) are fluctuating over time, while household food consumption expenditures are decreasing. Between the first and second waves, the average monthly real household expenditures increased by 19.6% to 257,244UShs. Then, they decreased by 18.9% to 208,727UShs between the second and third rounds, and finally increased by 23% to 256,640UShs between the third and last rounds. This translated into a decrease in the proportion of poor between the first two rounds, from 28.1 to 24.8%, an increase in the number of poor in 2010/11 at 29.1%, and a fall in the last survey at 27.2%. However, there are little fluctuations in asset indices, which globally increase over time. Agricultural households, representing more than 80% of the sample, are essentially small-size farmers, cultivating on average less than 5 acres. In terms of shocks' occurrences, the majority of households were exposed to food price shocks in waves 2 and 3 (63.3 and 51.7%, respectively) against only 34.2% in the last round. Agricultural shocks (droughts, floods, pest attacks and diseases…) were also relatively frequent, with around half of households being affected in the first three rounds.

Table 4.2 *Summary statistics by survey rounds*

	2005/6		2009/10		2010/11		2011/12	
	Mean	Sd.	Mean	Sd.	Mean	Sd.	Mean	Sd.
Monthly real household expenditure (UShs)	215,093	379,790	257,244	474,486	208,727	269,133	256,640	534,772
Monthly real food cons. per adult equiv. (UShs)	34,955	35,359	33,333	25,345	28,560	22,269	28,874	20,377
Asset index (unitless)	1.042	1.247	1.076	1.414	1.067	1.381	1.101	1.282
Land size (acres)	3.261	20.951	2.623	10.444	3.769	23.964	2.397	7.704
Household size	5.758	3.026	6.620	3.265	7.316	3.560	7.946	3.869
Proportion children (%)	0.551	0.231	0.515	0.408	0.521	0.389	0.549	0.383
Education head (years)	5.254	3.936	5.091	4.050	5.451	4.229	5.169	4.083
Age of head (years)	42.786	15.001	46.801	14.928	47.435	14.899	48.268	14.707
Female-headed (%)	0.271		0.287		0.310		0.317	
Poor (%)	0.281		0.248		0.291		0.272	
Agric. households (%)	0.825		0.845		0.821		0.807	
Rural households (%)	0.796		0.799		0.799		0.796	
Food price shocks (%)	baseline		0.633		0.517		0.342	
Agricultural shocks (%)	0.487		0.500		0.484		0.242	
Health shocks (%)	0.183		0.113		0.114		0.064	
Income shocks (%)	0.108		0.020		0.03		0.087	
Other shocks (%)	0.156		0.045		0.050		0.040	

Appendix D.1.A plots the distributions of households' welfare indicators (log consumption values and asset index) between 2005/6 and 2011/12. The striking feature of these distributional plots is their shifts to the right in a zigzag fashion, suggesting an overall improvement in households' assets accumulation over time coupled with significant downward and upward movements. These transitions are particularly pronounced with regards to consumption where for instance the plots of first and third surveys almost entirely overlap. These trends in asset holdings and consumption expenditures become apparent when they are expressed in growth rates, as in the second part of Appendix D.1.A which graphs the density functions of the average annual growth rates of assets and consumption. The median growth rate of asset index between 2005/6 and 2009/10 was only 3.3% against an impressive 18% in terms of consumption values. However, around 60.5% of households experienced a positive growth rate in their monthly real values of consumption during that period, whereas slightly more households (around 61.5%) accumulated assets. Between 2009/10 and 2010/11, the median rates of consumption and assets growth were both negative at respectively -19.8 and -0.8%, with only 37.6% displaying a positive rate of consumption growth and 44.5% for asset holdings. Finally, both the growth rates of both consumption and asset holdings were positive during the last sub-period, with a striking 29.3% increase in consumption compared to 3.2% in assets. 74.1% and 66.6% of surveyed households during this period reported a positive growth rate of their consumption and asset index.

4.5.4 Poverty dynamics, stochastic, and structural poverty

The analysis of poverty dynamics implies an explicit consideration of time. Indeed, empirical research on longitudinal data has revealed the importance of movements in and out of poverty and of the diversity of poverty trajectories from one period to another. Beyond the analysis of poverty evolutions based on cross-sectional data, it is particularly valuable to identify among poor households the chronically poor and those who are only transiently deprived. This is of utmost importance because not only the characteristics of these two types of poverty are not necessarily identical but also appropriate policy responses to tackle them might be different (Jalan and Ravallion, 2004; Ribas and Machado, 2007). Using the spells approach (Baulch and McCulloch, 1998), table 4.3 distinguishes chronically poor, transiently poor, and non-poor households between 2005 and 2012.

Table 4.3 *Percentage of households by poverty dynamics, by region: Spells approach*

		Regions			
Poverty status	All sample	Central	Eastern	Northern	Western
Never poor	0.472	0.705	0.375	0.273	0.512
Once poor	0.205	0.148	0.233	0.221	0.235
Twice poor	0.149	0.086	0.208	0.176	0.133
Thrice poor	0.106	0.049	0.124	0.169	0.084
Always poor	0.067	0.013	0.060	0.161	0.036

Using the full sample, around 6.7% of the households were chronically poor between 2005 and 2012, whereas almost half of the sample was never poor (47.2%). The percent of households into each spell of poverty then decreases with the number of spells, from 20.5% for once poor to 10.6% for thrice poor. Furthermore, the table sheds some light on regional heterogeneity in terms of poverty dynamics: households in the central region are particularly better-off with the highest proportion of non-poor (70.5%) and lowest percent of chronic poor (1.3%), while the northern and eastern regions display the worst welfare performances.

It is also possible to go further into the analysis of poverty dynamics by decomposing movements into and out of poverty into stochastic and structural transitions using both the official poverty line and the asset index. Structural movements are related to changes in assets accumulation while stochastic or transient changes refer to movements in consumption. In table 4.4, I present a poverty transition matrix between pairs of successive panel waves. Between two periods *t*-1 and *t*, a household will be stochastically poor if its asset index a_{ht} is at least above 1 in both periods while its monthly real values of consumption per adult equivalent c_{ht} lie below the official poverty line P_t in both periods. He will be structurally poor if both $a_{ht} < 1$ and $c_{ht} < P_t$ in *t*-1 and *t*. A household is downward mobile, meaning he is falling into poverty if $c_{ht-1} > P_{t-1}$, and $c_{ht} < P_t$. This mobility will be explained by stochastic movements if $a_{ht} > 1$, $\forall t$, whereas in case of structural movements, $a_{ht} > 1$ and $a_{ht-1} < 1$. Similarly, upward mobility implies that $c_{ht-1} < P_{t-1}$, and $c_{ht} > P_t$. If the household is climbing out of poverty for stochastic reasons, then both a_{ht-1} and a_{ht} are greater than 1 and if this mobility is due to structural factors, then $a_{ht-1} < 1$, and $a_{ht} > 1$. Finally, stochastically (structurally) non-poor households have $c_{ht} > P_t$, $\forall t$ and $a_{ht} < (>) 1$, $\forall t$.

By and large, the results from table 4.4 reveal that between pairs of successive panel waves, Ugandan households were overwhelmingly non-poor (more than 60% for each pair), while the shares of those twice poor, downward, and upward mobile were relatively close, ranging from 10 to 17%. Furthermore, the majority of household transitions into and out of poverty were attributed to stochastic movements rather than to assets depletion. For instance, over the first and second survey rounds, only 39.9% of chronic poor experienced a depletion of their assets while persistent poverty of 60.1% could be attributed to stochastic changes in their livelihood. The share of households that fell into poverty due to low asset levels during that period is less than the half of that of stochastically downward mobile. Among non-poor, only 26.4% hold assets that would be expected to yield a livelihood above the poverty line. Hence, the majority of these non-poor (73.6%) would also be vulnerable in case of shocks of particularly large magnitude. Between 2009/10 and 2010/11, the proportion of chronic and downward mobile slightly increases at the expense of other categories. For households that slid into (out of) poverty during that period, 47.7 (46.1%) were structurally mobile against 43.8 (42.8%) in the previous sub-period. Finally, the table highlights the importance of structurally persistent poverty over time. Indeed, the proportion of chronically poor households for structural reasons (reductions in asset holdings) is increasing over time, from 39.9% during the first sub-period to 49.3% in the last sub-period.

Table 4.4 *Poverty transition matrices*

		Poor				Non-poor			
				2009/10					
2005/6	Poor	*Twice poor*	13.02			*Upward mobile*	15.05		
				Stochastically poor	60.07			Stochastically mobile	57.19
				Structurally poor	39.93			Structurally mobile	42.81
	Non-poor	*Downward mobile*	11.78			*Twice non-poor*	60.15		
				Stochastically mobile	56.25			Stochastically non-poor	73.60
				Structurally mobile	43.75			Structurally non-poor	26.40
				2010/11					
2009/10	Poor	*Twice poor*	14.31			*Upward mobile*	10.49		
				Stochastically poor	54.02			Stochastically mobile	53.96
				Structurally poor	45.98			Structurally mobile	46.04
	Non-poor	*Downward mobile*	12.84			*Twice non-poor*	62.36		
				Stochastically mobile	52.33			Stochastically non-poor	72.18
				Structurally mobile	47.67			Structurally non-poor	27.82
				2011/12					
2010/11	Poor	*Twice poor*	16.80			*Upward mobile*	10.35		
				Stochastically poor	49.32			Stochastically mobile	60.88
				Structurally poor	50.68			Structurally mobile	39.11
	Non-poor	*Downward mobile*	12.33			*Twice non-poor*	60.52		
				Stochastically mobile	52.99			Stochastically non-poor	77.34
				Structurally mobile	47.01			Structurally non-poor	22.66

4.6 Estimation methods and results

In this section, the key propositions of the study are exposed (4.6.1) and the different econometric models for analyzing welfare dynamics (consumption growth and assets accumulation process), identifying critical welfare thresholds, and testing for single against multiple equilibria are presented (4.6.2 – 4.6.4). Finally, the section highlights the possibility of shifts in welfare equilibria due to differences in exposure to shocks and regional heterogeneity (4.6.5) and checks for the robustness of the econometric results by extending the definition of exposure to food price shocks (4.6.6).

4.6.1 Propositions

Two main propositions are tested regarding the effects of food price shocks on household's welfare growth and likelihood of being trapped into poverty. First, I hypothesize that being exposed to food price shocks is associated with differential welfare growth rates (consumption and assets accumulation) which signs depend on households' characteristics and initial conditions. Second, conditional on these characteristics and initial conditions, the higher the degree of exposure to food price shocks, the higher the likelihood of being trapped into poverty or converging towards lower levels of welfare equilibria.

Proposition 1: Let y_0, with $y_0 = \{c_0, a_0\}$ and $\mathbf{\Lambda}$ be respectively the initial welfare level (consumption levels c_0 or assets a_0) and household demographic characteristics. For two households h and j with identical initial welfare levels (i.e $y_{h,0} = y_{j0} = y_0$) and household characteristics at time *t* (net market position, household size, education, gender of the head, geographical location,…), then the household exposed to food price shocks will be likely to experience a lower welfare growth (consumption growth or assets accumulation) at time *t*+1 than a household who was unexposed. Formally, this means that:

$$\Delta \ln y_{h,t+1}\left(y_0, \mathbf{\Lambda} \middle| \theta_{ht}^f > 1\right) \leq \Delta \ln y_{j,t+1}\left(y_0, \mathbf{\Lambda} \middle| \theta_{jt}^f \leq 1\right)$$

Proposition 1.1: Given initial welfare levels (c_0 and a_0) and household h's demographic characteristics, the effects of food price shocks will be higher on consumption growth than on assets accumulation growth:

$$\Delta \ln c_{h,t+1}\left(c_0, \mathbf{\Lambda} \middle| \theta_{ht}^f > 1\right) \leq \Delta \ln a_{h,t+1}\left(a_0, \mathbf{\Lambda} \middle| \theta_{ht}^f > 1\right)$$

Proposition 1.2: Let two households h and j be exposed to food price shocks at time *t*+1, with the degree of exposure being higher for h (i.e. $\theta_{ht}^f \geq \theta_{jt}^f > 1$). In this case, conditional on household characteristics and initial welfare levels, the welfare growth rate between *t* and *t*+1 will likely be lower the higher the degree of exposure to food price shocks. Otherwise stated:

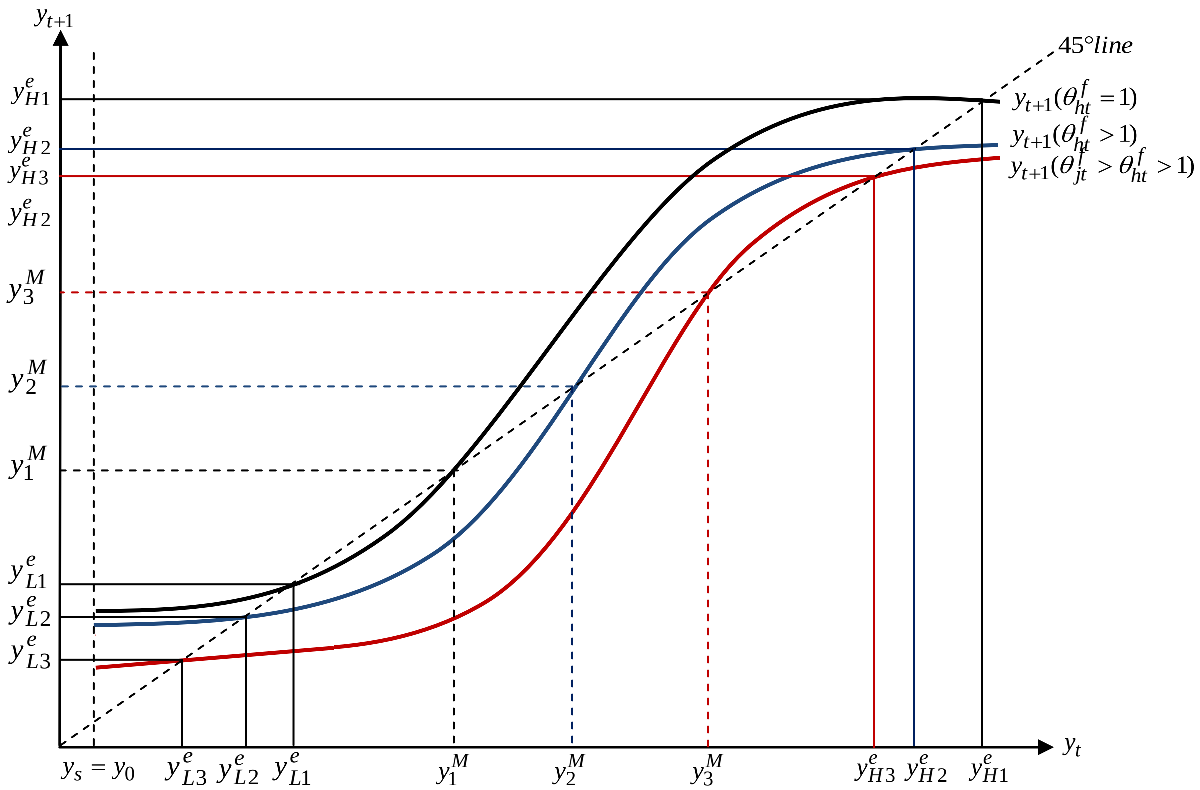
$$\Delta \ln y_{h,t+1}\left(y_0, \mathbf{\Lambda}, \theta_{ht}^f\right) \leq \Delta \ln y_{j,t+1}\left(y_0, \mathbf{\Lambda}, \theta_{jt}^f\right) \text{ for } \theta_{ht}^f \geq \theta_{jt}^f > 1$$

