Essays on spatial and vertical price transmission

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The course and research work during my PhD programme was a very fruitful experience and it allowed me to acquire some relevant skills. Indeed, I was able to learn how to code in R and Stata and manage large datasets to merge, aggregate and prepare the requested data.

Moreover, I learned how to deal with agriculture and development data. An issue, which I addressed, was to find a compromise between the work with the data, which are less rich than in other research sectors, and the possibility to obtain a relevant and consistent interpretation of the empirical results.

Finally, the PhD research work was a very good chance to learn to estimate and interpret advanced econometric and modelling techniques, like the seemingly unrelated regression model on panel data, IV panel model with fixed and random effects, the ARFIMA and Markov Switching threshold model for time series analysis and stationary and non-stationary panel models.

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Essays on spatial and vertical price transmission

Lodovico Muratori

Vorwort

Diese Promotionsarbeit setzt sich mit der Preisübertragung entlang der inländischen Value Chain ("vertical price transmission") und zwischen dem internationalen und den nationalen Märkten („spatial price transmission") auseinander. Sie entwickelt sowohl mikro- als auch makroökonomische Ansätze und besteht aus drei empirischen Papers:

1. Vertical price transmission, geographical dispersion and the structure of the Ugandan coffee market

2. Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data

3. Shocks, price transmission and Food consumption with changes in Price risk aversion.

Diese Promotionsarbeit trägt zur vorherigen Literatur in verschiedenen Hinsichten bei:

1. im Bezug auf „vertical price transmission" entwickelt der erste Kapitel der Promotionsarbeit ein strukturelles Model und schätzt die empirische Beziehung zwischen geographischer Ausstreuung und räumlichem Oligopson auf dem ugandischen Kaffeemarkt. Dieses Paper verbessert den Ansatz von (Sexton, 1990), weil (Sexton, 1990) nur eine "spatial price gap equation" benutzt, während diese Studie ein „system of well-founded behavioural equations" verwendet. Darüber hinaus ermöglicht die Anwendung in dieser Studie von der Methodologie von „Seemingly Unrelated Regression", einige empirischen Hypothesen zu testen. Die Ergebnisse der Analyse bestätigen, dass geographische Ausstreuung die Verdienstspanne der Traders bestimmt, dass Traders ihre Markmacht ausbeuten und sie den Landwirten zu viel Transport- und Transaktionskosten berechnen.

   Ein Regime vom räumlichen Oligopson entwickelt sich in diesem Kontext, weil Informationsasymmetrie auf dem ugandischen Kaffeemarkt vorhanden ist und weil die Landwirten der Transportkosten, die von den Traders wirklich getragenen werden, nicht völlig bewusst sind.

2. im Bezug auf „spatial price transmission" untersucht der zweite Kapitel der Promotionsarbeit die kurzfristige Auswirkung von „price insulating policies" auf die Preisübertragung zwischen dem internationalen und den nationalen Märkten für ausgewählte Sub-Sahara afrikanische

Länder und landwirtschaftliche Hauptgüter, indem die Studie sich auf hohe-Frequenz (monatliche) Daten fokussiert.

Die Anwendung von ökonometrischen Methodologien, die nicht-Linearitäten und Regime-Wechsel im "data generating process" berücksichtigen, ermöglicht, unterschiedliche Erkenntnisse aus dieser Studie als aus der vorherigen Literatur (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c) zu gewinnen.

Diese Arbeit schätzt insbesondere die kurzfristige Auswirkung von „price insulating policies", indem die empirische Analyse zwei Verhaltensregime der Zeitreihen von inländischen Preisen identifiziert: in einem Regime weisen inländische Preise einen aufsteigenden Trend auf, während sie im anderen Regime einen absteigendem Trend aufweisen. „Price insulating policies" haben eine Auswirkung in beiden Fällen, aber ihre Relevanz ist viel größer, wenn Preise steigern. Deswegen waren „price insulating policies" hilfreich, das jeweilige Land von „price shocks" auf dem internationalen Markt abzutrennen, wenn diese Politiken eher notwendig waren.

3. letztendlich untersucht der dritte Kapitel der Promotionsarbeit die Frage vom zeitabhängigen Risikoaversion-Parameter bezüglich der Lebensmittelverbrauchsentscheidungen von den „farm households", die gleichzeitig landwirtschaftliche Güter produzieren und verbrauchen. Die Ergebnisse der Analyse bestätigen, dass der Risikoaversion-Parameter zeitabhängig ist und dass die „farm households" eher risikoavers werden können, wenn sie widrigen Marktbedingungen entgegentreten. Darüber hinaus erbringt diese Studie Nachweis, dass die Landwirten nicht nur auf die unmittelbare Befriedung ihres Bedarfs zielen, sondern sie verhalten sich optimal und sich versichern mittelfristig ihrer Ernährungssicherheit. Die „farm households" bevorzugen ihre Einkünfte zu erhöhen als die landwirtschaftliche Güter, die sie ernten, direkt zu verbrauchen. Die Reduzierung vom „dietary energy consumption", den der Verkauf der Ernte auf dem Markt mit sich bringt, wird tatsächlich durch die Steigerung der Kaufkraft, die höhere Verkaufsprofiten zur Folge haben, völlig ausgeglichen.

Diese Arbeit ist das Ergebnis von einem dreijährigen dualen Promotionsstudiengang, der an der Universität Sapienza von Rom, Italien und der Friedrich-Schiller-Universität, Jena, Deutschland im Rahmen eines co-Tutelle-Abkommens zwischen den zwei Hochschulen durchgeführt wurde.

Das zweite Paper „Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data" wurde in Ko-Autorschaft mit Frau Susanne Fricke verfasst. Eine Erklärung über den Beitrag jedes Autors wird in dieser Promotionsarbeit beigelegt.

Essays on spatial and vertical price transmission

Lodovico Muratori

Preface

This PhD thesis deals with the analysis of spatial and vertical price transmission. The main contribution to previous literature are the following: i) on the vertical dimension, it models and estimates empirically the issue of geographical dispersion and spatial oligopsony in the Ugandan coffee market; ii) on the spatial dimension it investigates the impact of trade policies for selected SSA and main crops on price transmission looking at high-frequency (monthly) data, given non-linearities and regime switching in the data generating process; iii) finally, it investigates the correlated issue of time-varying household risk aversion parameters in the household food consumption decisions. This thesis develops both microeconomic and macroeconomic approaches and it is articulated in the following three empirical essays:

1. Vertical price transmission, geographical dispersion and the structure of the Ugandan coffee market
2. Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data
3. Shocks, price transmission and Food consumption with changes in Price risk aversion.

This is the final outcome of a three-year joint PhD programme carried out at the Sapienza University of Rome, Italy, and at the Friedrich-Schiller University of Jena, Germany, within the framework of a co-tutelle agreement between the two universities.

The first essay ("Vertical price transmission, geographical dispersion and the structure of the Ugandan coffee market") extends the vertical price transmission analysis through a structural approach, which evaluates whether spatial oligopsony power is prevailing in Ugandan coffee market and in case how strong it is. The first paper tests whether in markets, such as Uganda, where infrastructure quality is poor and transport costs are relevant, geographic dispersion of smallholder farmers allows traders to exploit their market power against farmers with a large impact on market structure and reduction of farmers' welfare. By building upon (Sexton, 1990), the study brings an original contribution to the literature, since (Sexton, 1990) develops just a theoretical model and it is not interested to do any econometric exercise. (Sexton, 1990) employs a single spatial price gap equation instead of a system of well-founded behavioural equations in agricultural markets, which is indeed a major improvement delivered by this essay. Moreover, in this analysis the approach to spatial price gap determination is combined with the oligopsony modelling and SUR technique in order to produce empirically testable hypotheses. Without such transformations the approach by (Sexton, 1990) cannot be employed for any empirical exercise. Indeed, the idea of the role of distance is taken from (Sexton, 1990) and introduced in an original way in a more sophisticated model, which is micro-founded at three levels, i.e. demand and supply of agricultural commodities by traders and farmers as well as conditional demand of inputs by farmers.

Since the wholesale-farmgate price spread is net of transport costs, results confirm that geographic dispersion of smallholder farmers plays a significant role on price margin and that there is room for local oligopsony, because traders exploit their market power and overcharge transport and transaction costs to farmers. Indeed, farmers are not able to skip traders in the value chain, because a significant information asymmetry is prevailing in the market. Traders exploit farmers' ignorance because the latter are small and dispersed as well as they lack information about current market prices because of villages remoteness and poor communications with marketplaces (Courtois and Subervie, 2015). Moreover, farmers are not aware of actual transport costs faced by traders, which carry larger quantities of coffee than single smallholder farmers and spread fixed costs over a larger amount of crop.

The second essay ("Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data") assesses the impact of trade policies on spatial price transmission of maize, rice and wheat in Cameroon, Kenya and Tanzania. This paper improves the existing literature in the field (see, inter alia, Anderson and Nelgen, 2012a, Anderson and Nelgen, 2012b and Anderson and Nelgen, 2012c), because it estimates the impact of tariff and non-tariff trade policies on spatial price transmission in the agricultural markets using monthly data. Employment of monthly data allows assessing more precisely short-lived movements of the analysed series, which could disappear because of aggregation bias at lower yearly frequency, thus providing a better identification of insulation policies. Furthermore, this essay focuses on the impact of both tariff and non-tariff barriers on spatial price transmission by taking advantage of the combination of the FAO-GIEWS (Global Information and early warning system) database and trade policies information from the FAO-FADPA (Food and Agriculture Policy Decision Analysis) with the recent release of the World Bank World Integrated Trade Solutions (WITS) Database (UNCTAD, 2016) (FAO, 2016) (FAO, 2016b) (World Bank, 2016). This latest WITS release provides monthly ad-valorem equivalent tariff rates consist of tariff, para-tariff and non-tariff measures. In particular, non-tariff barriers comprises technical measures, such as sanitary or environmental protection measures, as well as others traditionally used as instruments of commercial policy, e.g. quotas, price control, exports restrictions, or contingent trade protective measures, and also other behind-the-border measures, such as competition, trade-related investment measures, government procurement or distribution restrictions (UNCTAD, 2015).

The empirical methodologies of this study, like threshold, fractional integration and panel estimation, allow to separately estimate the confounding factors and clean the estimates of the variables of interest from them. In particular, while the confounders cannot be identified, the coefficients of the variables of interest are consistent and they can be properly identified, conditional on the estimate of the confounders. An additional value added of this work is the possibility to separately estimate the impact of trade policies within the two regimes of behaviour of the domestic price series: in the first regime the trend of domestic prices is increasing, in the second one the trend is decreasing. It highlights that trade policies play a role both in case of increasing and decreasing domestic prices, but their relevance is much larger, if prices are increasing. The policy implication is that trade policies were able to insulate the country from the price shocks on the international markets during the food price spike crisis, when it was mostly needed. By presenting high frequency analyses and techniques able to detect non-linearities in the data generating process we thus provide results which are different from the standard literature (Anderson and Nelgen, 2012b and Anderson and Nelgen, 2012c). Note however that although the impact of these instruments is proved to be relevant in the short term during the food price spike crisis, these policies could not be regarded as long term solutions.