Proposition 2: Let households *h* and *j* with identical initial conditions y_0 and demographic characteristics $\mathbf{\Lambda}$. Then the household with a higher degree of exposure to food price shocks is likely to suffer from a lower welfare equilibrium level. Formally, if y_h^e and y_j^e are the welfare equilibrium levels towads which households *h* and *j* are converging in the long run, then we have that:

$$y_h^e\left(y_0, \mathbf{\Lambda}, \theta_{ht}^f\right) \le y_j^e\left(y_0, \mathbf{\Lambda}, \theta_{jt}^f\right) \text{ if } \theta_{ht}^f \ge \theta_{jt}^f > 1$$

Figure 4.2 illustrates the above propositions through the hypothetic non-linear welfare dynamics as theorized by Carter and Barrett (2006). y_s represents the welfare subsistence level (consumption or asset holdings) below which accumulation is deemed impossible. For simplicity, households' initial welfare levels (y_0) are assumed equal to this survival threshold. Conditional on their initial welfare levels and demographical characteristics, the households' accumulation growth path depends on their exposure to food price shocks $y_{t+1}\left(\theta_{ht}^f\right)$.

Figure 4.2 *Hypothetic relationships between welfare dynamics and exposure to food price shocks*



In this setting, there are three types of welfare equilibria: low stable equilibria $y_{Li}^e, i = 1,2,3$, high stable equilibria $y_{Hi}^e, i = 1,2,3$, and unstable equilibria $y_i^M, i = 1,2,3$. Prior to any price shocks, households' welfare dynamics are given by the $y_{t+1}\left(\theta_{ht}^f = 1\right)$ curve, characterized by low and high stable equilibria y_{L1}^e and y_{H1}^e.

In case of exposure to food price shocks, households do not necessarily converge towards their potential welfare equilibria (y_{L1}^e and y_{H1}^e) but there are instead shifts in both their welfare dynamics and equilibria. For example, the household exposed to price shocks will follow a dynamic path (blue curve) located below that of an unexposed household and he will thus converge to much lower stable equilibria $y^e_{L2} < y^e_{L1}$ and $y^e_{H2} < y^e_{H1}$. Hence, given initial welfare levels and demographic characteristics, exposure to food price shocks leads to lower welfare growth path $y_{t+1}\left(\theta^f_{ht} > 1\right)$. When it comes to comparison of two households exposed to food price shocks, the one with a higher degree of exposure will be characterized by lower welfare equilibria: $y^e_{L3} < y^e_{L2} < y^e_{L1}$ and $y^e_{H3} < y^e_{H2} < y^e_{H1}$.

4.6.2 Parametric models of consumption and asset dynamics

The starting point of our estimation strategy is given by equation (4.10). 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 $\Delta \ln \theta^f_{ht}$ and other asset shocks $\left(\theta^k_t\right)$. Hence, our baseline empirical model is given by:

$$\Delta \ln c_{ht} = \sigma_0 + +\sum_{i=1}^{3} \beta_i \ln c^i_{ht-1} + \mathbf{\Lambda}'\boldsymbol{\alpha} + \sigma_1 \Delta \ln \theta^f_{ht} + \sum_{j=1}^{3} \nu_j \theta^{kj}_t + \left(\eta_h + \mu_{ht}\right) \qquad (4.14)$$

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)[87], 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^{k1}_{ht}) which

[87] 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 study, I used: 1 TLU = Camels 1.0; Cattle 0.7; Sheep/Goats: 0.1.

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 (4.14) which would suggest a homogeneous impact of price shocks. I extend this model by investigating the presence of nonlinear 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 (Dercon and Krishnan, 2000; 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:

$$\Delta \ln c_{ht} = \sigma_0 + \sum_{i=1}^{3} \beta_i \ln c_{ht-1}^{i} + \mathbf{\Lambda'\alpha} + \sigma_1 \Delta \ln \theta_{ht}^{f} + \sigma_2 \left(\Delta \ln \theta_{ht}^{f} \times vul_{ht}^{\theta}\right) + \sigma_3 vul_{ht}^{\theta} + \sum_{j=1}^{3} \nu_j \theta_t^{kj} + \varepsilon_{ht} \tag{4.15}$$

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. In addition, equation (4.15) can also be used to test both nonlinearities in price effects and our propositions 1 (and its corollaries) and 2. 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 nonlinearity simply implies testing the null hypothesis that $\hat{\sigma}_2$ is statistically different from 0. The proposition 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 dynamic consumption growth model in (4.15) can equivalently be written in levels as:

$$\ln c_{ht} = \beta_0 + \sum_{i=1}^{3} \beta_i \ln c_{ht-1}^{i} + \mathbf{\Lambda'\alpha} + \sigma_1 \Delta \ln \theta_{ht}^{f} + \sigma_2 \left(\Delta \ln \theta_{ht}^{f} \times vul_{ht}^{\theta}\right) + \sigma_3 vul_{ht}^{\theta} + \sum_{j=1}^{3} \nu_j \theta_t^{kj} + \varepsilon_{ht} \tag{4.16}$$

The estimation of these non-linear dynamic panel models 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[88]. 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 4.5 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 nonlinear effects of price shocks. Specification tests were performed using both serial correlation and over-identification tests.

[88] The choice between the Sargan and Hansen tests depends on whether the robust option is used, the Hansen test being applied in robust estimations.

Table 4.5 *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.

In all the four 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. Particularly, the results confirm our proposition 1 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 4.5 (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 nonlinear 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 4.5, 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[89], which means that the consumption levels of households reporting a 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 4.5. 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.

To see whether households located below and above this threshold are intrinsically different, Appendix D.2 summarizes some key statistics of these two groups of households. In line with our priors, households above the vulnerability threshold reported on average 24% higher food dependency, 18.8% higher market participation rate, and 80.1% lower per capita income than those below $\left(vul_h^{\theta}\right)^{\bullet}$. The last column of the appendix also reveals that these mean differences were statistically significant at 1% level. Furthermore, higher vulnerability appears to be negatively correlated with the education of the head insofar as highly vulnerable households are ruled by on average by less educated heads. Finally, I do not find any statistically significant difference between these two groups of households as of the household size.

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

[89] Alternatively, one could derive this threshold level through a dynamic panel threshold model using non-linear System-GMM as implemented by Masten et al (2008), Chami et al (2009) or Combes and Ebeke (2012).

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:

$$\begin{aligned} \Delta \ln a_{ht} &= \beta_0 + \sum_{i=1}^{3} \beta_i \ln a_{ht-1}^{i} + \mathbf{\Lambda'\gamma} + \beta_4 \Delta \ln \theta_{ht}^{f}(\mathbf{\Lambda}) \\ &\quad + \beta_5 \theta_t^k + \beta_6 a_{h,0} + \beta_7 \theta_t^k * apovstatus + (\tau_h + \mu_{ht}) \end{aligned} \tag{4.17}$$

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 (4.17). 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 4.6 displays the estimation results of equation (4.17) using a two-step S-GMM regression of Arellano-Bover (1995) and Blundell-Bond (1998). 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.

Table 4.6 *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.

In terms of the impact of shocks on assets accumulation growth, the 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%[90] fall in consumption growth rates. This validates our sub-proposition 1.1 that 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 nonlinear 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 equilibria.

Testing for poverty traps

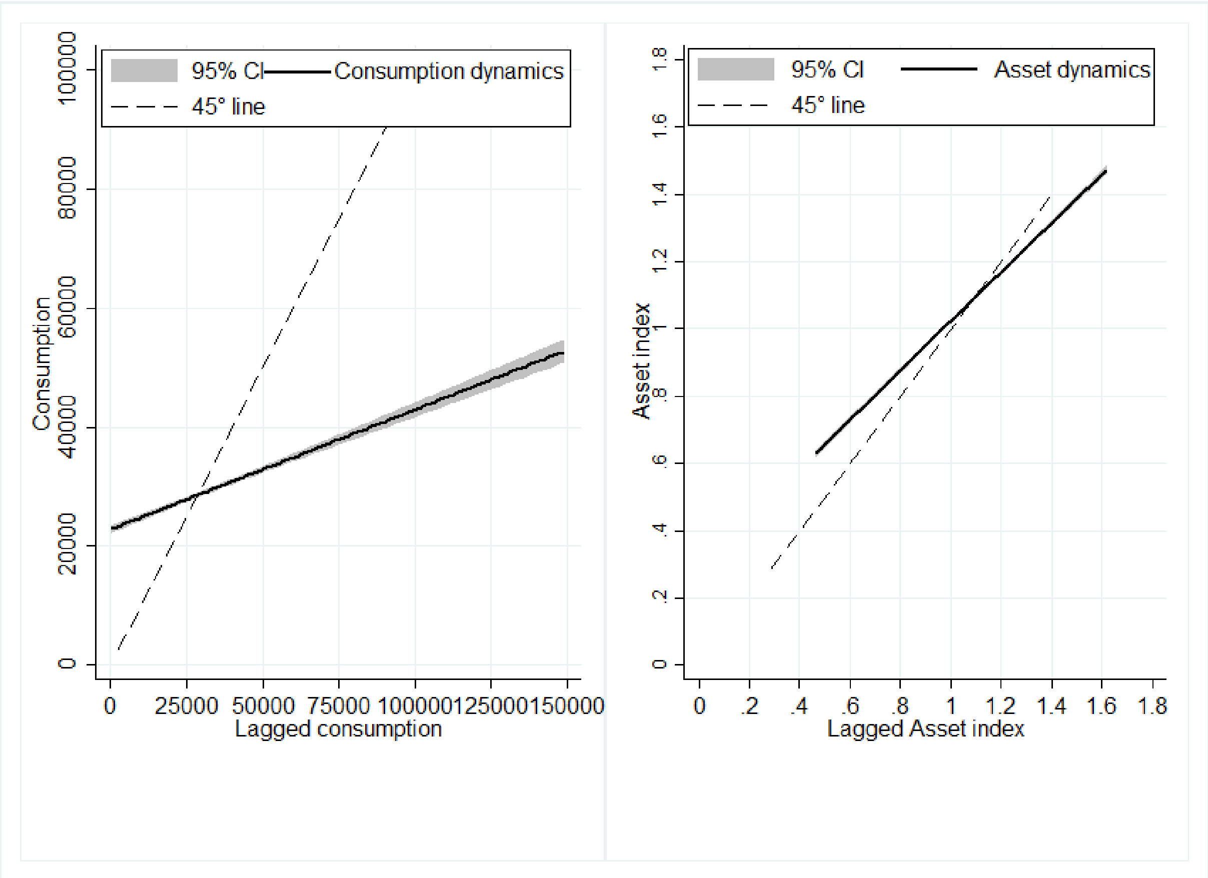
The results of the parametric models of consumption growth and assets accumulation process have revealed the existence of nonlinearities in household welfare dynamics. However, finding these nonlinearities does not necessarily imply the presence of poverty traps or guarantee welfare multiplia equilibria (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 4.5 and 4.6. 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

[90] The sum of $\hat{\sigma}_1$ and $\hat{\sigma}_2$ in model IV

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 4.3 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.

Figure 4.3 *Consumption and asset dynamics: Predicted values using parametric methods*



On the contrary, the 45 degree line cuts both consumption and asset dynamics' lines 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[91] for per capita real monthly consumption.

[91] This value represents the average of poverty lines for each survey round.

Testing for conditional convergence

The evidence of a single welfare equilibrium in either consumption values or assets accumulation suggests that households above that threshold are expected to converge downwards until they reach the stable equilibrium whereas those below the threshold will eventually improve their welfare levels and approach upwards the stable equilibrium. A standard empirical question is thus whether there is conditional convergence in the welfare data and, particularly, whether the convergence is occurring within or between villages or districts at identical speeds. Following Dercon (2004), I test parametrically these questions by estimating the following model:

$$\Delta \ln y_{ht} = \beta_0 + \beta_1\left(\ln y_{ht-1} - \ln \bar{y}^d_{ht-1}\right) + \beta_2 \ln \bar{y}^d_{ht-1} + \mathbf{\Lambda}'\boldsymbol{\gamma} + \beta_3 \Delta \ln \theta^f_{ht}(\mathbf{\Lambda}) + \beta_4 \theta^k_{ht} + \mu_{ht} \quad (4.18)$$

where the dependent variable is the growth rate of either consumption or asset holdings. $\bar{y}^d_{ht-1}$ stands for the average welfare level in village/district *d* in period *t*-1. All the other variables were defined previously.

The conditional convergence at the district level implies a negative and significant coefficient β_1, while the hypothesis of convergence at different speeds can be tested using a Wald test of $\beta_1 = \beta_2$. Table 4.7 presents both the estimated results of equation (4.18) using a two-step GMM regression and the conditional convergence tests for consumption and assets.