The third essay ("Shocks, price transmission and Food consumption with changes in Price risk aversion) looks seriously at the issue of time variant price risk aversion parameters. This is a fundamental question to address in the investigation of both spatial and vertical price transmission in a risky environment. To this end, the essay assesses the behaviour of farm households, which consume and produce crops at the same time, and answers the following key research questions: i) whether the occurrence of exogenous shocks induces a change of price risk aversion over time and then ii) how the time-varying risk aversion parameter affects production and consumption pattern by the farm households. This research employs the risk aversion parameter introduced by (Bellemare et al., 2013), which takes into account not just the household psychological risk attitudes, but also the market imperfections and availability of institutions which facilitate risk-bearing (Mendola, 2007) (de Janvry et al., 1991). Nevertheless, unlike (Bellemare et al., 2013) the essay develops a microfounded empirical model, where the risk aversion parameter is allowed to change over time and not just across households. This empirical model is estimated within a two-stage structural approach. The results of the empirical analysis suggest that the risk aversion parameter is not constant over time and that households can become more risk averse, if they face adverse market conditions in the previous periods. Furthermore, this paper provides evidence that peasants do not aim just at need satisfaction, but they behave in an optimal way and make sure their food security in the medium term. Indeed, they prefer to increase their income instead of directly consuming the harvested crop, because the reduction of dietary energy consumption derived from the giving up the harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained.

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First chapter

Vertical price transmission, geographical dispersion and the structure of the Ugandan coffee market

Vertical price transmission, geographical dispersion and the structure of the Ugandan coffee market

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Relation between price transmission and structure of agricultural markets is strongly debated in the literature and no consensus has been reached about symmetry, degree of such transmission and its mechanisms, so that further research is needed.
This paper tests whether in markets where infrastructure quality is poor and distance-related costs are relevant, geographic dispersion of smallholder farmers allows traders to exploit their market power against farmers with a large impact on market structure and reduction of farmers' welfare.
Following the intuition of Fafchamps et al. (2005), Sexton (2013) and Swinnen and Vandeplas (2014), the study provides a structural approach based on a set of well-founded behavioural equations to evaluate whether spatial oligopsony power is prevailing in agricultural markets and in case how strong it is. The paper designs also a far-reaching empirical test of the hypotheses through the seemingly unrelated regression technique. Moreover, it provides a strong empirical base to value chain studies, by exploiting the database of the Living Standard Measurement Study. The paper addresses the issue of transportation infrastructure as hindering factor of development in Uganda as outlined in several reports by World Bank, FAO and MAFAP and assesses the costs of such bottleneck, which are larger than transport expenditures.
Results confirm that geographic dispersion of smallholder farmers plays a significant role on price margin and that there is room for local oligopsony, because traders overcharge transport and distance-related costs to farmers.

Keywords: coffee value chain, wholesale-farm gate price spread, spatial dispersion, revenue distribution, traders' market power
JEL codes: O13, Q12, Q13

Introduction

Coffee, after petroleum, is the commodity with the highest turnover in international trade. Annual value of export revenues exceeds US$10 billion while annual retail sales of coffee are estimated at approximately US$50 billion. It is a highly labour intensive industry employing an estimated 100 million people in over 60 developing countries. It is particularly important to African economies, which represent a large share of exporting countries and is often a vital source of export revenues and income to producers, many of whom are smallholders (Collinson et al., 2005, 13).
The attempt of some governments to liberalize in the last few decades at least partially domestic agricultural markets, to integrate and upgrade their status in the global value chain is relevant for impact assessment of the structure of agricultural value chain on social welfare and development perspectives of developing countries. Due to this process the role of state-owned enterprises shrank and it was allowed to national and international private companies to participate in production, distribution, export of several agricultural products. Nevertheless, in many cases transition was not well managed: previously state-controlled markets did not turn in competitive ones, but in oligopsonistic markets with a large number of farmers and very small numbers of private or public traders (Fafchamps and Hill, 2008, 2).
Distribution of revenues along the value chain is of key interest for policy-makers, since modalities of participation of smallholder farmers in the value chain can be important in terms of poverty reduction and welfare and for regional food security. i.e. quantity and price of food supplied on the markets (Fafchamps and Hill, 2008, 2). Indeed, a larger or smaller spread can provide different incentives to farmers to cultivate some crops, to invest in order to increase productivity and yields as well as to market agricultural products.
In particular, coffee plays a significant role in the economy of Uganda in spite of several attempts by the government to diversify the national productive structure. This sector has a significant impact in terms of fight against poverty and income security, because coffee production is almost entirely dependent on about 500,000 smallholder farmers, 90 % of whose average farm size ranges from less than 0.5 to 2.5 hectares (MAFAP, 2012a, 5-6) (UCDA, 2015).
The paper tests whether in markets where infrastructure quality is poor and distance-related costs are relevant, geographic dispersion of smallholder farmers allows traders to exploit their market power against farmers with a large impact on market structure and reduction of farmers' welfare. Distance-related costs capture the expenditures of all services provided by traders to farmers, which are significantly correlated with distance: the main of which is trasportation of crops to the exporter yard. In this context, investments in infrastructure quality can foster competition, by reducing traders' market power, and curb poverty of rural areas.
The response variable which was chosen in order to assess the existence and the degree of spatial oligopsony is the wholesale-farm gate price spread, i.e. the difference between the wholesale export or domestic price net of marginal distance-related costs and the farm gate price. Several factors as small plot size hold by farmers, shortage of inputs, distance can affect such a spread. The paper disentangles the impact of such components.
Following the intuition of Fafchamps et al. (2005), Sexton (2013) and Swinnen and Vandeplas (2014), the study provides a structural approach to evaluate whether spatial oligopsony power is prevailing in the market and how intense it is.
By building upon Sexton (1990), the study brings an original contribution to the literature, since Sexton (1990) develops just a theoretical model and it is not interessed to do any econometric exercise. Sexton (1990) employs a single spatial price gap equation instead of a system of well-founded behavioural equations in agricultural markets, which is indeed a major improvement delivered by this paper.
Moreover, in this analysis the approach to spatial price gap determination is combined with the oligopsony modelling and SUR technique in order to produce empirically testable hypotheses. Without such transformations the approach by Sexton (1990) cannot be employed for any empirical exercise. Indeed, the idea of the role of distance is taken from Sexton (1990) and introduced in an original way in a more

sophisticated model, which is micro-founded at three levels, i.e. demand and supply of agricultural commodities by traders and farmers as well as conditional demand of inputs by farmers.
At the same time, the SUR estimation technique is not applied in the same way like in other oligopoly or oligopsony analyses. Indeed these previous articles ignore completely the issue of distance, which implies different problems of derivation and interpretation to be tackled. Seemingly unrelated regression framework is useful, in order to exploit simultaneity between equations and increase efficiency. Tests give proof that there is a significant correlation among the equations and that the empirical approach is justified.
Moreover, in this work there is a contribution in terms of empirical methodology, since SUR technique is run on a panel dataset, which is an econometrically sound, but a rarely employed approach. This work exploits a rich microeconomic database and provides a strong empirical base to value chain studies (World Bank, 2015).
Finally, the paper addresses the issue of transportation infrastructure as hindering factor of development in Uganda as outlined in Gollin and Rogerson (2010), MAFAP (2012a), MAFAP (2012b) and Ranganathan and Foster (2012) and assesses the costs of such bottleneck, which are larger than transport expenditures. Results confirm that geographic dispersion of smallholder farmers plays a significant role on price margin and that there is room for local oligopsony based on transport and distance-related costs.

Literature review

Relation between price transmission and structure of agricultural markets is strongly debated in the literature and no consensus has been reached about symmetry, degree of such transmission and its mechanisms (Vavra and Goodwin, 2005) (Meyer and Cramon-Taubadel, 2004).
Transmission between international and domestic prices and vice versa is referred as *spatial price transmission*, while transmission of price from consumers, triggered from demand shocks, to producers and vice versa is defined as *vertical price transmission* (Swinnen and Vandeplas, 2014).
A first contrast among researchers is about symmetry of price transmission. On the one hand, a branch of literature points out that symmetry is prevailing in the market (Ben-Kaabia and Gil, 2007) (Serra and Goodwin, 2003). On the other hand, some authors support the view that agents in the market pass more likely downstream price decreases than increases and pass on changes with delay (Vavra and Goodwin, 2005) (Zachariasse and Bunte, 2003) (Abdulai, 2000) (Abdulai, 2002) (Abdulai, 2000) (Frey and Manera, 2007). A further point of conflict among economists who show significant asymmetry and imperfection in the market concerns the mechanisms of price transmission.
Imperfect spatial transmission has been attributed to government intervention as tariffs and price stabilization measures, transport and marketing costs, degree of processing, market structure and consumer preferences (Rapsomanikis and Mugera, 2011), while imperfect vertical transmission is determined by the presence of asymmetric information along the value chain, the prevalence of "sticky prices", existence of labelling and advertising as well as of reputation costs due to the frequent price changes, inventory or selling strategies, exercise of market power by processing companies or retailers (Wohlgenant, 2001) (Meyer and Cramon-Taubadel, 2004) (Vavra and Goodwin, 2005).
For instance, in the EU prices increase in 2007/2008 was passed on to consumers, but decrease in 2008/2009 was not fully transmitted, hindering demand recovery and exacerbating negative impact of declining producer prices on farm household (European Commission, 2009). European Commission stressed that such discrepancies in price transmission were due to an excessive number of intermediaries along the value chain and inequalities in bargaining power between contracting parties (European Commission, 2009).
Nevertheless, this point cannot be always generalized, since the fact that producer prices vary more than consumer prices does not necessarily imply asymmetric changes (Swinnen and Vandeplas, 2014) (Bukeviciute et al., 2009).
Existing literatures focuses on consumer welfare and assumes a positive correlation between degree of

downstream vertical price transmission and consumer welfare. Indeed, a lower degree of price transmission can be exploited strategically by powerful intermediaries in the chain, who can capture a large share of the rents (Swinnen and Vandeplas, 2014, 3-4).
In particular, firms exploit the different responses by consumers to price increases or decreases and they trasmit more quickly to them the price upwards than the downwards adjustments (Bonnet and Villas-Boas, 2016). Indeed, consumers adapt to the new level of prices and do not react quickly to price reductions: they perceive the discount, but they do not increase strongly the demand, because they expect better deals (Kalyanaram and Little, 1994).
Consumers face also limits in purchasing, transporting and stockpiling products and they cannot demand as much as they would like because of such constraints (Gupta and Cooper, 1992). Furthermore, if the preference for a given brand is strong enough, the consumers can also remain loyal to its product, altough its price increases: consumers change their behaviour, only if the loss goes beyond a given threshold (Jacoby and Chestnut, 1978).
A branch of the literature comes to the conclusion that traders are efficient and provide a valuable service to smallholder farmers.
For instance, Sitko and Jayne (2014) analyse the maize value chain in Kenya, Zambia, Malawi, Mozambique and find that the reliance by the farmers on traders is not the only one alternative for remote farmers and that several producers, who can exploit other market channels, choose deliberately this selling strategy. Farmers opt for the service of intermediaries, because their activity provides to farmers some advantages.
Firstly, traders buy the harvest directly in the village: this is a significant gain for farmers located in the remote regions, which face high incidence of transport costs, without any possibility to exploit economies of scale in production or to lower the unit cost of transport.
Secondly, traders pay cash unlike parastatal marketing boards and processing firms, which issue check after a long lag period. Thirdly, traders purchase maize immediately after the harvest unlike marketing boards and processing firms, which wait that the crop is partially dry. Cash payment and early entry into the rural markets by traders release the capital constraints of farmers, which have strong financial needs at the harvest time (Sitko and Jayne, 2014).
Montalbano et al. (2017) conclude also from the analysis of the Ugandan maize value chain that the intermediaries are efficient: they do not exploit smallholder farmers and do not offer to farmers price below the prevailing market prices.

Sexton (2013) points out that increasing concentration, vertical coordination in food industry worldwide and growing relevance of differentiated products in terms of taste, appearance, brand appeal, fairness of production process and environment sustainability make easier to support the view that monopolistic competition is prevailing in the market. In this environment some firms are able to exert some market power and set prices with a significant impact on welfare and rent distribution among the actors involved in the value chain (Swinnen and Vandeplas, 2014) (Swinnen and Vandeplas, 2010) (Kikuchi et al., 2015) (Mesa and Gómez, 2011) (Fałkowski, 2010) (Osborne, 2005). According to this branch of literature several agricultural markets are oligopolistic or oligopsonistic and concentrated processors capture welfare against small and dispersed farmers.
Moreover, other authors express the view that asymmetry in price transmission is not due to exploitation of market power, but to vertical coordination, increasing returns to scale, risk-mitigating behaviour of agents and degree of processing (Swinnen and Vandeplas, 2014) (Wohlgenant, 2001) (Weldegebriel, 2004) (McCorriston et al., 2001) (Wang et al., 2006). In particular, the more stages in vertical market structure, the lower the pass-through of price changes along the value chain, independently from exploitation of market power by agents (Peltzman, 2000) (McCorriston and Sheldon, 1996) (Wang et al., 2006).
Disruptions in price transmission can also occur when there are large menu costs as advertising and labelling, information asymmetries and uncertainty about whether the shock is transitory or permanent (Ball and Mankiw, 1994) (Zachariasse and Bunte, 2003) (Owen and Trzepacz, 2002) (Levy et al., 1997) (Levy et al., 2002) (Blinder et al., 1998).

Ball and Mankiw (1994) point out that firms increase prices more quickly than decrease them, because they react to accumulated and anticipated inflation, particularly relevant in case of positive shocks.

Furthermore, actors can be reluctant to change prices because of reputation costs, inventory or selling strategies. Indeed, they are not sure whether competitors will do the same. Moreover, frequent price changes can reduce reputation and actors can postpone such adjustment to be sure that the shock is permanent (Blinder, 1994).

Such delays in price transmission could also come from risk minimization in inventory management. If prices reduce much and quickly, traders or retailers can run out of stock; if they increase suddenly, agents can be left with much unsold spoiled product (Ward, 1982) (Reagan and Weitzman, 1982).

Interpretation of the link between price transmission and market structure is ambiguous according to some researchers. For instance, Wang et al. stress that the interaction between industry technology and market power is puzzling and that in case of economies of scale price transmission can be stronger, weaker or identical to the competitive case (Wang et al., 2006).

Moreover, in most of countries agricultural markets are subject to large public intervention. If agents have expectation that government will more likely intervene if shocks reduce producer price rather than they increase it, expectation-induced price transmission could be asymmetric (Kinnucan and Forker, 1987).

A relevant role is played in small and open economies by external shocks which determine prices at the wholesale level (Vavra and Goodwin, 2005). Such disruptions are more relevant in developing countries than advanced economies, given higher adjustment and transaction costs in the former group and that external shocks play a key role in small producer countries (Vavra and Goodwin, 2005). Some authors argued that both consumers and producers in developing countries were hurt by food price spikes over the period 2007-2011, because farmers did not get significant benefits from high prices. Nevertheless, in this context empirical results of the effect of price volatility on consumers and farmers welfare as well as food security are mixed (Swinnen and Vandeplas, 2014).

In some industries oligopolistic or oligopsonistic structure can be offset by economies of scale with higher price transmission than expected (McCorriston et al., 2001).

Sexton (2013) and Crespi et al. (2012) emphasize that in today's agricultural markets to guarantee consistency and strict adherence of products and production processes to quality and safety standards is crucial. Therefore, exploitation of short-run oligopsony power by buyers against farmers could be detrimental to their long-run interests because such strategy reduces resources available in production and prevent enforcement of adequate standards (Crespi et al., 2012).

Sexton (2013) expresses the view that in high-quality supply chain, where buyer sunk and transaction costs for finding new suppliers are high, such buyers can opt for vertical integration or pay farmers as much and even more than in a competitive market.

Swinnen and Vandeplas (2014) show also that buyers can pay to farmers efficiency premia to ensure quality standards in environments with unequal bargaining power and market imperfections. Price transmission depends then on nature of vertical coordination and different types of transaction costs in the supply chain (Swinnen and Vandeplas, 2014). Moreover, partial price transmission can also take place in competitive markets due to intertemporal optimizing behaviour by agents, who respond more quickly to price increase than decrease (Azzam, 1999).

In general, empirical evidence about the process of price transmission along the value chain seems to be inconclusive and varies widely across countries and commodities, so that further research is needed (Vavra and Goodwin, 2005) (Meyer and Cramon-Taubadel, 2004).

In particular, some robustness analysis is necessary, because in some industries the functional form of costs determines the level of price transmission, unless there is a relevant knowledge about cost formation (Weldegebriel, 2004). This paper aims at testing the empirical hypothesis whether, in markets where infrastructure quality is poor and distance-related costs are relevant, geographic dispersion of smallholder farmers allows traders to exploit their market power against farmers with a large impact on market structure and reduction of farmers' welfare. In particular, the model studies the causes which contribute to the spread between the price obtained by traders at the point of competition (domestic market or

borders for exports), net of marginal distance-related costs, and the farm gate price, *wholesale-farmgate price spread*. Such indicator assesses the degree of competition and revenue distribution between farmers and traders.
This spread will be positive in some cases, since traders can exploit their market power against spatially dispersed farmers. Indeed, traders will not increase the farm gate price, even if they are able to receive higher consumer or export price.
This paper is thematically close to the branch of literature which deals with exploitation of market power by some actors in complex value chains like Peltzman (2000), McCorriston and Sheldon (1996), Sexton (2013), Vavra and Goodwin (2005) and Swinnen and Vandeplas (2014) as well as it addresses the coffee sector in Uganda, which is the main cash crop for Ugandan farmers.

Ugandan coffee value chain analysis

Coffe is an important cash crop for Ugandan smallholder farmers.
Both Arabica and Robusta are produced in Uganda in the ratio of 1:4 and coffee plants are inter-cropped with food crops like bananas and beans. Robusta is used as a "filler" in roasted and ground blends, and in instant coffee, while Arabica is sold as specialty or fair trade product (Collinson et al., 2005, 14).
Mostly, family labour is employed with a minimal use of agrochemicals (fertilizers, pesticides and fungicides), since part of production comes from wild forest coffee, which does not require any large human intervention (MAFAP, 2012a, 6).
Domestic consumption of coffee is small and it was around 4-10% of production in the period 2004-2010, in spite of some attempts by the authority to increase this value (MAFAP, 2012a, 8) (ICO, 2015).
Uganda ranks fourth after Burundi, Ethiopia and Honduras in terms of contribution of coffee exports in total export earnings in the period 2000-2010 with an average share of 18% during this time (ICO, 2015). In spite of that, ability of Uganda to increase international price by restricting exports or increasing domestic consumption is very limited, because its share in the global coffee market is small (MAFAP, 2012a, 8). Main export destination of Ugandan coffee is the European Union (over 70% of total exports) followed by Sudan (over 10%) and USA (about 3%). Remaining 15% of coffee exports is delivered in other 13 countries. Export market is very concentrated with 10 exporters making up 85% of exports. In particular, the leading company Ugacof Ltd. controls 15% of trade (MAFAP, 2012a, 8).
After coffee harvest of Robusta species, farmers usually sun-dry red cherries on the farm and sell their coffee as Kiboko (dry cherries). Most coffee sales are made at the farm gate to the traders who tour the countryside on bicycles or motorcycles. These Kibobo traders act as aggregators of very small amount of coffee: they do not enjoy large autonomy in setting the price and can be regarded as agents of either for bigger independent traders or for exporters. Generally, Kibobo traders dehull the cherries and sell occasionally the rough hulled green bean (referred to as "FAQ" or fair average quality) directly to exporters but more often to FAQ traders. The FAQ traders sell then to exporters' district depots or to exporters' yards in Kampala (Hill, 2010, 437) (MAFAP, 2012a, 10). After cleaning, sorting, grading, and drying of rough-hulled beans exporters or freight companies carry coffee by train, ferry or truck to the port of Mombasa, which it is the main sea outlet for Ugandan exports. From there, coffee is transported by sea to export destinations in 60 kilogram bags, which are stuffed into 20 feet or occasionally 40 feet containers (MAFAP, 2012a, 10).
Ugandan Arabica coffee is mostly grown in the districts of Kapchorwa and Mbale. Its value chain is similar to the one of Robusta, but in generally shorter, with more direct overseas marketing links than that for the latter variety (Collinson et al., 2005, 20). In the following figures the value chains for Robusta and Arabica are illustrated.