Table 4.7 *Conditional convergence tests of welfare dynamics: Two-step GMM estimation*

	Dependent variable:	
	$\Delta \ln c_{ht}$	$\Delta \ln a_{ht}$
β_0	0.855 (0.084)***	-0.007 (0.021)
β_1	-0.912 (0.025)***	-0.668 (0.030)***
β_2	-0.531 (0.078)***	-0.464 (0.071)***
β_3	-0.209 (0.019)***	-0.032 (0.018)*
β_4	-0.021 (0.010)**	-0.059 (0.031)*
$\mathbf{\Lambda}$	Included	Included
Convergence test Test: $\beta_1 = \beta_2$ (p-value)	0.000***	0.004***
Observations	6,519	6,519

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

The estimated coefficients β_1 are statistically significant and negative, shedding light on the convergence process within Ugandan districts in terms of consumption and assets accumulation. Similarly to Dercon (2004) in the Ethiopian case, these results suggest that richer districts are enjoying higher growth rates of consumption and assets accumulation ($\beta_2 - \beta_1$) than poorer districts. Furthermore, the Wald tests reject the null hypothesis that convergence across districts are occurring at identical speeds. Since β_1 is significantly larger, in absolute terms, than β_2, welfare convergence speeds are significantly different across districts than within the same districts.

4.6.3 Non-parametric models of consumption and asset dynamics

One of the main drawbacks of parametric methods developed above 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:

$$y_{ht} = f(y_{ht-1}) + \varepsilon_{ht}, \quad y_{ht} = \{c_{ht}, a_{ht}\}$$
$$\text{with } \varepsilon \sim N(0; \sigma_\varepsilon^2), \quad 1 \le h \le N, \quad and \quad 2 \le t \le T \tag{4.19}$$

The non-parametric bivariate relationship between the current welfare level y_{ht} and its lagged values portrayed in equation (4.19) 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 4.4 and 4.5, I only present the results of consumption (figure 4.4) and asset (figure 4.5) dynamics using location polynomial smoothing and LOWESS estimates. Other non-parametric techniques, such as splines, provided substantially identical welfare recursion diagrams and are thus omitted for brevity. 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 4.4 *Consumption dynamics: LOWESS estimates and Kernel-weighted local polynomial smooth*

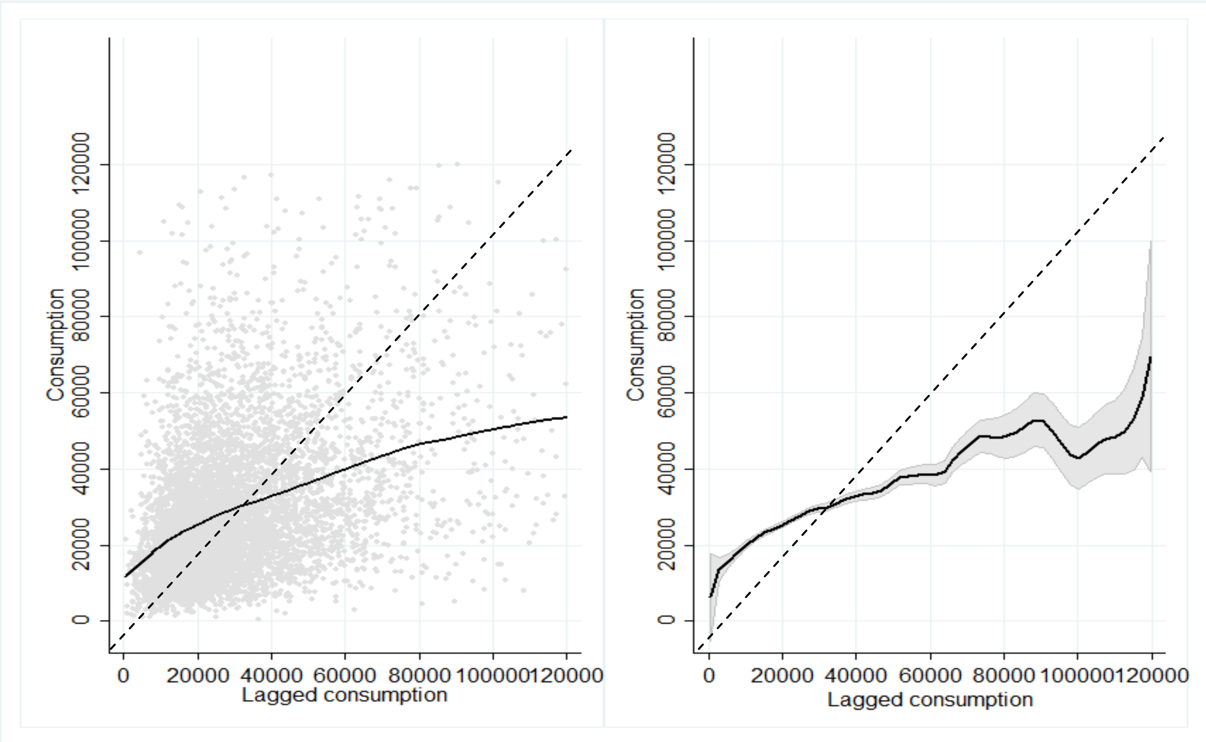
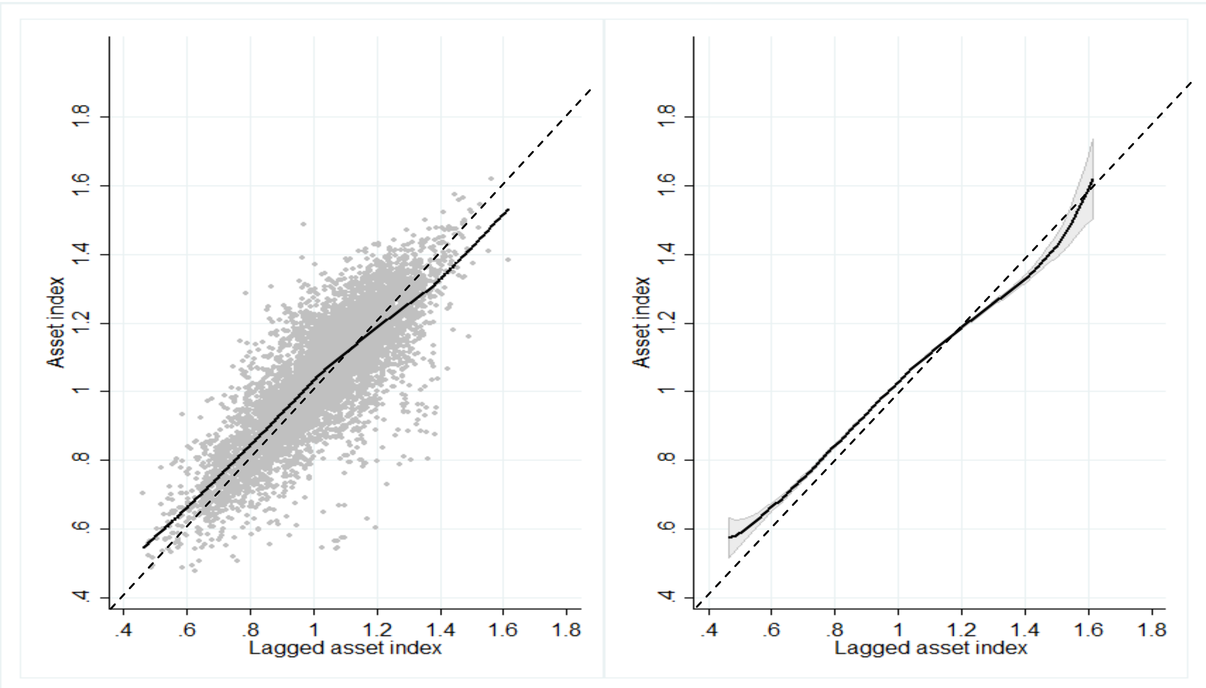


Figure 4.5 *Asset dynamics: LOWESS estimates and Kernel-weighted local polynomial smooth*



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.

4.6.4 Semi-parametric methods

Semi-parametric methods include both parametric components (such as time dummies and other explanatory variables), and a non-parametric component $f(y_{ht-1})$, 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:

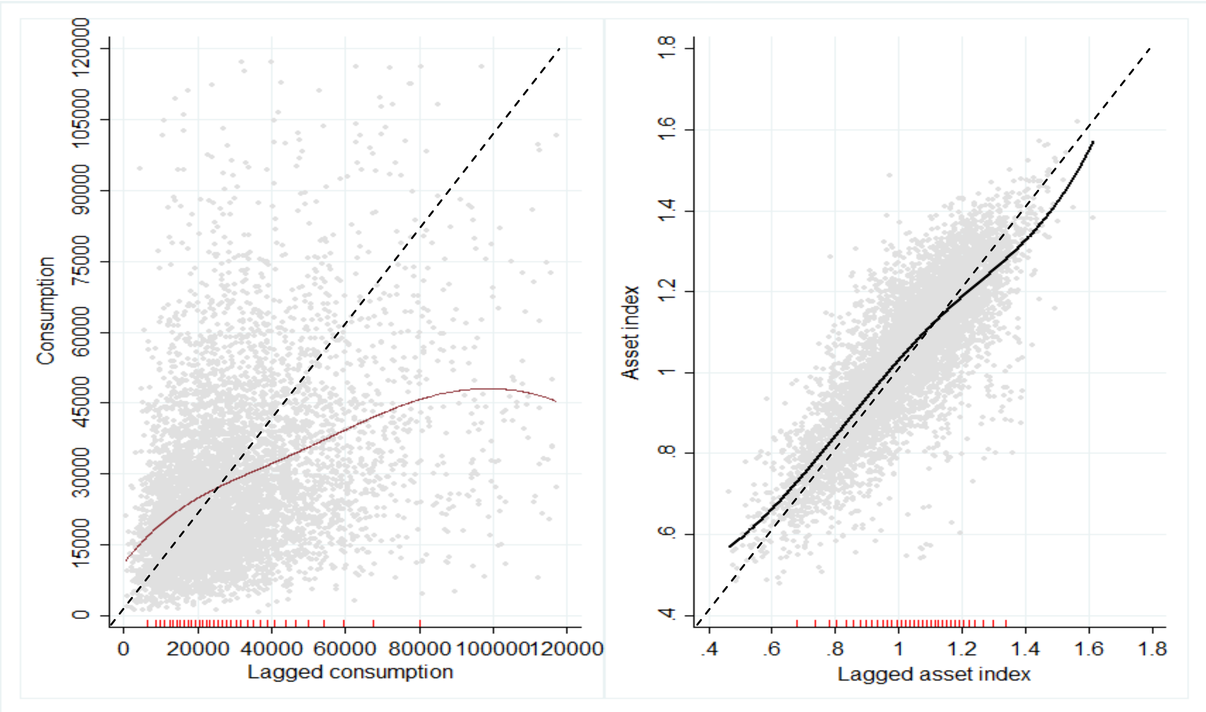
$$y_{ht} = \mathbf{X_{ht}\beta} + f(y_{ht-1}) + \eta_h + \mu_{ht} \qquad (4.20)$$

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[92]. 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 4.6.

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.

[92] Other semi-parametric estimators include Baltagi and Li's (2002) semi-parametric fixed effects estimator, Yatchew's difference estimator, or Robinson's double residual estimator.

***Figure 4.6** Semi-parametric penalized spline regression estimation: Consumption and asset dynamics*



4.6.5 Shifts in welfare equilibria, exposure to food price shocks, and regional heterogeneity

So far, the 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. For example, table 4.3 has revealed that the poverty profile of Ugandan households is not uniformly distributed across the country, some regions being particularly more vulnerable than others. 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 4.8 and 4.9 report the estimated approximate locations of welfare dynamic equilibria by sub-groups of population. In terms of consumption, table 4.8 reveals that sub-groups of the Ugandan population are moving towards different welfare thresholds, regardless of the specified econometric method.

Table 4.8 *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 99^{th} percentile and replaced by values observed at that percentile. CI stands for confidence intervals.

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%[93] 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). These sequences of welfare equilibria conform to our proposition 2 stating that the higher the degree of exposure to food price shocks, the lower the level of attainable welfare equilibrium.

[93] The average value from the different estimation methods in table 4.8.

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 4.8 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 4.9 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 $\left(vul_h^{\theta}\right)^{\bullet}$.

Table 4.9 *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

4.6.6 Sensitivity of estimation results to the definition of shock variable

In this last section, I examine whether the previous 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 (4.12) 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 the 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 (4.12), $\hat{\varepsilon}_{hct}$, 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 4.10.

Table 4.10 *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.

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%.

4.7 Conclusions

Recently, empirical studies on households' vulnerability to covariate and idiosyncratic shocks have been increasingly prominent, especially in developing countries. Of particular interest have been the poverty impacts of high food prices in rural and poor communities. It has been established that in many settings, increases in food prices were detrimental for the majority of households in developing countries, as they are primarily pure consumers or net buyers of agricultural products. However, most of these studies are developed under a cross-sectional approach and therefore fall short of uncovering the potential effect of price changes on poverty dynamics or persistent poverty. This last essay has tried to fill this empirical gap by analyzing the structure of household welfare dynamics in a context characterized by high food price volatility and differential exposure to food price shocks. It has particularly tested the assumption that households that faced large increases in food prices were likely to experience high risks of thrusting into poverty traps 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, the 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 households 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 out 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.