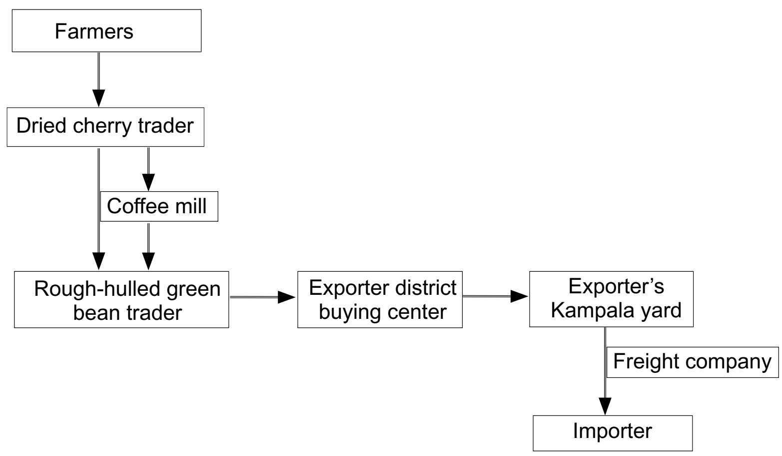

Figure 1: Robusta Value Chain in Uganda (Collinson et al., 2005, 19)

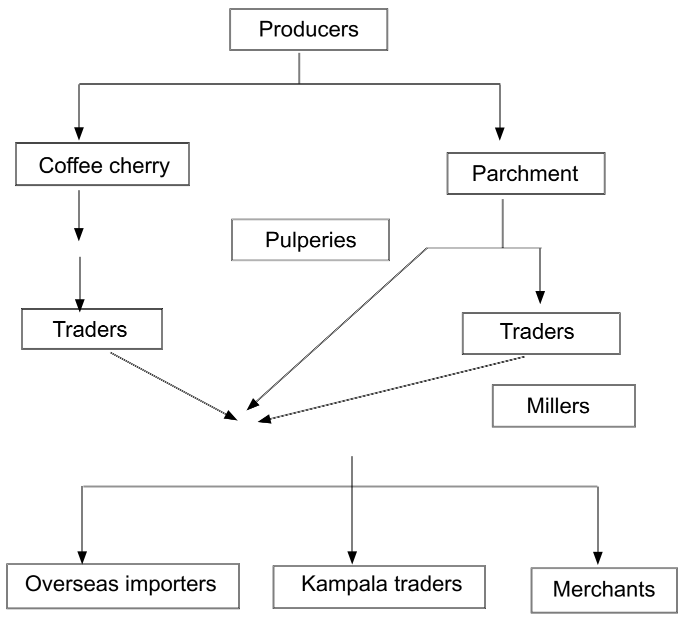

Figure 2: Arabica Value Chain in Uganda (Collinson et al., 2005, 20)

Model

Consider an agricultural market, where traders and farmers negotiate for quantity and price. The hypothesis to be verified is that, in markets where infrastructure quality is poor and distance-related costs are relevant, geographic dispersion of smallholder farmers allows traders to exploit their market power against farmers with a large impact on market structure and reduction of farmers' welfare. Distance-related costs capture the expenditures of all services provided by traders to farmers, which are significantly correlated with distance: the main of which is trasportation of crops to the outlet market. All other services, which are independent from the distance, like provision of credit, cannot be studied with the model developed in this paper.

To reasonably investigate the Uganda coffee sector, several stages in the value chain are aggregated. In particular, for simplicity's sake farmers are implementing within the farm the entire production process before sale to domestic consumers or export, even if more actors of the value chain are involved in the actual process.

Collection of agricultural products and marketing services are core business of traders, who do not transform at all any agricultural products. Traders are homogeneous in behaviour and available technology;

therefore the market area, where they compete, extends in n identical directions and is measured by a radius L.
Traders are willing to expand their supply markets to provide domestic consumers or exporters with larger amount of agricultural products.
Without loss of generality it is assumed that farmers produce and sell a quantity R of a single homogeneous crop. The farmer supply function is conditional on available technology T and a vector E of some exogenous factors, like climate, plot size and price received for the sold quantity:

$$R = f(T, E) \tag{1}$$

As confirmed by LSMS-ISA data and reports by MAFAP, fertilizers and pesticides are little used and coffee production is mainly a very labour intensive activity in a very labour-abundant country, where there is little incentive to substitute labour with more expensive inputs (MAFAP, 2012a, 6). Therefore, in Ugandan coffee production process there is low substitution between processing inputs. Moreover, a fixed ratio between inputs and agricultural output is prevailing, given the limited labour productivity increase in picking coffee cherries. Based on the analysed production process, Leontief production function seems to be the most suitable one (Sexton, 1990) (MAFAP, 2012a) (Collinson et al., 2005) (Wohlgenant, 2001).
Therefore, technology T can be described by the following Leontief production function (Diewert, 1971):

$$R = Min_i \left\{ \frac{x_i}{b_i} : i = 1, ..., K \right\} \tag{2}$$

where x_i is the conditional factor demand by the farmers and b_i is the relative technological conversion factor between inputs x_i and output R. In this functional form no substitution between the processing inputs is possible. According to the standard microeconomic theory the Leontief production function corresponds to the Leontief Cost function, which can be expressed in the following Gorman polar form:

$$C(R, p_i^x) = \sum_i b_i p_i^x + \sum_i \sum_j b_{i,j} (p_i^x p_j^x)^{1/2} R \tag{3}$$

where p_i^x and p_j^x are the prices of the *i-th* and *j-th* processing input and b the relative coefficient, given that $b_{i,j} = b_{j,i}$ (Appelbaum, 1982, 289). Gorman polar form has several advantages for empirical studies and estimation, given its aggregation properties, then it is used implicitly in many production studies. In particular, such a functional form allows different firms to have different cost curves but all of them are linear and parallel (Appelbaum, 1982, 291).
By applying Shephard's Lemma to equation 3, it is possible to derive conditional factor demand of processing inputs by farmers, x_i (Diewert, 1971):

$$x_i = \left[\frac{\partial C(R, p_i^x)}{\partial p_i^x} \right] = \left[b_{i,i} R + \sum_i b_{i,j} \left(\frac{p_j^x}{p_i^x} \right)^{1/2} R + b_i \right] \tag{4}$$

Traders face variable and fixed costs for delivery and marketing services:

$$C(R) = wR + t(R) + f \quad \textbf{if} \quad \mathbf{R > 0} \tag{5}$$

where w is the farm gate price of agricultural products, $t(R)$ variable distance-related costs paid by traders due to f.o.b pricing and f set-up fixed costs of delivery and marketing service. In this framework, the main distance-related cost is due to the trasportation of the crops to the outlet market.
In particular, cost function of processing inputs is negative exponential. By assumption, transport technology available to traders exhibits constant returns to scale and marginal variable costs t' can be taken as constant and not dependent on R. Nevertheless, some economies of scale occur over some $R > 0$, because strictly positive fixed set-up costs are spread over increasing inputs. Moreover, w is a function of agricultural product R and distance L (Sexton, 1990, 711).

In a competitive market traders maximize profit and equilibrium condition is reached when marginal revenues are equal to marginal costs, under the constraint of costs and quantity demanded of R:

$$Max\,[\Pi = PR - t(R) - wR - f] \rightarrow \frac{d\Pi}{dR} = 0 \tag{6}$$

where P is wholesale domestic or export price for agricultural products. By taking the first-order derivative:

$$\frac{d\Pi}{dR} = P - t' - w - R(\frac{dw}{dR}) \tag{7}$$

At this point, it is possible to take in account distance L, which introduces a wedge between price obtained by farmers and the one paid by traders. In spite of such wedge, positive distance-related costs do not necessarily imply imperfect competition, if distance-related costs, which are charged to farmers by traders, are equal to actual distance-related expenditures. In this case, distance-related costs play a similar role to expenditures for production factors.

When all markets are served, equilibrium condition is reached, if farm gate price net of distance-related costs is equal for all rival farmers at common borders:

$$w_i + tL_{ij} = w_j - tL_{ji} \tag{8}$$

where t is distance-related costs for unit of geographical distance, L_{ij} and L_{ji} represent geographical distance. Since distance is fixed in the short run as well as rival traders are symmetric, the radius of market area for each trader is symmetric in all n directions, i.e. $L_{ij} = L_{ji}$. This assumption corresponds to the one of standard oligopsony theory that the number of firms is fixed in the market in the short run (Sexton, 1990, 712).

By assumption, technology available to traders exhibits constant returns to scale and t can be taken as constant and not dependent on R. Solve equation 8 for L:

$$L = \frac{1}{2t}[w_i - w_j] \tag{9}$$

Take first-order derivative of 9 with respect to R:

$$\frac{dL}{dR} = \frac{1}{2t}\left[\frac{dw_i}{dR} - \frac{dw_j}{dR}\right] \tag{10}$$

By applying total derivative theorem, $(\frac{dw}{dR})$ can be written as:

$$\frac{dw}{dR} = \frac{\partial w}{\partial R} + \frac{\partial w}{\partial L}\frac{dL}{dR} \tag{11}$$

Given that firms are symmetric, in equilibrium $w_i = w_j = w$.

Let define $\frac{dL}{dR} = \theta\,(\partial w/\partial R)$ as a general conjecture and introduce it in equation 11 in order to get the following result:

$$\frac{dw}{dR} = \frac{\partial w}{\partial R} + \frac{\partial w}{\partial L}\theta\frac{\partial w}{\partial R} \tag{12}$$

By plugging 12 in equation 7 and re-ordering members, it is possible to get:

$$(P - t' - w) = R\frac{\partial w}{\partial R} + R\frac{\partial w}{\partial L}\theta\frac{\partial w}{\partial R} \tag{13}$$

After some manipulation, previous equation becomes:

$$(P - t' - w) = R\frac{\partial w}{\partial R}[1 + \frac{\partial w}{\partial L}\theta] \tag{14}$$

which is an equivalent expression to the *mark-up pricing policy* with respect to the spread between the wholesale domestic or export price net of marginal distance-related costs and the farm gate price.

In particular, $\left(\frac{\partial w}{\partial R}\right) = \left(\frac{\partial \sum_i p_i^x}{\partial R}\right)$, where $\sum_i p_i^x$ is the sum of the costs paid by farmers for all production inputs. Therefore equation 14 can be expanded taking in account all three market levels, although the market of agricultural products, where the traders and the farmers negotiate for quantity and price, is the main focus of the study:

$$(P - t' - w) = \left(\frac{\partial w}{\partial R}\right) R \left[1 + \theta \left(\frac{\partial w}{\partial L}\right)\right] = \left(\frac{\partial \sum_i p_i^x}{\partial R}\right) R \left[1 + \gamma L\right] \tag{15}$$

given that $\theta \left(\frac{\partial w}{\partial L}\right) = \gamma L$. Under the assumption of f.o.b. pricing, distance-related costs are transferred from exporters entirely to traders and at least partially to farmers. This price transmission process has also an impact in terms of production. If traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers, the latter are willing to supply less coffee for a given price.

The sketched model can be empirically tested in order to assess whether traders exploit their market power against farmers, based on geographical dispersion of the latter.

Data

The model can be applied to data collected by the Ugandan Statistical Office and the World Bank team within the framework of the Living Standard Measurement Study (LSMS). This database is integrated with data coming from Doing business and World Development Indicator database. A panel dataset is build for the waves 2010-2011 and 2011-2012.

The Agriculture survey of the LSMS concerns agricultural firms of small and middle size and it is very valuable for the analysis entailed in this paper. Indeed, coffee production is almost entirely dependent on about 500,000 smallholder farmers, 90 % of whose average farm size ranges from less than 0.5 to 2.5 hectares (MAFAP, 2012a, 5-6) (UCDA, 2015). The database contains information about employed production factors, i.e. organic and inorganic fertilizers, pesticides, hired and family labour. Such variables are taken as production inputs x_i.

For each factor the quantity purchased and the expenditure are provided. Factors for which a price cannot be recorded were probably obtained by the farmer for free and then they will be not regarded as cost in the production function.

Indeed, it is very likely, that not all inputs are bought by farmers on the market, since some of them are easily obtained by animal dung, which are raised within the farm, or saved from the previous seasons, like seeds, or exchanged with fellow farmers, like some chemical fertilizer or pesticides. Inability to record use of such inputs would bias a productivity estimate. Nevertheless, in this work the focus is on cost structure and price formation and not on productivity. Therefore, as long as farmers have not used or used, but not purchased such production factors, setting the relative costs to zero seems not be wrong, since these farmers did not pay out any money for them. Moreover, limited use of agrochemicals, as documented by the MAFAP, makes not surprising that many farmers report no employment of some of the mentioned inputs (MAFAP, 2012a, 6).

In a similar way, reported non-hired labour other than family work, provided by neighbours as exchange or for social reasons, is not going to be taken in account, since it does not contribute to costs.

For each household total costs of hired labour and workdays are available. On the basis of these values, it is possible to compute an average daily wage for each household across the different tasks, gender and age of the workers (men, women and children). This daily wage is applied for person-workdays for family members to get total opportunity cost of family labour. For some hired jobs, no workdays are available, since it was possibly a piecework, to which the average daily wage across all households is assigned. This information available at the household level enables to take in account regional wage differentials.

The model takes also in account spatial dimension of the market. In this insight, distance-related costs play a role in determination of the spread between wholesale domestic or export price and farm gate

price. The bulk of distance-related costs is due to the trasportation of crops to the outlet market: from the LSMS database it seems that there are several ways to deliver agricultural products, which lead to different transport costs. Very frequently, dry cherries are collected at the farm gate by kiboko traders who tour the country by motorcycle or bicycle, which leads to zero or low transport costs for farmers.
Uganda is a landlocked country and its main sea outlet for exports is the port of Mombasa in Kenya. This aspect represents a major constraint to transaction cost efficiency, since transport costs between Kampala and Mombasa are a burden on the industry and reduce net prices to producers, as Uganda must remain competitive on world markets in relation to other origins which do not have to bear high internal costs of this kind (Collinson et al., 2005, 26).
Therefore, transaction costs for Ugandan coffee are quite high and made of transport costs between the farm and the exports' yard in Kampala, costs to export, i.e. for inland transportation between Kampala and the port of Mombasa and for loading and customs procedures there, which cannot be identified separately from each other.
Costs of export can be taken for the year of the LSMS survey from the Doing Business Database. They are expressed in deflated US Dollars for a 20 feet container of a weight of 10 tonnes, it is possible to obtain the average costs to export per kilo and to convert it to Ugandan Shillings like the other variables in the LSMS with the *PPP Conversion Factor to Market Rate* (World Bank, 2014) (World Bank, 2015).

Costs to export are paid by exporters, who are not able to increase export price to take in account such expenses, because international demand is exogenous. Such costs to export correspond to the variable t in the equations 5, 6 and they are reasonably variable within a given range. Marginal cost t' as in equation 7 are constant by assumption and therefore equal to the average costs to export per kilogram given in the Doing Business Database. It can be assumed that costs to export are transferred by exporters to traders and by the latter to farmers, based on the experience that historically low prices have squeezed trader margins to an average of less than 1% of revenue, and grower price levels to close to, or less than, the cost of production (Collinson et al., 2005, 24). Wholesale export price net of marginal distance-related costs $(P - t')$ is equivalent in this sense to the *f.o.b. price* at the port of Mombasa.

Moreover, distance-related costs between the farm and Kampala are sometimes carried by farmers, sometimes by traders. It is expected that traders who collect the kiboko at the farm gate will pay lower farm gate price on average (Fafchamps et al., 2005).

Through these operations it is possible to get a database of 1041 households which harvested coffee during the LSMS-ISA survey wave 2010-2011 or 2011-2012 or during both.
Uganda LSMS sampling design warrants representativeness at national and sub-national level, like for agro-ecological zones (Himelein, 2012). Such sampling algorithm implies that the selected sub-sample of 1041 households is representative of the population of coffee producers, because coffee production is regionally concentrated in few districts (Bundibugyo, parts of Hoima, Kabarole, Mbarara, Bushenyi, Mubende, Luweero, Mukono, Masaka, Iganga, Jinja, Kalangala, Mpigi and Kampala) which make up a specific agro-ecological zone (Mwebaze, 2006).

Empirical Strategy

In the specific case of the Ugandan coffee value chain, domestic price spread can be ignored, because domestic consumption of coffee is negligible. Indeed, from the ICO data it is possible to compute that domestic consumption was around 4-10% of production in the period 2004-2010 (MAFAP, 2012a, 8) (ICO, 2015). Therefore, just demand for exports and international price spread are taken in account. In particular, international demand is taken as exogenous, given that Uganda has a small share of world coffee market.

The following model is run for empirical estimation:

$$F = \begin{cases} \ln R_i = \ln a + \eta \ln \left(\frac{w_i}{S} \right) + \beta C + \xi_1 & \text{(a)} \\ x_i/R_i = b_{i,i} + \sum b_{i,j} \left(\frac{p^x_j}{p^x_i} \right)^{1/2} + b_i/R_i + \xi_2 & \text{(b)} \\ (P_{int} - t' - w_i) = \frac{\left(\sum_i b_i p^x_i + \sum_i \sum_j b_{i,j} (p^x_i p^x_j)^{1/2} R_i \right)}{\left[1 + \theta_{int} \left(\partial w_i / \partial L \right)_{int} \right]^{-1}} + \gamma L + \xi_3 & \text{(c)} \end{cases}$$

where *t'* are distance-related costs between the exporter yard and the border paid by traders (f.o.b. pricing), C are climatic control variables for rainfall estimates, L distance variables, S is the implicit GDP deflator, P_{int} the international price and ξ_r is the disturbance term of the *r-th* equation of the system. All other variables have been already defined.

Since it is assumed that technology available to traders exhibits constant returns to scale, marginal and average distance-related costs are equal and correspond to parameter *t'*.

C consists of C_1, the average 12-month total rainfall (mm) for the time 2001-2010, and C_2, 12-month total rainfall (mm) between January and December for the survey year (2010 or 2011).

L is made of L_1, distance from Kampala (km), and L_2, remoteness index. L_1 is calculated as the geographic distance between the GPS co-ordinates of the plot and the city of Kampala, while L_2 is an average of distance of the village centre from some facilities of primary importance for the community.

Other control variables in (a) like parcel size were tested, but they are not significant. Main reason for this insignificance is that much coffee is wild and collected by farmers in the forest and on common land.

Variables *t'*, P_{int}, $p^x_{i/j}$, C, w and L are exogenous, because farmers are small and dispersed.

Equation (a) describes microeconomic supply function by farmers, given farm gate price, exogenous climatic variables and the prevailing market structure. Equations (b) and (c) describe behavioural microeconomic relations, i.e. optimal substitution strategy between production factors, given exogenous prices of inputs, and pricing behaviour of farmers, given production function and the prevailing market structure.

Equation b corresponds to conditional factor demand, equation 4, and consists of two sub-equations b.1 and b.2 for two groups of inputs employed in production process, respectively other inputs (fertilizer, pesticides, etc.) and labour. Equation (c) corresponds to equation 15 and is the focal point of analysis, since the wholesale-farmgate price spread assesses market competition degree and revenue distribution between farmers and traders.

Availability of panel data for the waves 2010-2011 and 2011-2012 increases quality of estimation and allows to take in account household heterogeneity. If the model is run on the unbalanced panel instead of the balanced one there will be an efficiency increase, therefore no balanced panel is extracted from the unbalanced one (Baltagi, 2006).

Given the panel structure of the database, all previous equations should be indexed by h (household ID) and t (year). In order to simplify notation, indexes h and t were not introduced in the equations, but the two dimensions are taken in account in the estimation.

Microeconomic supply, substitution between production factors and pricing behaviour cannot be regarded as contemporaneously uncorrelated with each other. Indeed, farmers decide at the same time how much coffee they supply and which inputs they employ in production, given exogenous factor prices, distance-related costs for unit of geographical distance and farm gate price offered by traders.

The empirical approach is data-driven. In particular, the alternative between SUR, which implies correlation between the equations in the system through the disturbance term, and equation-by-equation OLS, which means that there is no correlation between such equations, is checked through the likelihood ratio and Breusch-Pagan test for indipendent errors. Both tests conclude that SUR is the most adeguate technique. In particular, likelihood ratio test confirms that the null hypothesis, that correlation between the equations is zero, is easily rejected as shown in table 3.

Breusch-Pagan test for independent errors informs that several correlation coefficients between the residuals of equations in regarded specifications are significantly different from zero, as it can be easily seen in tables 4 and 5. Therefore, to employ a seemingly unrelated equations (SUR) model seems to be fully justified. This methodology allows to exploit simultaneity between equations and to increase efficiency (Zellner, 1962).

Due to significant correlation of disturbance terms across the different equations, an equation-by-equation OLS produces consistent, but inefficient estimates. Therefore, a GLS- SUR estimation is required because of its sizeable advantages in terms of efficiency over an OLS estimation (Greene, 2008, 254-257). Although the number of observation units is much larger than the time periods, the system can be successfully estimated. Indeed, by means of a pre-multiplied matrix, which maps the unrestricted coefficients into the restriction set by the sketched model, the dimension of the covariance matrix is reduced and its generalized inverse can be easily computed (Henningsen and Hamann, 2007, 7-8).

There could be endogeneity due to household unobserved heterogeneity in the database. Equation-wise Hausman test between fixed and random effect estimators produces mixed results as shown in table 6 and does not fully support random effect specification. In order to carry out some robustness analysis, a seemingly unrelated regression - least square dummy variables (SUR-LSDV) and a seemingly unrelated regression - random effect (SUR-RE) are estimated.