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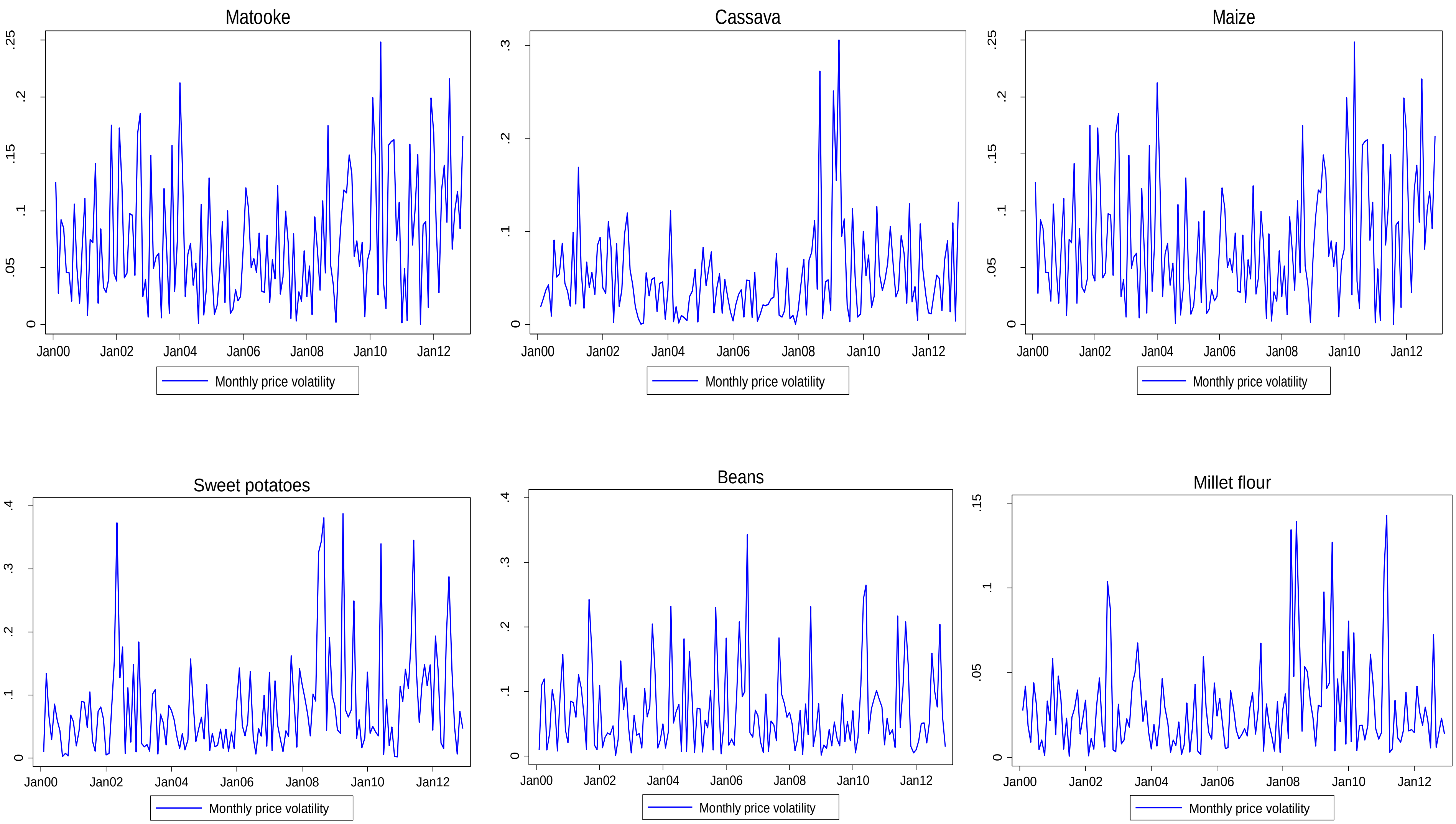
APPENDICES

Appendix A

Additional data and estimation results for Essay I

Appendix A.1 *Monthly price volatility plots (January 2000 – December 2012)*



Appendix A.2 *Monthly price volatility by main agricultural seasons, 2000m1 – 2012m12*

Agricultural seasons	Months	Matooke	cassava	Maize	Sweet potatoes	Beans	Millet flour	Average
	March	0.057	0.053	0.043	0.072	0.041	0.034	0.050
Planting 1	April	0.075	0.069	0.049	0.083	0.067	0.032	0.063
	May	0.101	0.046	0.075	0.081	0.058	0.028	0.065
	Average	0.078	0.056	0.056	0.079	0.055	0.031	0.059
	June	0.056	0.053	0.093	0.121	0.097	0.038	0.076
Harvest 1	July	0.087	0.047	0.087	0.110	0.069	0.032	0.072
	August	0.048	0.036	0.078	0.091	0.051	0.025	0.055
	Average	0.064	0.045	0.086	0.108	0.072	0.031	0.068
	September	0.080	0.065	0.065	0.087	0.172	0.033	0.084
Planting 2	October	0.083	0.055	0.068	0.049	0.092	0.027	0.062
	November	0.043	0.044	0.112	0.066	0.064	0.024	0.059
	Average	0.068	0.055	0.081	0.068	0.109	0.028	0.068
	December	0.079	0.039	0.078	0.061	0.045	0.015	0.053
Harvest 2	January	0.070	0.030	0.081	0.090	0.050	0.028	0.058
	February	0.011	0.062	0.071	0.066	0.035	0.031	0.046
	Average	0.084	0.043	0.076	0.072	0.043	0.025	0.057
Conclusion		$H_1<P_2<P_1<H_2$	$H_2<H_1<P_2<P_1$	$P_2<H_2<P_2<H_2$	$P_2<H_2<P_1<H_1$	$H_2<P_1<H_1<P_2$	$H_2<P_2<P_1=H_1$	$H_2<P_1<H_2=P_2$

Note: P_1, P_2, H_1, and H_2 denote respectively the first and second planting seasons, and the first and second harvest seasons in Uganda.

Appendix A.3 *Estimated results of Multivariate VARs*

	Matooke	Cassava	Maize	Sweet potatoes	Beans	Millet flour
Matooke$_{t\text{-}1}$	0.689	-0.156	-0.082	0.093	-0.132	0.029
	(0.076)***	(0.062)**	(0.082)	(0.109)	(0.068)*	(0.038)
Cassava$_{t\text{-}1}$	-0.013	0.756	-0.180	0.328	-0.287	-0.063
	(0.108)	(0.088)***	(0.106)*	(0.085)***	(0.126)**	(0.054)
Maize$_{t\text{-}1}$	-0.006	0.026	0.375	0.026	0.058	-0.059
	(0.074)	(0.060)	(0.080)***	(0.107)	(0.087)	(0.027)*
Sweet potatoes$_{t\text{-}1}$	0.079	0.106	0.015	0.458	0.016	0.024
	(0.048)*	(0.048)**	(0.064)	(0.085)***	(0.069)	(0.030)
Beans$_{t\text{-}1}$	-0.023	-0.031	0.108	0.057	0.507	-0.017
	(0.066)	(0.054)	(0.051)*	(0.096)	(0.078)***	(0.033)
Millet flour$_{t\text{-}1}$	0.178	-0.110	-0.249	0.046	-0.011	0.638
	(0.153)	(0.125)	(0.145)*	(0.221)	(0.179)	(0.077)***
Matooke$_{t\text{-}2}$	0.437	0.023	-0.035	0.098	-0.116	0.005
	(0.080)***	(0.065)	(0.086)	(0.116)	(0.094)	(0.040)
Cassava$_{t\text{-}2}$	0.031	0.195	-0.062	0.082	0.046	-0.059
	(0.108)	(0.088)**	(0.116)	(0.156)	(0.126)	(0.054)
Maize$_{t\text{-}2}$	-0.010	-0.024	0.274	-0.017	0.008	-0.033
	(0.074)	(0.060)	(0.080)***	(0.107)	(0.087)	(0.037)
Sweet potatoes$_{t\text{-}2}$	0.031	0.053	-0.063	0.146	0.015	-0.036
	(0.059)	(0.048)	(0.064)	(0.085)*	(0.069)	(0.030)
Beans$_{t\text{-}2}$	-0.014	0.027	0.199	0.010	0.413	-0.009
	(0.064)	(0.052)	(0.069)***	(0.092)	(0.075)***	(0.032)
Millet flour$_{t\text{-}2}$	0.080	-0.180	-0.400	-0.358	-0.056	0.290
	(0.154)	(0.126)	(0.166)***	(0.202)*	(0.180)	(0.077)***
break	-0.008	0.041	-0.006	0.018	-0.021	0.032
	(0.025)	(0.020)**	(0.027)	(0.036)	(0.029)	(0.012)**
Cons	0.001	-0.001	0.000	-0.001	0.001	-0.001
	(0.005)	(0.004)	(0.005)	(0.007)	(0.006)	(0.002)
Adjusted R^2	0.390	0.432	0.300	0.275	0.402	0.359

Note: Standard errors into brackets. ***, **, *, denote significance levels at 1, 5, and 10%, respectively

Appendix A.4 *Matrix of pairwise correlations of food price volatilities*

	Matooke	Cassava	Maize	Sweet potatoes	Beans	Millet flour
Matooke	1					
Cassava	-0.255 (0.001)***	1				
Maize	0.191 (0.018)**	-0.303 (0.000)***	1			
Sweet potatoes	0.076 (0.347)	0.315 (0.000)***	0.283 (0.000)***	1		
Beans	-0.010 (0.898)	0.114 (0.157)	0.089 (0.266)	0.136 (0.091)*	1	
Millet flour	0.022 (0.787)	-0.264 (0.001)***	0.127 (0.115)	0.139 (0.086)*	-0.030 (0.712)	1

Note: ***, **, and * denote significance levels at 1, 5, and 10%, respectively

Appendix B

Additional data and estimation results for Essay II

***Appendix B.1** Testing and correcting for attrition in the Uganda National Panel Surveys*

The prominence of available panel data in the recent decades has helped researchers to undertake the analysis of economic relationships that would have otherwise been impossible. Indeed, among the main advantages of longitudinal data, they usually provide the researcher with a large number of data points (*N*T*), thereby increasing both the degrees of freedom and the efficiency of econometric estimations by reducing the collinearity of explanatory variables. By tracking the same individuals or households over an extended period of time, panel data can control for their unobserved heterogeneity, investigate the dynamics of their welfare indicators such consumption, income, or asset holdings, and test for some microeconomic theories such as the Permanent Income Hypothesis (PIH), and consumption or asset smoothing.

Despite the well-recognized and documented advantages of panel data, they generally suffer from sample selection and attrition. The former arises when the observed sample is not a random draw from the population of interest which can potentially lead to inconsistency and bias in the estimation of parameters of interest. The latter, often dubbed “the panel researcher’s nightmare” (Winkles and Withers, 2000), arises when the individuals or households that have dropped out of the panel are systematically different from those who have stayed. Consequently, the results based on the remained surveyed individuals may no longer be representative of the original population. If the drop-out is entirely random, then there is nothing further the researcher can do.

In the present appendix, we present the procedure used to test and correct for the attrition bias[94]. To test for the consistency of the results, two tests are successively presented: the attrition probits’ tests of Fitzgerald et al. (1998) and the pooling tests of Becketti, Gould, Lillard and Welch (1988) (henceforth, BGLW test). The correction of attrition bias is then done through the *inverse probability weighting* (IPW) procedure (Fitzgerald et al., 1998; Wooldridge, 2002)

Tests of attrition bias

In table B.1.1, we summarize the number of population (and households) in the Uganda National Panel Surveys (UNPS) used in the present study as well as the attrition rate from the original sample. Out of the 3,123 households (representing 16,759 individuals) that were initially sampled for the panel dataset, 83.5% (or 2,607 households) were successively tracked in 2009/10 (UNPS-2010). In the third survey, this percent slightly decreased to 82.1% (2,564 households) and in the UNPS-2012, around 1,000 households were not successively tracked. These numbers give an attrition rate relatively high (above 15%).

[94] The sample design of the LSMS (Living Standards Measurement Surveys) and LSMS-ISA (LSMS-Integrated Surveys on Agriculture) of which the UNPS are part eliminates or at least minimize the risk of sample selection problems.

Table B.1.1 *Summary of the number of population and households in the UNPS and the attrition rate*

	Population interviewed	Number of households sampled	Number of households successively tracked	Attrition rate from the original sample
UNPS-2006: Baseline survey	16,759	3,123	3,123	0.00
UNPS-2010	17,511	3,123	2,607	16.30
UNPS-2011	18,810	3,123	2,564	17.90
UNPS-2012	16,139	3,123	2,356	24.56

To test whether the observed attrition was random, we estimate a probit model (Fitzgerald et al., 1998) in which the dependent variable (*attrition*) takes 1 if the household drops out of the sample after the first wave and 0 otherwise[95]. The independent variables are all baseline variables likely to affect the attrition. Among these variables, we include household characteristics such as household size, household composition (proportions of household members between 0 and 4, 5-14, 19-34, 35-54, and 55 and beyond), monthly real values of consumption per adult equivalent, the estimated values of productive assets, and the cultivated land size (in acres). We also add household head characteristics (years of education, age and its squared value, and sex), regional dummies, as well as the household's net position in the food market.

Results of the probit model, reported in table B.1.2, show that most explanatory variables negatively affected the probability of dropping out of the panel after the first survey. It appears that on average households that were most likely to be re-interviewed in all waves have significantly larger family, have a head significantly older, and are essentially agricultural (all the estimated coefficients associated with different net position in the food market are negative). However, monthly values of consumption significantly and positively influence the probability of dropping out of the sample. In addition, the value of the pseudo R-squared from the attrition probit is only 14.5%, implying baseline variables only explain about 14.5% of the panel attrition between 2005/6 and 2011/12.

To perform the BGLW test, we first interact the dependent variable from table B.1.2 (attrition) with all the independent variables from the attrition probit and regress the log of monthly real values of consumption on household and auxiliary variables and their interactions with the attrition variable (Outes-Leon and Dercon, 2011; Baulch and Quisumbing, 2011). We then perform an *F*-test to check whether the attrition dummy variable and its interactions with household and auxiliary variables are jointly significant to zero, with the null hypothesis that the observed attrition status of

[95] In doing so, we are only treating a special form of attrition in which attrition is an absorbing state (Wooldridge, 2002: 585), meaning that once individuals/households have dropped out of the survey (at t=2 or beyond), they cannot reenter. In the general case, surveyed units can reenter the sample after leaving. In the UNPS, only 20 households reenter after leaving in 2009/10.

a household is random. We find an *F*-test of 4.63 with a *p*-value of 0.000, meaning that the observed attrition in the Ugandan panel dataset was primarily non-random and therefore needs to be corrected for.