SUR-LSDV accounts for household fixed effects: from results in table 7 it is possible to see that share of household effects, which are significant at least at 5 %, amounts to 75.6 % in equation c, but barely to 23.3% in equation a, to 0.6% in equation b.1 and to 4% in equation b.2.

Both specifications control for cross-equation correlation through residuals and for household heterogeneity, but they are based on different assumptions. While SUR-LSDV leaves the relation between household heterogeneity and covariates in all equations unconstrained as well as allows to estimate and test household effects, SUR-RE assumes that household heterogeneity and covariates in all equations are orthogonal and that household heterogeneity behaves like idiosyncratic error term.

From this output it is possible to conclude that entrepreneurial ability of farmers is not very relevant, if production of green coffee is achieved without employment of advanced techniques or by collecting coffee cherries in forests as it is the case in Uganda. On the contrary, given the impact of distance-related costs on raw agricultural commodity final price, distance plays an important role. In this sense, distance represents a large part of heterogeneity among farm household. Indeed, distance affects very likely farm gate price in equation c, but not other inputs and labour requirement in equations b.1 and b.2 or supplied quantity in equation a. Distance influences supplied quantity only through farm gate price.

Therefore, endogeneity due to household unobserved heterogeneity is very attenuated, since farmers are small, dispersed and accept the farm gate price offered by traders as well as production of coffee in Uganda does not require very relevant level of ability. In this case, an IV approach will not produce any significant improvement, given that instruments are weak. Moreover, estimated simultaneous equation model SUR controls for residual minor endogeneity.

While SUR-RE introduces some bias since the orthogonality assumption is not fully supported, this distortion is little since farmer heterogeneity comes mostly from distance and not from farmers' entrepreneurial ability or other omitted variables. Moreover, SUR-LSDV does not make possible an appropriate identification strategy, because it does not allow to identify separately distance as explanatory variable. Therefore, a SUR-RE model is also estimated with four different specifications.

System F is the most general version of the model. For robustness analysis, the model is run with five different specifications. Specification 1 is estimated as SUR-LSDV. Specifications 2, 3, 4, 5 are SUR-RE models. In particular, in specification 1 there are neither L nor C, but household dummy variables are separately identified, specification 2 is run with L and C. Specification 3 is estimated with C, but without L. Specification 4 includes L, but not C. Specification 5 does not entail neither C nor L.

Specifications 1, 2 and 3 are reference approaches for the analysis carried out in this paper. Nevertheless, specifications 4 and 5 were also estimated in order to provide a complete picture. Indeed, variables C and L have many missing data which cannot be otherwise imputed, therefore their introduction results in a significant reduction in sample size. In spite of these shortcomings, asymptotic validity of the specifications 1, 2 and 3 is not undermined and their evaluation can be regarded as main contribution to the analysis of the topic dealt with in this paper.

Estimation results

The output of all specifications is reported in tables 7, 8, 9, 10 and 11.
Goodness-of-fit of specification 1 (SUR-LSDV) is high because Mc Elroy R^2 is 0.68. Goodness-of-fit of specifications 2, 3, 4, 5 (SUR-RE) decreases, but it is still good. In particular, for specifications 2 and 3 the Mc Elroy R^2 is between 0.29 and 0.34[1].
In all specifications, all variables in the second equation on other input requirement are not significant, while in the third equation on labour requirement the reciprocal of coffee supply is large and highly significant. This result confirms that coffee production is a labour-intensive process and that Ugandan farmers employ small quantity of fertilizers and pesticides. In general, low levels of wages in agricultural sector fosters a substitution of other inputs (fertilizer, pesticides, etc.) with labour. The most interesting result is given in the fourth equation. Only in specification 5 the marginal effect of labour costs is significant, but still quite small. In all other specifications any input costs variable is not significant.
Regression output is able to confirm also the hypothesis made in the first part of the paper, i.e. that traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers. In specification 2 only D_1, distance from Kampala (km), is significant and its magnitude is between 10^4 and 10^5 times the value of the coefficients of the factor costs in all specifications. As shown in table 12 marginal effect of distance on wholesale-farm gate price spread is between 2.3 and 2.4 Ugandan Shillings (UGX) each kilogram of coffee and kilometre of distance. Since wholesale-farm gate price spread is defined as $(P_{int} - t' - w)$ and *t'* and P_{int} are exogenous and constant across households, the mentioned marginal effect implies a reduction of the farm gate price by 2.3 and 2.4 Ugandan Shillings (UGX) each kilogram of coffee for each kilometre far away from Kampala. This value corresponds to an average decrease between 6 % and 7 % of the farm gate price each kilometre, because the average farm gate price is about 35 UGX each kilogram. This result confirms that traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers.
The remoteness index is not significant in all models. Only actual distance from the export yard in Kampala and not accessibility to primary community services, e.g. outlet markets, is relevant for coffee revenue distribution.
At the same time, distance from Kampala and the remoteness index are negatively correlated ($\rho = -0.62^{***}$), which can give a hint that some primary services in the surroundings of Kampala could be less accessible to citizens because of city size and higher population density. In spite of that, farmers could regard as more convenient to own a plot in the surroundings of Kampala, in order to overcome more easily distance barriers and take on a larger share of coffee price.
To have a better insight in the impact of distance on market structure, direct effect of supply on price and the one of price on supply as well indirect effect of distance on both can be computed and compared. From results of specification 2 relevant partial elasticity parameters are calculated and reported in table 12.
From this computation it is evident that direct effect of supply on price and of price on supply is smaller than indirect effect of distance on both. In this context, geographical distance determines market structure and plays a significant role for farmers' welfare, since this cash crop provides a large part of income for over 500,000 households.
Due to this empirical relevance, any policies should take in account such aspect as a barrier to competitive

[1]Mc Elroy R^2 is computed in the following way: $R^2_{McE} = 1 - \frac{\hat{\epsilon}'\hat{\Omega}^{-1}\hat{\epsilon}}{y'\hat{\Omega}^{-1}y}$ where $\hat{\Omega}^{-1}$ is the estimated positive definite contemporaneous covariance matrix, $\hat{\epsilon}$ the error vector and y the dependent variable (McElroy, 1977). This measure of goodness-of-fit should be evaluated with caution, because some doubts on its reliability were cast (Srivastava and Giles, 1987, 346-351) (Jitthavech, 2010).

coffee market and to poverty reduction of rural areas. On the basis of the output analysed, in the last part of this work some policy implications are discussed in order to design a strategy to foster a structure of the agricultural value chain which maximizes social welfare and increase competitiveness of the sector.

Policy implications

Empirical analysis proved the relevance of distance as disincentives to farmers in supplying larger quantity of coffee. Indeed, traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers.
Farmers are not able to skip traders in the value chain, because a significant information asymmetry is prevailing in the market. In particular, traders exploit farmers' ignorance because the latter are small and dispersed as well as they lack information about current market prices because of villages remoteness and poor communications with marketplaces (Courtois and Subervie, 2015). Moreover, farmers are not aware of actual distance-related costs faced by traders, which carry larger quantities of coffee than single smallholder farmers and spread fixed costs over a larger amount of crop.
The market share in world coffee export of Uganda is quite small, therefore an increase in coffee supply could have a positive impact on the available income of households without worsening the international coffee price.
This paper shows that costs increase more quickly because of bottlenecks in transportation infrastructure than of expenditures for production factors.
Improvement of transportation network can lead to larger production and higher efficiency of the coffee value chain, by reducing traders' market power. Indeed, there are no other major constraint in increasing coffee supply by farmers (Gollin and Rogerson, 2010) (Ranganathan and Foster, 2012). Labour is indeed largely available in a country with fast-growing and young population (World Bank, 2014). Other factors like small parcel size do not seem to represent a significant barrier to increase in supply, as long as competition for wild coffee or common land does not become too fierce. This perspective is not probably immediate, because population density in Uganda is not very high (World Bank, 2014).
Geographical distance is obviously a physical constraint which cannot be easily overcome. Proposals to provide incentives to farmers to move closer to Kampala cannot be regarded as a reasonable policy recommendation. Indeed, increasing agglomeration could have large negative side-effects and worsen even more the quality of accessibility to primary services in the area of Kampala and increases household poverty.
Instead, improvement of transport quality could have very positive side-effects, providing to businesses in other sectors incentives to delocalize production outside the central region and reduce the negative impact of congestion in the area of Kampala. This policy could indirectly foster a more balanced regional development.

Conclusions

This study was able to deal with revenue distribution along the Ugandan coffee value chain and to prove that spatial dispersion of farmers is a very important factor in the relationship between farmers and traders, which provides market power to the latter. The analysis gave hints that there is a large room for local oligopsony by traders, based on high delivery costs. In particular, traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers.
Distance-related costs consists of all expenditures for the services provided by traders to farmers, which are significantly correlated with distance: the main of which is trasportation of crops to the exporter yard.
Marginal effect of distance on wholesale-farm gate price spread is between 2.3 and 2.4 Ugandan Shillings

(UGX) each kilogram of coffee and kilometre of distance. This value corresponds to an average decrease between 6% and 7% of the farm gate price each kilometre, because the average farm gate price is about 35 UGX each kilogram. From the computation entailed in this paper it is evident that direct effect of supply on price and of price on supply is smaller than indirect effect of distance on both.

In this context, the exploitation of the farmer geographical dispersion by the traders determines an oligopsonistic coffee market structure and plays a significant role for farmer welfare, since this cash crop provides a large part of income for over 500,000 households.

This study comes to divergent conclusions with respect to the ones in Sitko and Jayne (2014) and Montalbano et al. (2017), where evidence is provided that intermediaries are efficient and give to the smallholder farmers better marketing possibilities.

This discrepancy is due to the fact that Sitko and Jayne (2014) and Montalbano et al. (2017) analyse the maize market, while this study evaluates the coffee market. While maize is one of the most important staple crop and is harvested in all districts in Uganda, coffee is a cash crop, it is not consumed at all domestically and it can be grown only in few specific regions (MAFAP, 2012a, 8) (ICO, 2015) (Haggblade and Dewina, 2010).

The above mentioned difference implies that smallholder farmers opt for the sale of the harvested maize to traders only if these intermediaries are efficient and pay the right price to them, while coffee producers are not able to skip traders in the value chain.

Indeed, farm households are aware of the market price of maize, because this crop is largely traded and consumed in Uganda (Haggblade and Dewina, 2010). In addition, smallholder farmers can easily skip the traders, because they can sell their harvest in their neighbourhood to other farmers, who lost the harvest, or to local non-farm households.

Instead, coffee cannot be sold in the farmers' neighbourhood, because it is not domestically consumed in Uganda. The only one way to obtain some revenues from the coffee production is to bring the harvest to the exporter yard in Kampala. Farmers can transport the harvest by themselves to Kampala or they can sell it to the traders (Haggblade and Dewina, 2010).

Several factors make impossibile for smallholder farmers to sell directly the crop to the exporters and allow traders to overcharge distance-related costs to the producers: the limited storage possibilities in the farm households, regulatory and technical barriers as well as information asymmetry (MAFAP, 2012a) (Svensson and Yanagizawa, 2009).

Insufficient storage space is much more relevant for coffee than for maize: while maize can be sold at any time after the harvest to the neighbours, coffee producers need to wait for the time when traders are willing to purchase the harvest, often long after the harvest, when the beans are sun-dried.

Furthermore, coffee beans can be exported only if they comply with a set of quality requirements, sanitary and phytosanitary standards: this constraint prevents smallholder farmers to deliver harvest directly to the exporters. Instead, the requirements for the sale of maize, in particular if it is sold informally or locally, are far lower.

Moreover, farmers, who are small and dispersed, are not aware about current coffee market prices because of villages remoteness and poor communications with marketplaces and because this crop is not traded locally at all (Courtois and Subervie, 2015). Farmers are also not aware of actual distance-related costs faced by traders, which carry larger quantities of coffee than single smallholder farmers and spread fixed costs over a larger amount of crop (Svensson and Yanagizawa, 2009) (Ferris et al., 2008).

This study confirms also that coffee production is a labour-intensive process and that Ugandan farmers employ small quantity of fertilizers and pesticides. In general, low levels of wages in agricultural sector fosters a substitution of other inputs (fertilizer, pesticides, etc.) with labour. A set of adequate policies to address the exploitation of market power by traders would consist of investment in quality of transportation and roads in order to reduce delivery time and costs. This strategy would shrink the ability of traders to exploit information asymmetry against farmers and to overcharge distance-related costs to the latter.

Such approach is able to produce further positive side-effects and foster de-localization of other businesses outside the central region of Kampala and lower negative effects of congestion around Kampala. Moreover, an increase in coffee supply could also have a positive impact on the available income of households without worsening the international coffee price, since the market share in world coffee export of Uganda is quite small.

Since there are many open questions and a strong interest for the analysed field, the author is keen to expand this analysis in future research works. For instance, it would be stimulating to disentangle the complex trading relations between Kiboko and FAQ traders and to figure out how the complexity of the value chain impacts sector efficiency.

An interesting research purpose would be also to model the optimal area of local oligopsony for traders and which effect specific policies can have on the market structure. Finally, interaction between international coffee market and behaviour of domestic actors was not investigated. This issue could be also an another stimulating avenue for further research.

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Mathematical annex

In this annex an alternative derivation of spatial equilibrium analysis is given, which makes clear the similarity of the model developed in this paper with (Sexton, 1990)'s approach. Equation 13 can be also expressed in form of elasticity.

Given the general conjecture $\frac{dL}{dR} = \theta\left(\partial w / \partial R\right)$ employed in the analysis, dividing both sides of equation 15 by w as well as multiplying and dividing the second addend of the right-hand side for L, equation 13 becomes:

$$\frac{P - t' - w}{w} = \frac{R}{w}\frac{\partial w}{\partial R} + \frac{\partial w}{\partial L}\frac{dL}{dR}\frac{R}{w}\frac{L}{L}$$

Then, it is possible to get relative wholesale-farm gate price spread in terms of elasticity:

$$\frac{P - t' - w}{w} = \epsilon_{w,R} + \epsilon_{w,l} \cdot \eta_{L,R}$$

because relative total and partial derivatives can be expressed in terms of elasticity by means of total derivative theorem:

$$\eta_{w,R} = \epsilon_{w,R} + \epsilon_{w,l} \cdot \eta_{L,R}$$

In particular, $\epsilon_{w,l}$ is partial elasticity of farm gate price to geographical distance and depends on distance-related costs under the assumption of f.o.b. pricing. These costs are transferred from exporters entirely to traders and at least partially to farmers.

$\epsilon_{w,R}$ is inverse elasticity of supply of agricultural products. The $\eta_{L,R} = \left(\frac{dL}{dR}\frac{R}{L}\right)$ represents the market area competition and it is analogue to the conjectural variation of the standard oligopoly/oligopsony theory (Sexton, 1990, 711). In equation 11 it seems to be more natural to regard $\left(\frac{dR}{dL}\right)$, which by symmetry of derivatives, is equivalent to $\left(\frac{dL}{dR}\right)$.

The latter point can be made clearer by applying the implicit function theorem. It can be indeed showed that $\left(\frac{dR}{dL}\right)$ is the negative of the ratio between marginal effect of market area on farm gate price and marginal effect of supply of agricultural product on farm gate price:

$$\left(\frac{dR}{dL}\right) = -\frac{dw/dL}{dw/dR}$$

Indeed, it is possible to resolve the equation for $\left(\frac{dw}{dR}\right)$ and replace the result in equation 7. Then, total derivative theorem is applied to $\left(\frac{dw}{dL}\right)$ and it is possible to get the same equation 14.

$\left(\frac{dR}{dL}\right)$ describes the perception by traders how a pure change in market area is going to affect supply by farmers, net of the effect that a change of farm gate price will have on the supply of agricultural products by farmers. If traders exploit their market power overcharging distance-related costs between farm and exporter yard in Kampala to farmers, the latter are willing to supply less coffee for a given price. The parameter $\left(\frac{dR}{dL}\right)$ corresponds to the conjectural variation of the standard oligopsony theory (Sexton, 1990, 711).

Table 1: Acronyms and Abbreviations

Symbol	Meaning
UCDA	Uganda Coffee Development Authority
UGX	Ugandan Shilling
WDI	World development Indicators (World Bank)
ICO	International Coffee Organisation
OLS	Ordinary Least Squares
FGLS	Feasible Generalized Least Square
SUR	Seemingly Unrelated Regressions
MAFAP-FAO	Monitoring and Analysing Food and Agricultural Policies - Food and Agriculture Organization
FAQ	Fair Average Quality (Coffee)
f.o.b.	Free On Board
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
f	Fixed costs in the farmers production function
b_i	Technological Conversion Factor between inputs x_i and output R (Leontief production function)
θ	Conjectural Variation
$\eta_{w,R}$	Total Elasticity of farm gate price to coffee supply
$\epsilon_{w,R}$	Partial Elasticity of farm gate price to coffee supply
$\epsilon_{w,l}$	Partial Elasticity of farm gate price to market area radius
$\eta_{L,R}$	Total Elasticity of market area radius to coffee supply

Table 2: Variables

Symbol	Meaning	Level	Source	Notes
L_1	Distance between the household and Kampala (GPS co-ordinates)	Household	LSMS (Uganda)	Specification of L (Market Area Radius)
L_2	Avg. distance between village center and some facilities of primary importance	Community	LSMS (Uganda)	Specification of L (Market Area Radius): Remoteness Index
R	Quantity of coffee sold	Household	LSMS (Uganda)	
w	Farm gate price (UGX)	Household	LSMS (Uganda)	Ratio between Value of sale and Quantity of coffee sold
x_i	Quantity of i-th input (conditional factor demand)	Household	LSMS (Uganda)	Labour; Other inputs (Pesticides, Organic and inorganic Fertilizers)
$p^x_{i/j}$	Input Costs	Household	LSMS (Uganda)	Labour; Other inputs (Pesticides, Organic and inorganic Fertilizers)
P_{int}	International coffee price	International	ICO	ICO composite indicator price
S	World GDP deflator	International	WDI (World Bank)	Average of the GDP deflator of the consumer countries
t	Cost to export	Country	Doing Busines (World Bank)	Converted in UGX per kilogram of coffee

Table 3: Likelihood ratio test

$$F = \begin{cases} \ln R_i = \ln a + \eta \ln \left(\frac{w_i}{S}\right) + \beta C + \xi_1 & \text{(a)} \\ x_i/R_i = b_{i,i} + \sum b_{i,j} \left(\frac{p_j^x}{p_i^x}\right)^{1/2} + b_i/R_i + \xi_2 & \text{(b)} \\ (P_{int} - t' - w_i) = \frac{\left(\sum_i b_i p_i^x + \sum_i \sum_j b_{i,j} (p_i^x p_j^x)^{1/2} R_i\right)}{\left[1 + \theta_{int} \left(\partial w_i / \partial L\right)_{int}\right]^{-1}} + \gamma L + \xi_3 & \text{(c)} \end{cases}$$

H_0: Residuals of the m equations are uncorrelated.

Model	Degree of freedom (model)	LR test	Degree of freedom (statistic)	p-value
OLS (restricted) (H_0 valid)	17			
SUR (not restricted) (H_0 not valid)	26	34. 33	9	7.8e-05 ***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 4: Residuals Correlation *(Specifications 1, 2, 3)*

Specification 1				
	Eq. a	Eq. b.1	Eq. b.2	Eq. c
Eq. a	1.00	-0.02	0.05	-0.62***
Eq. b.1	-0.02	1.00	0.04	-0.06*
Eq. b.2	0.05	0.04	1.00	-0.32***
Eq. c	-0.62***	-0.06*	-0.32***	1.00
Specification 2				
	Eq. a	Eq. b.1	Eq. b.2	Eq. c
Eq. a	1.00	-0.02	-0.42***	-0.21***
Eq. b.1	-0.02	1.00	0.04	0.00
Eq. b.2	-0.42***	0.04	1.00	-0.04
Eq. c	-0.21***	0.00	-0.04	1.00
Specification 3				
	Eq. a	Eq. b.1	Eq. b.2	Eq. c
Eq. a	1.00	-0.02	-0.37***	-0.17***
Eq. b.1	-0.02	1.00	0.04	-0.03
Eq. b.2	-0.37***	0.04	1.00	-0.30***
Eq. c	-0.17***	-0.03	-0.30***	1.00

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: Residuals Correlation *(Specifications 4, 5)*

Specification 4				
	Eq. a	Eq. b.1	Eq. b.2	Eq. c
Eq. a	1.00	-0.03	-0.10**	-0.17***
Eq. b.1	-0.03	1.00	0.04	0.01
Eq. b.2	-0.10**	0.04	1.00	0.04
Eq. c	-0.17***	0.01	-0.04	1.00

Specification 5				
	Eq. a	Eq. b.1	Eq. b.2	Eq. c
Eq. a	1.00	-0.02	0.03	-0.44***
Eq. b.1	-0.02	1.00	0.04	-0.03
Eq. b.2	0.03	0.04	1.00	-0.33***
Eq. c	-0.44***	-0.03	-0.33***	1.00