Table B.1.2 *Attrition Probit for household consumption (n=3,123)*

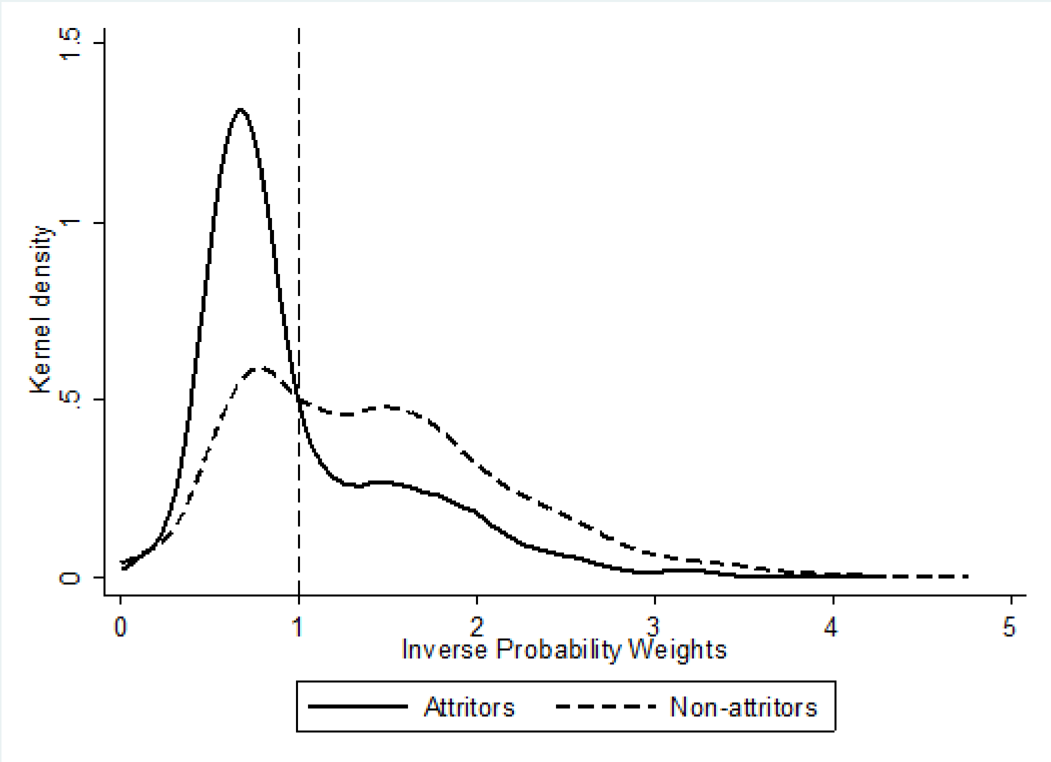
	Coefficient	Standard errors (a)	*z*-statistic (*p*-value)
Years of education	-0.004	0.009	-0.50 (0.619)
Age	-0.037	0.012	-3.09 (0.002)***
Age squared	0.000	0.000	2.57 (0.010)***
Sex: *1 if female-headed*	0.032	0.061	0.52 (0.602)
Household size	-0.017	0.017	-1.01 (0.313)
% of household members between: *0-4 years*	-0.873	0.270	-3.23 (0.001)***
5-14 years	-0.898	0.247	-3.64 (0.000)***
15-19 years	-0.712	0.269	-2.65 (0.008)***
20-34 years	-0.401	0.219	-1.84 (0.066)*
35-54 years	-0.245	0.207	-1.19 (0.235)
Land size (acres)	-0.004	0.004	-1.17 (0.241)
Value of assets (log)	-0.029	0.022	-1.30 (0.195)
Region dummy: *1 if Eastern region*	-0.004	0.081	-0.04 (0.964)
1 if Northern region	-0.163	0.096	-1.70 (0.090)*
1 if Western region	0.343	0.096	3.58 (0.000)***
Monthly consumption (log)	0.154	0.053	2.89 (0.004)***
Net food market position: *1 if SNS*	-0.900	0.080	-9.99 (0.000)***
1 if SNB	-0.722	0.076	-9.46 (0.000)***
1 if INS	-0.953	0.183	-5.19 (0.000)***
1 if INB	-0.843	0.175	-4.82 (0.000)***
Constant	0.109	0.631	0.17 (0.862)
Pseudo – R squared		0.145	
Log Pseudolikelihood		-1,440.117	

Note: ([a]): clustered-robust standard errors, at the village level (322 clusters). SNS, SNB, INS, and INB denote respectively, significant net sellers, significant net buyers, insignificant net sellers, and insignificant net buyers. *** and * denote significance levels at 1 and 10%, respectively.

Computing Inverse Probability Weights (IPW) to correct for attrition bias

To correct for the non-randomness of the attrition, we follow Moffit et al. (1999) by computing *inverse probability weights* (*IPW*). The procedure consists in first calculating the predicted probabilities from the unrestricted retention probit model using the same set of variables as in table *B.1.2* and then re-estimating the same model by excluding household demographics and head characteristics. The *IPW* are then computed as the ratio between the restricted and unrestricted probabilities. The average value of the *IPW* was 1.331 with a standard deviation of 0.742. The *IPW* for non-attritors were found to be larger than those of attritors, with 1.429 against 1.010. These *IPW* are then using in all econometric estimations to account for the attrition bias.

Figure B.1.1 *Kernel distribution of IPW for attritors and non-attritors*



Appendix B.2 *Demand elasticities under separability*

Type of elasticity	Symbol	Formula
Conditional expenditure elasticity	η_i	$\eta_i = 1 + \frac{\mu_i}{s_i^*}$ where $\mu_i = \Phi_i\left(\beta_i + \frac{2\lambda_i}{b(P)}\ln\left[\frac{x}{a(P)}\right]\right)$ and $s_i^* = \Phi_i s_i + \phi_i$
Conditional Marshallian elasticity	ε_{ij}^u	$\varepsilon_{ij}^u = \frac{\mu_{ij}}{s_i^*} - \delta_{ij}$ where $\mu_{ij} = -\delta_{ij} + \frac{\Phi_i}{s_i}\left\{\gamma_{ij} - \mu_i\left(\alpha_j + \sum_{k=1}^{n}\gamma_{jk}\ln p_k\right) - \frac{\lambda_i\beta_i}{b(P)}\left[\ln\left(\frac{x}{a(P)}\right)\right]^2\right\}$ and δ_{ij} = 1 if $i = j$ and 0 otherwise.
Conditional Hicksian elasticity	ε_{ij}^c	$\varepsilon_{ij}^c = \frac{\mu_{ij}}{s_i^*} + \eta_i s_j^*$

Source: Banks et al., 1997; Shonkwiler and Yen, 1999

Appendix B.3 *Estimated average shadow elasticities by food net market position*

	Net market position	$E(w^* / p_i)$	$E(c_i / w^*)$	$E(w^* / x)$
	B	0.164 (0.047)***	0.145 (0.013)***	-0.033 (0.018)**
Matooke	**C**	0.087 (0.027)***	0.122 (0.022)***	-0.062 (0.018)***
	D	-0.050 (0.001)***	-0.124 (0.013)***	0.127 (0.068)*
	E	0.029 (0.138)	-0.120 (0.014)***	0.103 (0.059)*
	B	0.070 (0.050)	0.070 (0.020)**	-0.033 (0.018)**
Cassava	**C**	0.117 (0.037)***	0.076 (0.018)***	-0.062 (0.018)***
	D	0.051 (0.021)*	-0.042 (0.022)*	0.127 (0.068)*
	E	0.313 (0.149)**	-0.051 (0.019)***	0.103 (0.059)*
	B	-0.034 (0.046)	0.070 (0.019)**	-0.033 (0.018)**
Potatoes	**C**	0.083 (0.032)***	0.046 (0.024)*	-0.062 (0.018)***
	D	-0.066 (0.013)***	-0.041 (0.021)*	0.127 (0.068)*
	E	0.237 (0.132)*	- 0.024 (0.023)	0.103 (0.059)*
	B	-0.222 (0.064)***	0.046 (0.026)*	-0.033 (0.018)**
Maize	**C**	0.033 (0.042)	0.071 (0.019)***	-0.062 (0.018)***
	D	-0.046 (0.017)**	0.039 (0.023)	0.127 (0.068)*
	E	-0.540 (0.176)***	0.047 (0.021)**	0.103 (0.059)*
	B	0.012 (0.063)	0.009 (0.015)	-0.033 (0.018)**
Bean	**C**	0.051 (0.040)	-0.011 (0.016)	-0.062 (0.018)***
	D	-0.073 (0.019)***	-0.017 (0.016)	0.127 (0.068)*
	E	0.209 (0.106)*	-0.011 (0.015)	0.103 (0.059)*
	B	0.069 (0.051)	0.087 (0.013)***	-0.033 (0.018)**
Meat and	**C**	0.057 (0.025)**	0.089 (0.012)***	-0.062 (0.018)***
fish	**D**	-0.241 (0.109)**	-0.075 (0.010)***	0.127 (0.068)*
	E	-0.133 (0.147)	-0.064 (0.012)***	0.103 (0.059)*
	B	0.104 (0.051)**	-0.018 (0.015)	-0.033 (0.018)**
Fruits and	**C**	-0.099 (0.035)***	0.005 (0.012)	-0.062 (0.018)***
vegetables	**D**	0.063 (0.014)***	-0.036 (0.015)**	0.127 (0.068)*
	E	0.132 (0.085)*	-0.009 (0.013)	0.103 (0.059)*
	B	0.073 (0.063)	0.015 (0.018)	-0.033 (0.018)**
Fats and	**C**	0.060 (0.031)*	0.032 (0.015)*	-0.062 (0.018)***
oils	**D**	-0.194 (0.026)***	-0.016 (0.016)	0.127 (0.068)*
	E	0.249 (0.157)*	-0.015 (0.016)	0.103 (0.059)*
	B	0.120 (0.073)*	0.045 (0.014)**	-0.033 (0.018)**
Other	**C**	0.106 (0.050)**	0.039 (0.014)*	-0.062 (0.018)***
foods ([a])	**D**	0.302 (0.131)**	-0.009 (0.016)	0.127 (0.068)*
	E	0.042 (0.023)*	0.020 (0.015)	0.103 (0.059)*
Alcohol	**B**	0.030 (0.024)	-0.094 (0.038)**	-0.033 (0.018)**
and	**C**	0.007 (0.017)	-0.068 (0.033)*	-0.062 (0.018)***
tobacco	**D**	0.067 (0.033)**	-0.080 (0.033)**	0.127 (0.068)*
	C	0.005 (0.065)	-0.112 (0.038)***	0.103 (0.059)*

Note: **B**: Significant net sellers; **C**: significant net buyers, **D**: insignificant net sellers, and **E:** insignificant net buyers. (***), (**), and (*) denote significance levels at 1, 5, and 10% respectively. Standard errors are reported into brackets.
Source : Own computations using UNPS data

Appendix C

Additional data and estimation results for Essay III

Appendix C.1 *Patterns of crop choice combinations, 2005 – 2012*

Binary sixplet	Number of farmers									
	W_1	W_2	W_3	W_4	Pooled	Binary sixplet	W_1	W_2	W_3	W_4	Pooled
(1, 0, 0, 0, 0, 0)	10	5	10	7	32	(0, 1, 1, 0, 1, 0)	56	48	64	55	223
(0, 1, 0, 0, 0, 0)	11	9	22	14	56	(0, 1, 1, 0, 0, 1)	38	39	35	33	145
(0, 0, 1, 0, 0, 0)	15	11	4	10	40	(0, 1, 0, 1, 1, 0)	7	15	31	18	71
(0, 0, 0, 1, 0, 0)	7	6	3	2	18	(0, 1, 0, 1, 0, 1)	22	30	42	31	125
(0, 0, 0, 0, 1, 0)	7	7	4	6	24	(0, 1, 0, 0, 1, 1)	12	16	14	17	59
(0, 0, 0, 0, 0, 1)	26	22	14	28	90	(0, 0, 1, 1, 1, 0)	17	11	18	26	72
(1, 1, 0, 0, 0, 0)	3	10	14	9	36	(0, 0, 1, 1, 0, 1)	17	6	5	9	37
(1, 0, 1, 0, 0, 0)	4	5	4	4	17	(0, 0, 0, 1, 1, 1)	16	19	14	17	66
(1, 0, 0, 1, 0, 0)	8	12	5	6	31	(1, 1, 1, 1, 0, 0)	22	31	23	12	88
(1, 0, 0, 0, 1, 0)	20	20	17	23	80	(1, 1, 1, 0, 1, 0)	45	75	77	80	277
(1, 0, 0, 0, 0, 1)	2	1	0	2	5	(1, 1, 1, 0, 0, 1)	10	4	2	1	17
(0, 1, 1, 0, 0, 0)	31	20	38	38	127	(1, 0, 1, 1, 1, 0)	44	37	39	61	181
(0, 1, 0, 1, 0, 0)	6	16	18	6	46	(1, 0, 1, 0, 1, 1)	23	18	23	17	81
(0, 1, 0, 0, 1, 0)	16	13	15	28	72	(1, 1, 0, 0, 1, 1)	21	17	19	19	76
(0, 1, 0, 0, 0, 1)	31	35	22	40	128	(1, 1, 0, 1, 0, 1)	7	3	4	3	17
(0, 0, 1, 1, 0, 0)	14	7	5	4	30	(1, 0, 0, 1, 0, 1)	7	12	6	63	88
(0, 0, 1, 0, 1, 0)	26	29	19	33	107	(1, 1, 0, 1, 1, 0)	19	31	58	34	142
(0, 0, 1, 0, 0, 1)	46	31	41	34	152	(1, 0, 1, 1, 0, 1)	1	1	3	1	6
(0, 0, 0, 1, 1, 0)	7	7	4	6	24	(1, 0, 0, 1, 1, 1)	19	27	23	29	98
(0, 0, 0, 1, 0, 1)	7	6	1	2	16	(0, 1, 1, 1, 1, 0)	81	92	102	91	366
(0, 0, 0, 0, 1, 1)	11	10	3	6	30	(0, 1, 0, 1, 1, 1)	19	23	16	17	75
(1, 1, 1, 0, 0, 0)	10	7	17	6	40	(0, 1, 1, 0, 1, 1)	52	39	24	42	157
(1, 1, 0, 1, 0, 0)	6	7	12	8	33	(0, 1, 1, 1, 0, 1)	70	90	60	49	269
(1, 1, 0, 0, 1, 0)	16	18	36	39	109	(0, 0, 1, 1,1 , 1)	16	22	16	10	64
(1, 1, 0, 0, 0, 1)	2	1	2	2	7	(1, 1, 1, 1, 1, 0)	182	189	218	255	844
(1, 0, 1, 1, 0, 0)	5	7	3	4	19	(1, 1, 1, 1, 0, 1)	30	11	9	6	56
(1, 0, 1, 0, 1, 0)	68	61	43	57	229	(1, 1, 1, 0, 1, 1)	21	17	19	19	76
(1, 0, 1, 0, 0, 1)	3	1	1	0	5	(1, 1, 0, 1, 1, 1)	13	19	16	10	58
(1, 0, 0, 1, 1, 0)	10	24	14	26	74	(1, 0, 1, 1, 1, 1)	40	20	26	25	111
(1, 0, 0, 1, 0, 1)	1	1	2	1	5	(0, 1, 1, 1, 1, 1)	74	97	78	55	304
(1, 0, 0, 0, 1, 1)	5	17	10	16	48	(1, 1, 1, 1, 1, 1)	116	69	70	42	297
(0, 1, 1, 1, 0, 0)	36	37	38	30	141	Total	1,587	1,579	1,589	1,581	6336

Note: Each element in the *sixplet* is a binary variable for the crop combination *Matooke* – Cassava – Maize – Potatoes – Beans - Other cereals having 1 if the specific crop was grown by the farmer and 0 otherwise. W_1 to W_4 denote the 4 panel waves used. The “total” row gives the sum for each wave. The number of farmers that did not grow any of the selected crops (the omitted category (0, 0, 0, 0, 0, 0) can be obtained by the difference between the sample size (1,598 per wave) and the above “total” row.

Appendix C.2 *Farmer's characteristics by GPS measurement status (2005/6 and 2009/10)*

	2005/6[a]				2009/10[a]			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Plot size								
GPS-based areas (acres)	3.249	3.249	-		2.644	2.644	-	
Farmer's self report (acres)	3.984	3.136	9.476	-6.340**	3.025	2.589	4.827	-2.237***
Number of plots	1.935	1.998	1.534	0.464***	2.011	2.058	1.824	0.233***
Plot ouput and input use								
Total value of harvest (UShs)	814,910.8	810,039.7	846,605.4	-36,565.7	2,018,187	2,036,901	1,943,330	93,571*
Total value of inputs (UShs)	83,880.23	68,994.05	180,615.8	-111,621.75**	61,036.43	59,306.45	67,956.33	-8,649.88*
Plot location (km)	1.535	.946	5.379	-4.434***	-	-	-	-
Less than 15 min	-	-	-	-	0.695	0.755	0.416	0.339***
Between 15-30 min	-	-	-	-	0.115	0.112	0.129	-0.017
Between 30-60 min	-	-	-	-	0.081	0.062	0.169	-0.107***
Between 1-2 hours	-	-	-	-	0.057	0.041	0.132	-0.091***
Tenure system					0.025	0.008	0.101	-0.093***
Freehold	0.070	0.074	0.049	0.025*	0.387	0.421	0.249	0.172***
Leasehold	0.027	0.026	0.033	-0.007	0.039	0.034	0.060	-0.026**
Customary	0.706	0.714	0.656	0.058**	0.496	0.475	0.576	-0.100***
Soil quality								
Good	0.475	0.473	0.488	-0.015	0.568	0.567	0.573	-0.006
Fair	0.433	0.431	0.442	-0.011	0.314	0.319	0.294	0.024
Poor	0.103	0.107	0.076	0.031***	0.093	0.095	0.085	0.010
Plot slope								
Gentile	0.359	0.367	0.304	0.064**	0.389	0.394	0.369	0.025***
Flat	0.501	0.494	0.545	-0.051*	0.444	0.439	0.464	-0.025
Other (Hilly, steep, valley)	0.155	0.154	0.158	-0.004	0.144	0.149	0.119	0.030*
Household characteristics								
Household size	5.884	5.867	5.993	-0.126	6.708	6.706	6.719	-0.011
Age of the head	43.686	44.172	40.544	3.628***	46.588	47.239	43.900	3.338***
Dependency ratio	1.327	1.360	1.124	0.236***	1.525	1.570	1.345	0.224***
Education of the head	4.833	4.657	5.970	-1.313***	4.798	4.591	5.725	-1.134***
Sex of the head	0.734	0.731	0.751	-0.020	0.721	0.721	0.719	0.002
Central	0.218	0.201	0.292	-0.086***	0.215	0.203	0.261	-0.058***
Eastern	0.262	0.273	0.193	0.079***	0.256	0.258	0.246	0.013
Northern	0.261	0.253	0.311	-0.059**	0.279	0.246	0.414	-0.168***
Western	0.259	0.268	0.203	0.065***	0.243	0.289	0.055	0.234***
Non-farm income	598,177.6	468,997.7	1,4338,824	-964,826.3***	538,240.5	530,907.9	568,566.8	-37,658.9**

Note:* **A**, **B**, and **C** refer respectively to the entire sample, the sample restricted to plots with observed GPS-based measures, and plots without GPS-based measures. The last column **D** computes the difference between **B** and **C**.

Appendix C.3 *Farmer's characteristics by GPS measurement status (2010/11 and 2011/12)*

	2010/11				2011/12			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Plot size								
GPS-based areas (acres)	4.202	4.202	-	-	2.377	2.377-	-	-
Farmer's self report (acres)	2.729	2.401	3.944	-1.543***	2.622	2.444	2.879	-0.435*
Number of plots	1.779	1.794	1.724	0.071	1.854	1.884	1.810	0.073
Plot ouput and input use								
Total value of harvest (UShs)	967,971.4	940,134.5	1,070,611	-130,476.5	1,401,579	1,281,891	1,574,111	-292,220
Total value of inputs (UShs)	57,016.6	50,640.78	80,525.41	-29,884.63***	54,304.94	47,756.04	63,745	-15,989.2***
Less than 15 min	0.708	0.776	0.456	0.320***	0.691	0.793	0.545	0.249***
Between 15-30 min	0.133	0.120	0.182	-0.063***	0.199	0.196	0.204	-0.007
Between 30-60 min	0.086	0.070	0.143	-0.073***	0.185	0.152	0.233	-0.082***
Between 1-2 hours	0.050	0.026	0.140	-0.114***	0.099	0.080	0.126	-0.046***
Tenure system								
Freehold	0.412	0.456	0.249	0.207***	0.347	0.392	0.283	0.109***
Leasehold	0.019	0.022	0.010	0.011**	0.047	0.041	0.055	-0.014**
Customary	0.538	0.492	0.705	-0.213***	0.545	0.533	0.562	-0.029*
Soil quality								
Good	0.612	0.592	0.687	-0.095***	0.590	0.608	0.564	0.045***
Fair	0.349	0.367	0.285	0.082***	0.464	0.459	0.470	-0.011
Poor	0.040	0.045	0.023	0.021***	0.122	0.124	0.119	0.004
Plot slope								
Gentile	0.379	0.389	0.343	0.045**	0.354	0.363	0.342	0.021*
Flat	0.487	0.479	0.518	-0.039*	0.466	0.490	0.433	0.057***
Other (Hilly, steep, valley)	0.137	0.138	0.133	0.004	0.122	0.129	0.112	0.017*
Household characteristics								
Household size	7.533	7.488	7.703	-0.215	8.114	8.029	8.239	-0.210*
Age of the head	48.537	48.774	47.659	1.115*	48.633	49.589	47.254	2.335***
Dependency ratio	1.709	1.722	1.663	0.059	1.907	1.809	2.048	-0.239***
Education of the head	5.110	4.958	5.674	-0.717***	4.811	4.596	5.120	-0.524***
Sex of the head	0.720	0.721	0.718	0.003	0.714	0.718	0.707	0.011
Central	0.207	0.226	0.134	0.092***	0.201	0.160	0.260	-0.101***
Eastern	0.266	0.256	0.305	-0.049**	0.256	0.249	0.267	-0.018
Northern	0.285	0.246	0.426	-0.059***	0.295	0.281	0.314	-0.033**
Western	0.239	0.271	0.121	0.149***	0.248	0.311	0.158	0.152***
Non-farm income	537,708.8	540,858.1	526,015.1	14,843	659,108.2	405,719.4	1,024,370	-618,650.6***

Note:* **A, B**, and **C** refer respectively to the entire sample, the sample restricted to plots with observed GPS-based measures, and plots without GPS-based measures. The last column **D** computes the difference between **B** and **C**.

Appendix C.4 *OLS estimation results of Observed GPS-based plot area measures (in acres)*

Dependent variable: Observed GPS-based areas (acres)	2005/6	2009/10	2010/11	2011/12
Plot size				
Farmer's self report (acres)	0.959 (0.021)***	0.922 (0.14)***	0.901 (0.150)***	0.888 (0.201)***
Number of plots	-0.898 (0.345)***	-0.526 (0.099)***	-0.882 (0.081)***	-0.305 (0.139)**
Plot output and input use				
Total value of harvest (UShs)	-0.004 (0.243)	0.084 (0.042)**	0.165 (0.054)***	0.127 (0.114)
Total value of inputs (UShs)	0.006 (0.111)	0.122 (0.034)***	0.091 (0.188)	0.066 (0.039)*
Plot location (km)	-0.149 (0.154)	-	-	-
Less than 15 min	-	-0.343 (0.049)***	-0.255 (0.055)***	0.230 (0.175)*
Between 15-30 min	-	0.574 (0.617)	0.026 (0.084)	0.030 (0.196)
Between 30-60 min	-	0.367 (0.075)***	0.076 (0.010)***	-0.153 (0.184)
Tenure system				
Freehold	0.196 (11.442)	-0.015 (0.723)	-0.089 (0.069)	-0.021 (0.029)
Leasehold	0.926 (0.572)	-0.512 (0.912)	-0.068 (0.087)	-0.076 (0.030)***
Customary	-0.075 (1.661)	0.378 (0.748)	-0.219 (0.704)	-0.344 (0.366)
Soil quality				
Good	1.661 (1.357)	-0.153 (0.373)	0.428 (0.324)	0.191 (0.188)
Fair	2.247 (1.371)*	-0.794 (0.399)**	-0.709 (0.441)*	-0.299 (0.117)**
Plot slope				
Gentile	-1.214 (1.313)	0.171 (0.360)	0.082 (0.098)	0.222 (0.192)
Flat	-1.674 (1.317)	-0.455 (0.363)	-0.300 (0.146)*	-0.299 (0.217)
Household characteristics				
Household size	0.393 (0.167)**	0.198 (0.038)***	0.214 (0.193)	0.109 (0.057)*
Age of the head	0.016 (0.029)	0.020 (0.008)**	0.042 (0.038)	-0.001 (0.005)
Dependency ratio	-0.314 (0.438)	-0.140 (0.108)	-0.615 (0.341)*	-0.077 (0.064)
Education of the head	0.016 (0.133)	0.031 (0.036)	0.035 (0.170)	-0.031 (0.029)
Sex of the head	0.924 (1.252)	0.044 (0.056)	0.083 (0.051)	0.076 (0.003)***
Central	-0.237 (0.045)***	0.055 (0.356)	-0.071 (0.004)***	-0.032 (0.001)***
Eastern	1.368 (1.222)	0.449 (0.521)	-0.259 (0.794)	-0.247 (0.286)
Northern	0.593 (0.035)***	0.079 (0.005)***	0.081 (0.125)	0.046 (0.028)*
Non-farm income	-0.013 (0.041)	-0.009 (0.081)	-0.002 (0.053)	0.001 (0.004)
Multiple imputation results				
Observed GPS-Based areas	3.249	2.467	4.202	2.377
Imputed GPS-Based areas	3.625	2.556	4.516	2.412

Appendix C.5 *Estimated ARIMA models for monthly real price series 1999 (9) – 2012 (12)*

Commodity	ARIMA results([a])
Matooke	$\left(1-0.515L^3\right)\left(1-L\right)p_t=\left(1+0.413L^2\right)\varepsilon_t$ (0.047) (0.039)
Cassava	$\left(1-0.732L^2\right)\left(1-L\right)p_t=\left(1+0.396L+0.411L^2\right)\varepsilon_t$ (0.093) (0.089) (0.046)
Maize	$\left(1-0.965L\right)\left(1-L\right)p_t=\left(1+0.122L\right)\varepsilon_t$ (0.021) (0.047)
Potatoes	$\left(1-0.770L^3\right)\left(1-L\right)p_t=\left(1+0.522L+0.887L^2\right)\varepsilon_t$ (0.049) (0.047) (0.049)
Beans	$\left(1-0.812L^3\right)\left(1-L\right)p_t=\left(1+0.654L\right)\varepsilon_t$ (0.052) (0.063)
Other cereals (rice, millet, sorghum)	$\left(1-0.885L^3\right)\left(1-L\right)p_t=\left(1+0.171L^2\right)\varepsilon_t$ (0.027) (0.026)

Note: ([a]): The general ARIMA model has the following form: $A(L)(1-L)^d\, p_t=\alpha+B(L)\varepsilon_t$, where $A(L)=1-\rho_1L-\rho_2L^2-...-\rho_pL^p$ and $B(L)=1+\theta_1L+\theta_2L^2+...+\rho_qL^q$ are polynomials in lag operator L; ε_t are errors terms assumed to be white noise. The Box-Jenkins methodology has been used to determine the values of *p* (autoregressive terms) and *q* (moving average terms) in the ARMA (*p, q*) process through the Bayesian information criteria (BIC). *d* (the order of integration of the price series p_t) was 1 for all commodities. Standard errors are reported below each ARIMA specification.

Appendix C.6 *Unbiasedness tests of expected-price formation hypotheses (OLS estimation)*

cmdt	**Naive expectations model**						**Adaptive expectations model**					
	α	β	F – Stat.	R^2_{adj}	Unbiasedness *F-Stat*	Reject H_0 ?	α	β	F – Stat.	R^2_{adj}	Unbiasedness *F-Stat*	Reject H_0 ?
k_1	167.384	0.491	179.41	0.284	81.16	Yes	123.235	0.640	189.44	0.254	31.25	Yes
	(12.727)	(0.037)					(15.781)	(0.046)				
k_2	56.806	0.911	1268.92	0.679	15.17	Yes	21.575	1.025	1193.94	0.683	16.37	Yes
	(11.228)	(0.026)					(12.758)	(0.030)				
k_3	109.139	0.843	1537.45	0.646	168.29	Yes	53.565	0.974	3504.25	0.674	96.96	Yes
	(7.343)	(0.021)					(5.602)	(0.017)				
k_4	108.574	0.706	754.72	0.487	120.77	Yes	92.901	0.763	2150.11	0.420	131.83	Yes
	(6.991)	(0.025)					(10.508)	(0.016)				
k_5	161.831	0.817	908.10	0.669	170.66	Yes	91.454	0.929	1630.09	0.737	41.48	Yes
	(15.409)	(0.027)					(11.721)	(0.023)				
k_6	255.321	0.768	28.76	0.544	5.15	No	104.109	0.964	200.52	0.606	23.36	Yes
	(137.682)	(0.143)					(64.109)	(0.068)				

	Quasi-rational expectations model						**Mixed expectations model ([a])**					
	α	β	F – Stat.	R^2_{adj}	Unbiasedness *F-Stat*	Reject H_0 ?	α	β	F – Stat.	R^2_{adj}	Unbiasedness *F-Stat*	Reject H_0 ?
k_1	19.187	1.059	4922.38	0.550	10.53	Yes	5.086	1.031	123.32	0.832	5.01	No
	(5.727)	(0.015)					(8.085)	(0.029)				
k_2	34.311	1.086	6721.69	0.798	22.04	Yes	0.888	1.043	483.29	0.775	5.82	No
	(6.536)	(0.013)					(3.081)	(0.015)				
k_3	9.349	1.018	1301.91	0.889	4.23	No	4.945	1.013	475.83	0.834	5.54	No
	(4.891)	(0.009)					(2.319)	(0.005)				
k_4	18.170	1.051	2188.59	0.736	50.16	Yes	1.977	1.012	176.58	0.619	5.26	No
	(2.007)	(0.008)					(3.772)	(0.008)				
k_5	56.832	1.077	8661.10	0.828	30.04	Yes	9.549	1.026	100.34	0.807	4.13	No
	(9.148)	(0.011)					(5.937)	(0.010)				
k_6	38.812	1.043	6149.52	0.691	28.11	Yes	4.555	1.026	452.48	0.700	2.84	No
	(14.373)	(0.013)					(13.295)	(0.016)				

Note: k_1, k_2, k_3, k_4, k_5, and k_6 refer respectively to *matooke*¸ cassava, maize, potatoes, beans, and other cereals. Standard errors into brackets.

([a]) For each price series, different values of λ were tested ($\lambda = 0.1;0.2;...;0.9$). Here, I only report the model with the "optimal" weights (best statistical fits): 0.3 for cassava and beans; 0.4 for *matooke* and potatoes; 0.5 for maize and 0.6 for other cereals.

Appendix C.7 *Definition and descriptive statistics of relevant variables*

Definition of variables	*Matooke*		Cassava		Maize		Potatoes		Beans		Other cereals	
	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
y_i : Actual yields (kg/ha)	3,187.57	1,712.66	4,864.67	1,744.65	2,675.34	1,538.78	3,061.79	1,255.16	2,813.08	1,414.98	1,718.60	969.85
y_i^e : Expected yields (kg/ha)	2,520.76	1,164.42	3,124.86	1,314.80	2,495.60	1,048.41	2,722.69	912.37	2,065.28	919.38	1124.23	1,039.80
vy_1^e : Yield risk (unitless)	674.125	1,078.684	1,116.002	2,714.136	1,542.151	576.417	1,820.589	715.485	766.703	1,482.178	265.690	742.097
A_i : Multiply imputed area planted of crop *i* (ha)	0.136	0.469	0.189	0.719	0.178	0.673	0.102	0.701	0.138	0.566	0.111	0.365
s_i : Multiply imputed acreage share of crop *i* *(%)*	0.120	0.191	0.151	0.196	0.137	0.177	0.088	0.132	0.130	0.166	0.090	0.131
p_i : Market price of crop *i* (Ushs/kg), deflated by UBOS' All items consumer price index	404.937	163.655	566.410	205.772	780.087	215.044	439.861	152.87	993.879	231.798	1,258.768	344.449
$p_{N,i}^e$: Expected output price of crop *i* from naive expectations model	392.320	204.261	516.690	226.659	739.508	220.706	437.842	122.563	975.849	295.929	1238.239	377.296
$p_{R,i}^e$: Expected output price of crop *i*, rational expectations model (ARIMA model)	373.550	138.792	525.429	196.176	760.973	239.576	423.196	124.186	968.780	226.281	1222.099	330.374
$p_{A,i}^e$: Expected output price of crop *i*, adaptive expectations model	388.770	154.727	490.462	201.653	703.204	189.053	423.870	127.223	953.207	253.796	1,186.577	347.950
$p_{MX,i}^e$: Expected output price of crop *i*, mixed expectations model (with optimal λ)	383.659	104.889	526.517	164.223	750.834	199.748	424.179	89.293	957.878	229.497	1,220.348	303.900
$vp_{N,i}^e$: Expected price risk of crop *i* using naive expectations model	187.582	131.765	137.599	92.821	174.200	85.952	112.213	82.322	144.582	79.572	244.325	185.538
$vp_{R,i}^e$: Expected price risk of crop *i* using rational expectations model (ARIMA model)	119.366	94.710	110.382	77.122	159.386	81.420	90.405	71.322	126.595	70.387	196.606	169.701
$vp_{A,i}^e$: Expected price risk of crop *i* using adaptive expectations model	206.288	134.715	195.269	127.616	236.437	118.922	152.973	117.996	190.274	109.491	346.534	253.844
$vp_{MX,i}^e$: Expected price risk of crop *i* using mixed expectations model	164.892	104.948	145.512	88.527	205.962	92.786	122.062	89.347	154.489	72.580	302.576	214.757

Note: *SD:* Standard deviations

Appendix C.8 *Dynamic Multivariate fractional logit estimation results – Models with (I) and without (II) unobserved heterogeneity*

	Matooke		Cassava		Maize		Potatoes		Beans		Other cereals	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
$s_{1,t-1}$	0.313*	0.324	-0.038	-0.079	-0.078	-0.101	-0.069	-0.023	-0.184	-0.201	-0.193	-0.200
$s_{2,t-1}$	-0.465**	-0.477**	0.412***	0.437***	-0.007	-0.039	-0.299*	-0.343**	-0.298*	-0.328*	-0.062	-0.098
$s_{3,t-1}$	-0.378*	-0.389*	-0.510 **	-0.515**	0.424**	0.429**	-0.584***	-0.589***	-0.561***	-0.579***	-0.596***	-0.616***
$s_{4,t-1}$	-0.151*	-0.170*	-0.261**	-0.264*	-0.412*	-0.432*	0.572***	0.591***	-0.101	-0.107	-0.099***	-0.103***
$s_{5,t-1}$	-0.698***	-0.725***	-0.431**	-0.469**	-0.489**	-0.471**	-0.582***	-0.638**	0.678***	0.682***	-0.625**	-0.635**
$s_{6,t-1}$	-0.686**	-0.724**	-0.226	-0.263	-0.085	-0.098	-0.422*	-0.447*	-0.189	-0.192	0.366*	0.364*
$s_{1,1}$	2.861 ***	2.927***	1.277***	1.337***	1.580***	1.644***	1.867***	1.937***	2.105***	2.149***	1.329***	1.388***
$s_{2,1}$	0.727***	0.780***	1.960***	1.966***	1.332***	1.344***	1.345***	1.374***	1.086***	1.088***	1.130***	1.144***
$s_{3,1}$	1.379***	1.416***	1.613***	1.637***	2.704***	2.733***	1.679***	1.702***	1.726***	1.748***	1.625***	1.648***
$s_{4,1}$	1.460***	1.514***	1.136***	1.185***	1.439***	1.481***	2.903***	2.944***	1.412***	1.441***	1.049***	1.096***
$s_{5,1}$	2.511***	2.538***	1.602***	1.607***	1.752***	1.753***	1.830***	1.815***	2.690***	2.691***	1.577***	1.596***
$s_{6,1}$	1.235***	1.314***	0.993***	1.028***	1.219***	1.253***	1.172***	1.200***	1.277***	1.291***	2.408***	2.412***
p_1^e	0.364***	0.365***	0.072***	0.072***	0.087***	0.087***	0.088***	0.089***	0.104***	0.105***	0.061***	0.061***
p_2^e	0.081***	0.082***	0.352***	0.349***	0.095***	0.097***	0.094***	0.097***	0.090***	0.093***	0.080***	0.084***
p_3^e	0.051***	0.052***	0.069***	0.068***	0.397***	0.396***	0.069***	0.066***	0.064***	0.064***	0.054***	0.054***
p_4^e	0.027***	0.027***	0.031***	0.030***	0.032***	0.031***	0.449***	0.450***	0.027***	0.028***	0.017***	0.016**
p_5^e	0.112***	0.114***	0.070***	0.071***	0.068***	0.069***	0.072***	0.073***	0.405***	0.404***	0.050***	0.051***
p_6^e	0.049***	0.048***	0.057***	0.058***	0.055***	0.056 ***	0.056***	0.056***	0.054***	0.054***	0.422***	0.421***
y_1^e	8.605***	8.376***	8.279***	8.760***	7.423***	7.523***	9.063***	9.949***	7.228***	6.182***	6.741***	6.506***
y_2^e	6.502	5.042	10.189***	10.894***	11.680***	11.372***	13.052***	13.806***	9.175***	9.432***	9.142***	9.913***
y_3^e	1.282	1.069	6.817***	5.184***	6.020***	6.635***	7.813***	7.696***	5.315***	5.528***	5.860***	6.603***
y_4^e	5.974*	5.918*	9.833***	9.095***	9.368***	9.525***	11.572***	11.895***	8.762***	8.005***	8.069***	7.548***
y_5^e	1.020**	1.522*	1.395***	1.518***	1.496***	1.640***	1.387***	1.069***	1.792***	1.955***	1.324***	1.808***

Appendix C.8 (continued)

	Matooke		**Cassava**		**Maize**		**Potatoes**		**Beans**		**Other cereals**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
y_6^e	3.693*	7.643*	5.382*	5.379*	6.294**	6.326**	10.314***	10.368***	7.097***	7.139***	5.337*	5.251
vp_1^e	-4.676***	-4.593***	-4.742***	-4.737***	-4.854***	-4.785***	-5.665***	-5.695***	-4.347***	-4.263***	-4.079***	-3.935***
vp_2^e	-3.887***	-3.780***	-3.421***	-3.458***	-3.671***	-3.605***	-4.105***	-4.142***	-2.845***	-2.761***	-3.510***	-3.379***
vp_3^e	-4.076***	-4.003***	-3.382***	-3.379***	-3.296***	-3.234***	-4.071***	-4.087***	-3.144***	-3.076***	-2.786***	-2.655***
vp_4^e	-4.717***	-4.640***	-3.832***	-3.861***	-3.998***	-3.954***	-4.934***	-4.964***	-3.536***	-3.464***	-3.506***	-3.401***
vp_5^e	-4.059**	-2.002*	-3.177***	-3.004***	-3.421*	-3.002**	-4.0195*	-4.017**	-3.325**	-3.568*	-3.251*	-2.011
vp_6^e	-2.021***	-1.056	-3.115	-3.000*	-3.804***	-2.058*	-4.751***	-1.348***	-3.867***	-3.195*	-3.498**	-2.025***
vy_1^e	-0.142***	-0.108***	-0.114***	-0.089***	-0.089***	-0.075***	-0.091**	-0.069**	-0.111***	-0.079**	-0.086**	-0.036
vy_2^e	-0.059***	-0.034	-0.023***	-0.006*	-0.042***	-0.024	-0.069*	-0.037	-0.043*	-0.030	-0.077*	-0.025
vy_3^e	-0.044	-0.027	-0.051	-0.049	-0.046*	-0.048*	-0.036	-0.035	-0.064*	-0.046	-0.098*	-0.078*
vy_4^e	-0.060*	-0.021	-0.462*	-0.047	-0.543	-0.042	-0.107*	-0.052	-0.168*	-0.035	-0.156	-0.012
vy_5^e	-0.012*	-0.044	-0.039*	-0.000	-0.013	-0.069*	-0.037	-0.030	-0.130***	-0.061*	-0.042	-0.066*
vy_6^e	-0.121***	-0.080***	-0.119***	-0.097***	-0.095***	-0.741**	-0.144***	-0.122***	-0.107***	-0.086***	-0.140***	-0.128***
mar	-0.006	-0.074	-0.035***	-0.016*	0.040***	0.052***	0.015***	0.019***	0.037***	0.049***	-0.010	-0.030***
$marcv$	-8.639***	-8.522***	-5.129***	-5.176***	-4.907***	-4.840***	-5.722***	-5.750***	-4.591***	-4.492***	-4.589***	-4.475***
dmt	-2.947**	-3.549*	-4.431***	-6.185***	-4.438***	-6.528***	-5.252***	-8.002***	-4.415***	-5.880***	-2.170	-3.970***
$dmtcv$	-3.523	-3.493	-9.317***	-9.143***	-6.658***	-6.551***	-9.971***	-10.050***	-8.559***	-8.571***	-6.642***	-6.242***
tld	0.702***	0.688***	0.695***	0.682***	0.619***	0.614***	0.712***	0.701***	0.692***	0.690***	0.703***	0.706***
ldq	0.024*	0.054	0.048*	0.102**	0.077**	0.148***	0.051*	0.145***	0.057*	0.131***	0.067**	0.126**
$ldir$	0.204	0.112	0.098	0.204*	0.099	0.040	0.144	0.049	0.157	0.124	-0.106	-0.157
$ldsp$	0.149	0.147*	0.014	0.044	0.017	0.047	0.103	0.149*	0.038	0.133*	0.091	0.129
$educ$	0.018	-0.002	0.007	-0.003	0.013	-0.011*	0.011	-0.007	0.020	-0.007	0.012	-0.022***
age	-0.381*	0.145	-0.167	-0.015	-0.314	-0.040	-0.074	0.007	-0.156	0.025	0.013	0.085
sex	0.048	0.059	-0.103	0.099*	-0.111	0.095*	-0.193	0.102*	-0.123	0.043	-0.139	0.067
λ	0.206***	0.230***	0.812***	0.839***	0.259***	0.320***	0.553***	0.625***	0.645***	0.698***	0.253***	0.385***
hsz	0.143*	0.042	0.109**	0.074	0.045*	0.005	0.058**	0.025	0.067*	0.012	0.052*	0.011
Cons	29.106	27.422	39.894***	31.344***	88.980***	39.160***	56.563***	40.809***	74.488***	28.303***	23.729***	27.344***

Note: In models I, unobserved heterogeneity is allowed to be correlated with some variables and the Mundlak-Chamberlain approach has been applied. In models II, unobserved heterogeneity is ignored during estimation. To preserve space, coefficient parameters of time-averaged variables have been omitted from the table but are available upon author's request. Results are obtained after normalization of the coefficients of "other crops" share. ***, **, and * denote statistical significance at 10, 5, and 1% levels, respectively.

Appendix C.9 *Static Multivariate fractional logit estimation results – Models with (I) and without (II) unobserved heterogeneity*

	Matooke		Cassava		Maize		Potatoes		Beans		Other cereals	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
p_1^e	0.409***	0.416***	-0.068***	-0.064***	-0.081***	-0.078***	-0.083***	-0.081***	-0.079***	-0.076***	-0.059***	-0.056***
p_2^e	-0.106***	-0.117***	0.365***	0.359***	-0.112***	-0.123***	-0.113***	-0.127***	-0.108***	-0.121***	-0.103***	-0.122***
p_3^e	-0.062***	-0.064***	-0.056***	-0.054***	0.436***	0.440***	-0.057***	-0.056***	-0.062***	-0.063***	-0.046***	-0.045***
p_4^e	-0.048***	-0.053***	-0.043***	-0.048***	-0.038***	-0.042***	0.461***	0.463***	-0.045***	-0.049***	-0.032***	-0.037***
p_5^e	-0.069***	-0.069***	-0.054***	-0.056***	-0.050***	-0.051***	-0.054***	-0.055***	0.448***	0.453***	-0.039***	-0.043***
p_6^e	-0.060***	-0.058***	-0.071***	-0.072***	-0.071***	-0.070***	-0.065***	-0.062***	-0.064***	-0.061***	0.457***	0.469***
y_1^e	11.629***	12.146***	12.027***	15.748***	12.740***	18.848***	13.285***	15.561***	12.395***	14.764***	11.376***	11.353***
y_2^e	7.168	5.276	15.723***	17.570***	18.653***	18.986***	19.723***	14.938***	18.058***	12.699***	16.794***	17.083***
y_3^e	1.582	0.845	8.299***	7.314***	10.388***	7.391***	11.122***	9.227***	10.097***	7.942***	9.362***	6.149***
y_4^e	9.808***	6.203*	14.124***	8.165***	15.961***	16.095***	16.786***	11.582***	15.493***	17.910***	14.293***	8.831***
y_5^e	1.930***	1.661*	2.493***	6.912***	2.764***	5.303***	2.849***	6.507***	2.639***	6.344***	2.503***	3.358***
y_6^e	4.878	3.760	5.572**	6.250**	9.068***	9.785***	12.014***	12.714***	10.863***	11.398***	7.023**	7.428**
vp_1^e	-6.400***	-3.797***	-7.021***	-4.364***	-7.760***	-4.875***	-8.120***	-5.309***	-7.557***	-4.638***	-6.864***	-3.753***
vp_2^e	-5.829***	-2.965**	-6.241***	-3.356***	-6.940***	-3.783***	-6.880***	-3.795***	-6.259***	-3.097***	-6.568***	-3.197***
vp_3^e	-5.504***	-3.195***	-5.356***	-3.025***	-5.712***	-3.201***	-6.055***	-3.606***	-5.725***	-3.164***	-5.058***	-2.398***
vp_4^e	-6.854***	-3.993***	-6.594***	-3.736***	-7.286***	-4.190***	-7.692***	-4.642***	-7.077***	-3.913***	-6.562***	-3.278***
vp_5^e	-5.049**	-3.020*	-4.107***	-3.054***	-5.035*	-4.032**	6.003	2.003	-5.043**	-4.002	-5.051*	-3.001
vp_6^e	5.011***	3.023	4.015	-3.014	-5.084***	-4.018	-6.079***	-2.005***	-5.123***	4.001	-5.098**	-4.005***
vy_1^e	-0.277***	-0.113***	-2.570***	-0.103***	-0.256***	-0.090***	-0.249***	-0.081***	-0.266***	-0.093***	-0.265***	-0.057***
vy_2^e	-0.463***	-0.388***	-0.403***	-0.430***	-0.447***	-0.348***	-0.498***	-0.463***	-0.476***	-0.288***	-0.517***	-0.058***
vy_3^e	-0.205***	-0.173*	-0.178***	-0.028*	-0.167***	-0.173***	-0.204***	-0.251***	-0.203***	-0.032*	-0.245***	-0.067*
vy_4^e	-0.598***	-0.124*	-0.654***	-0.829**	-0.666***	-0.727*	-0.607***	-0.418**	-0.683***	-0.628*	-0.633***	-0.408*
vy_5^e	-0.097**	-0.059*	-0.092*	-0.023*	-0.147***	-0.084**	-0.099**	-0.049*	-0.142***	-0.085**	-0.220***	-0.071*
vy_6^e	-0.416***	-0.087**	-0.401***	-0.469***	-0.372***	-0.256*	-0.445***	-0.112***	-0.409***	-0.417**	-0.416	-0.100***
mar	-0.026	-0.080	-0.049***	-0.020*	0.043***	0.059***	0.035***	0.029***	0.040***	0.056***	-0.019	-0.031***

Appendix C.9 (continued)

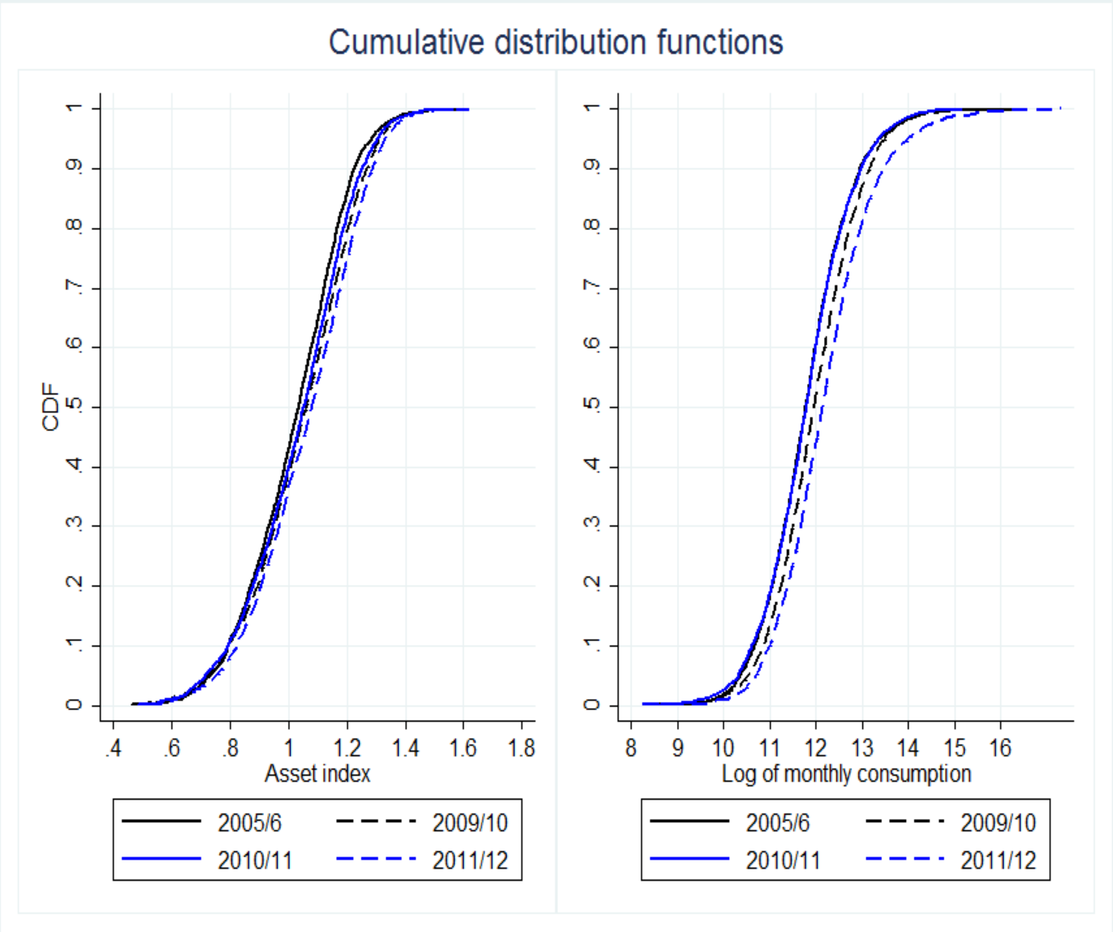
	Matooke		**Cassava**		**Maize**		**Potatoes**		**Beans**		**Other cereals**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**	**I**	**II**
$marcv$	-10.544***	-6.866***	-8.375***	-4.753***	-8.447***	-4.513***	-8.569***	-4.771***	-8.221***	-4.290***	-7.731***	-3.729***
dmt	0.3037	-0.103	-0.647***	-0.253*	-0.498***	0.756***	-0.704***	0.368***	-0.717***	0.712***	-0.285	-0.392***
$dmtcv$	-5.189**	-3.759*	-10.504***	-8.251***	-9.554***	-7.528***	-12.522***	-10.702***	-12.034***	-9.848***	-9.570	-6.900***
tld	0.384***	0.848***	0.365***	0.812***	0.255***	0.725***	0.377***	0.879***	0.324***	0.832***	0.299***	0.815***
ldq	0.132**	0.081*	0.156***	0.138***	0.194***	0.179***	0.166***	0.203***	0.170***	0.181***	0.190***	0.139***
$ldir$	0.134	0.168	0.092	0.284**	0.086	0.121	0.112	0.072	0.117	0.153	-0.070	-0.082
$ldsp$	0.061	0.181*	0.126	0.131	0.142	0.055	0.076	0.202**	0.150	0.192**	0.081	0.211**
$educ$	0.008	0.003	0.011	0.003	0.014	-0.006	0.001	-0.006	0.011	-0.003	0.009	-0.038***
age	0.043	-0.041	0.291	-0.205**	0.143	-0.342***	0.374	-0.210**	0.312	-0.220**	0.471	-0.186*
sex	0.225	0.053	0.097	0.134**	0.069	0.096	0.042	0.029	0.091	0.029	0.117	0.095
λ	0.951***	0.845***	0.766***	0.739***	0.148***	0.951***	0.455***	0.421***	0.457***	0.429***	0.419***	0.522****
hsz	0.462***	0.119*	0.426***	0.160***	0.324***	0.126**	0.400***	0.173***	0.404***	0.094*	0.436***	0.152***
Cons	18.451	43.421	44.108***	45.249***	53.119***	20.801***	57.605***	94.041***	52.647***	21.793***	47.028***	31.802***

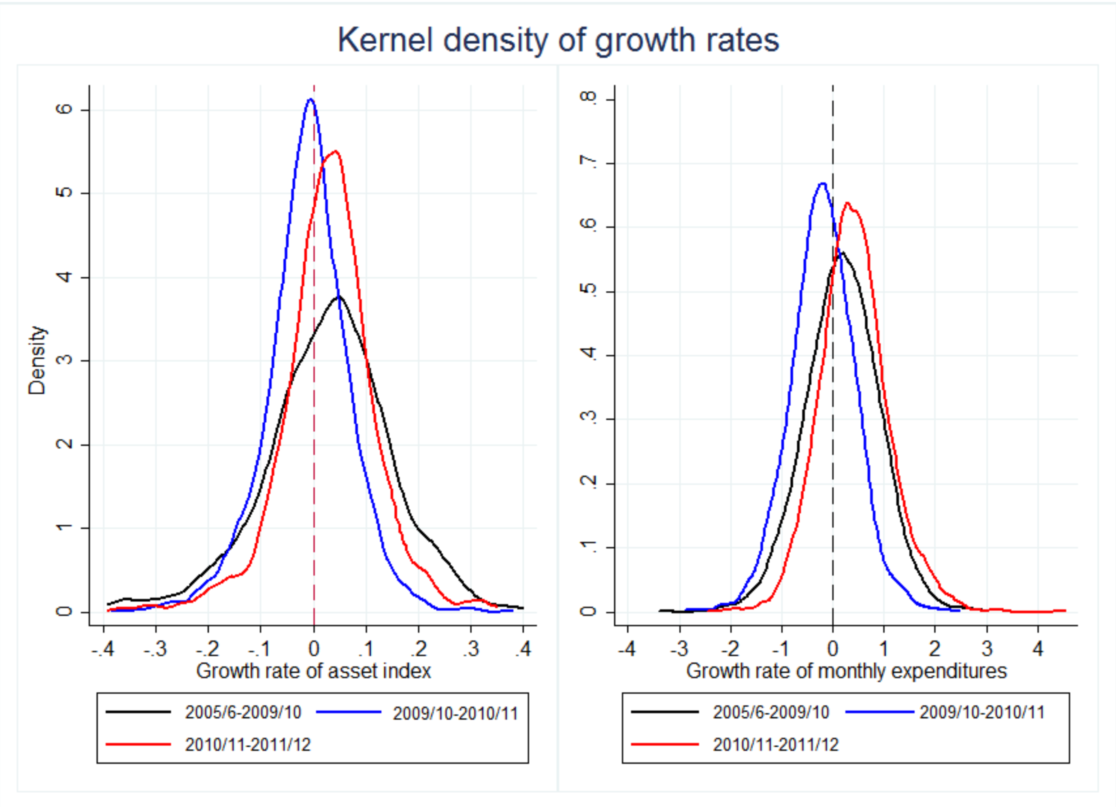
Note: In models I, unobserved heterogeneity is allowed to be correlated with some variables and the Mundlak-Chamberlain approach has been applied. In models II, unobserved heterogeneity is ignored during estimation. To preserve space, coefficient parameters of time-averaged variables have been omitted from the table but are available upon author's request. Results are obtained after normalization of the coefficients of "other crops" share. . ***, **, and * denote statistical significance at 10, 5, and 1% levels, respectively.

Appendix D

Additional data and estimation results for Essay IV

Appendix D.1 *Cumulative distributions and growth rates of households' welfare*





Appendix D.2 *Test of equality between households above and below the vulnerability index* $\left(vul_h^{\theta}\right)^{\bullet}$

	x_a^j	x_b^j	Δx^j	$\Delta x^j / x_b^j$	Equality test
j_1	0.783	0.544	0.240	0.441	77.069
	(0.139)	(0.221)			[0.000]***
j_2	0.585	0.398	0.188	0.471	40.387
	(0.312)	(0.281)			[0.000]***
j_3	23,501	87,197	-94,379	-0.801	-220
	(19,311)	(161,592)			[0.000]***
j_4	3.435	6.038	-2.603	-0.431	-36.247
	(3.217)	(4.229)			[0.000]***
j_5	7.285	7.298	-0.013	-0.002	-0.172
	(3.470	(3.676)			[0.864]

Note: x_a^j and x_b^j denote the reported values of the characteristic *j* for households above and below the vulnerability threshold, respectively. $\Delta x^j = x_a^j - x_b^j$. The equality test is a *t*-test with unequal variances checking whether the mean values of the characteristic *j* are significantly different between households above and below the threshold $\left(vul_h^{\theta}\right)^{\bullet}$. Standard deviations and standard errors are reported into parentheses and into brackets, respectively. *** indicates coefficients statistically significant at 1% level. The characteristics under investigation include: j_1: Food dependency, measured by the ratio of food consumption to total household expenditures; j_2: Market participation, approximated by the share of food purchased into total value of food consumption; j_3: monthly real income per adult equivalent; j_4: Years of education of the head; j_5: Household size.