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Equation-wise Hausman test

$$F = \begin{cases} \ln R_i = \ln a + \eta \ln\left(\frac{w_i}{S}\right) + \beta C + \xi_1 & (a) \\ x_i/R_i = b_{i,i} + \sum b_{i,j}\left(\frac{p_j^x}{p_i^x}\right)^{1/2} + b_i/R_i + \xi_2 & (b) \\ (P_{int} - t' - w_i) = \frac{\left(\sum_i b_i p_i^x + \sum_i \sum_j b_{i,j}(p_i^x p_j^x)^{1/2} R_i\right)}{\left[1 + \theta_{int}\left(\partial w_i/\partial L\right)_{int}\right]^{-1}} + \gamma L + \xi_3 & (c) \end{cases}$$

H_0: Random effect estimator is consistent
(individual heterogeneity and covariates are uncorrelated)

Model	χ^2 test	Degree of freedom	p-value
Eq. a	0.035	1	0.85
Eq. b.1	1.19	2	0.55
Eq. b.2	27.94	2	8.6e-07***
Eq. c	8.53	3	0.036*

Note: Equation b consists of two sub-equations b.1 and b.2 for two groups of inputs employed in production process, respectively other inputs (fertilizer, pesticides, etc.) and labour.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 7: Specification 1 (SUR-LSDV)

Dependent Variables	Eq. a Coffee Supply (log)	Eq. b.1 Other inputs requirement	Eq. b.2 Labour requirement	Eq. c Farmgate- wholesale price spread
Deflated farm gate Price (log)	0.52***			
	(0.038)			
Ratio input prices (labour/other inputs)		−0.0074		
		(0.014)		
(1/Coffee Supply)		5.08	354***	
		(6.21)	(48.9)	
Ratio input prices (other inputs/labour)			21	
			(104.7)	
Labour Costs				0.00035
				(0.00019)
Costs (other inputs)				−0.0009
				(0.0006)
Labour/other inputs costs (interaction)				−0.00002
				(0.000013)
Share of significant household dummy variables (%)				
Significance level (s_f)	Eq. a	Eq. b.1	Eq. b.2	Eq. c
$s_f \leq 0.1\%$	**0.8**	**0.45**	**2.4**	**71.6**
$0.1\% < s_f \leq 1\%$	**9.8**	**0.15**	**0.2**	**3**
$1\% < s_f \leq 5\%$	**12.7**	–	**1.4**	**1**
$5\% < s_f \leq 10\%$	10.9	–	1	23.95
$s_f > 10\%$	65.8	99.4	95	0.45
Mc Elroy R^2 (system-related)	0.68			
Num. obs. (each equation)	1041	1041	1041	1041

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ *(Standard error in brackets)*

Table 8: Specification 2 (SUR-RE)

Dependent Variables	Eq. a Coffee supply (log)	Eq. b.1 Other inputs requirement	Eq. b.2 Labour requirement	Eq. c Farmgate- wholesale price spread
Intercept	5.2	4.7	59.1^{*}	5938.3^{***}
	(4.3)	(3.0)	(24.4)	(189.1)
Deflated farm gate Price	0.3^{***}			
	(0.0326)			
Avg 12-month total rainfall (2001-2010)	-2.8^{*}			
	(1.1)			
12-month total rainfall (2010)	2.5^{*}			
	(1.1)			
Ratio input prices (labour/other inputs)		−0.0034		
		(0.008)		
(1/Coffee Supply)		−0.3	348.1^{***}	
		(4.6)	(39.3)	
Ratio input prices (other inputs/labour)			40.9	
			(52.1)	
Labour Costs				0.00001
				(0.00005)
Costs (other inputs)				−0.00007
				(0.00014)
Labour/other inputs (interaction)				0.00007
				(0.000003)
Distance from Kampala				2.3^{***}
				(0.5)
Remoteness Index				5.3
				(3.5)
Mc Elroy R^2 (system-related)	0.34			
Num. obs. (each equation)	544	1041	1041	544

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ *(Standard error in brackets)*

Table 9: Specification 3 (SUR-RE)

Dependent Variables	Eq. a Coffee Supply (log)	Eq. b.1 Other inputs requirement	Eq. b.2 Labour requirement	Eq. c Farmgate-wholesale price spread
Intercept	6.7	4.3	21.3	8518.5***
	(4.4)	(3.0)	(24.2)	(71.5)
Deflated farm gate Price	0.3***			
	(0.03)			
Avg 12-month total rainfall (2001-2010)	−2.5*			
	(1.1)			
12-month total rainfall (2010)	1.9			
	(1.1)			
Ratio input prices (labour/other inputs)		−0.004		
		(0.008)		
(1/Coffee Supply)		1.0	489.1***	
		(4.6)	(38.1)	
Ratio input prices (other inputs/labour)			33.5	
			(51.8)	
Labour Costs				0.00018
				(0.00009)
Costs (other inputs)				−0.00033
				(0.00026)
Labour/other inputs (interaction)				−0.00001
				(0.00001)
Mc Elroy R^2 (system-related)		0.29		
Num. obs. (each equation)	544	1041	1041	1041

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ *(Standard error in brackets)*

Table 10: Specification 4 (SUR-RE)

Dependent Variables	Eq. a Coffee Supply (log)	Eq. b.1 Other inputs requirement	Eq. b.2 Labour requirement	Eq. c Farmgate- wholesale price spread
Intercept	1.6^{***}	5.1	62.0^{*}	6002.8^{***}
	(0.1)	(3.0)	(25.1)	(190.8)
Deflated farm gate Price (log)	0.6^{***}			
	(0.03)			
Ratio input prices (labour/other inputs)		−0.003		
		(0.008)		
(1/Coffee Supply)		−1.1	358.2^{***}	
		(4.6)	(41.3)	
Ratio input prices (other inputs/labour)			48.0	
			(54.8)	
Labour Costs				0.000006
				(0.00005)
Costs (other inputs)				−0.00006
				(0.0001)
Labour/other inputs (interaction)				0.0000002
				(0.000003)
Distance from Kampala				2.4^{***}
				(0.5)
Remoteness Index				4.6
				(3.5)
Mc Elroy R^2 (system-related)		0.33		
Num. obs. (each equation)	1041	1041	1041	544

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ *(Standard error in brackets)*

Table 11: Specification 5 (SUR-RE)

Dependent Variables	Eq. a Coffee Supply (log)	Eq. b.1 Other inputs requirement	Eq. b.2 Labour requirement	Eq. c Farmgate- wholesale price spread
Intercept	1.7^{***}	4.6^{*}	-10.5	8493.5^{***}
	(0.1)	(2.1)	(19.4)	(74.0)
Deflated farm gate Price (log)	0.6^{***}			
	(0.02)			
Ratio input prices (labour/other inputs)		-0.004		
		(0.006)		
(1/Coffee Supply)		0.1	553.2^{***}	
		(3.3)	(31.0)	
Ratio input prices (other inputs/labour)			40.7	
			(42.9)	
Labour Costs				0.00025^{**}
				(0.00009)
Costs (other inputs)				-0.00041
				(0.00024)
Labour/other inputs costs (interaction)				-0.00001
				(0.00001)
Mc Elroy R^2 (system-related)	0.19			
Num. obs. (each equation)	1041	1041	1041	1041

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ *(Standard error in brackets)*

Table 12: Estimated elasticities [based on specification 2 (SUR-RE)]

Partial elasticity of farm gate price to distance	$\left(\frac{\partial w}{\partial L}\frac{L}{w}\right)$	**-11**
Partial elasticity of coffee supply to distance	$\left(\frac{\partial R}{\partial L}\frac{L}{R}\right)$	**-3.72**
Partial elasticity of farm gate price to coffee supply	$\left(\frac{\partial w}{\partial R}\frac{R}{w}\right)$	3.3
Partial elasticity of coffee supply to farm gate price	$\left(\frac{\partial R}{\partial w}\frac{w}{R}\right)$	0.3

Marginal effect of distance on wholesale-farm gate price spread (Eq. c)	Average farm gate price	Partial price elasticity of wholesale-farm gate price spread to distance
2.3 - 2.4 UGX each Kg/Km	35 UGX each Kg	6% - 7%

Note: Elasticity parameters are evaluated at the mean of each variable

Second chapter

Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data

Declaration on the contribution to the chapter "Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data" (co-authorship)

We, ***Lodovico Muratori and Susanne Fricke***,

declare that

we worked jointly on the paper "Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data", which is included as the second chapter of the Ph.D. thesis on "Essays on spatial and vertical price transmission" submitted by Lodovico Muratori in the framework of a co-tutelle agreement to the Sapienza University of Rome, Italy and the Friedrich-Schiller-University of Jena, Germany.

In particular, the contribution of each of the authors to the above mentioned paper is explained in details in the following table (contribution in %):

% contribution of each author		
	Lodovico Muratori	***Susanne Fricke***
Conceptual development	60	40
Literature research	50	50
Data search	70	30
Methodology	70	30
Methodological implementation	50	50
Results description and representation	60	40

Yours faithfully,

Lodovico Muratori

Susanne Fricke

Spatial price transmission and trade policies: new evidence from selected sub-Saharan African countries and crops with high frequency data

Lodovico Muratori[*] and Susanne Fricke[†]

This paper extends the existing literature on spatial price transmission in agricultural markets by estimating the impact of tariff and non-tariff trade policies using monthly data.
The study assesses the conjunctural impact of price insulating policies on spatial price transmission of maize, rice and wheat in Cameroon, Kenya and Tanzania in the period 2005-2015. We separately estimate the impact of trade policies within two regimes of behaviour of the domestic price series: while in the first regime the trend of domestic prices is increasing, the second regime reveals a decreasing trend. Our findings show that trade policies play a significant role both in case of increasing and in case of decreasing domestic prices; their relevance, however, being much larger if prices are increasing. The results show that trade policies were able to insulate the countries from the price shocks on international markets during the food price spike crisis. However, although the impact of these instruments is proved to be relevant as a counter-cyclical measure during the food price spike crisis, these policies cannot be regarded as structural solutions.
While monthly price series are provided in GIEWS, we obtained monthly ad-valorem equivalent tariff rates by a time disaggregation of the yearly effectively applied weighted average tariff rate from the WITS (World Bank Integrated Trade Solutions)/UNCTAD-TRAINS (Trade Analysis Information System) database through the monthly trade policies from the FAO-FADPA.
Moreover, employing monthly data allows for a more precise assessment of short-lived movements in the analysed series, which could disappear because of a time aggregation bias at lower yearly frequencies. This facilitates a better identification of insulation policies. By presenting high frequency analyses and techniques that are able to detect non-linearities in the Data Generating Process (DGP), this study provides results which differ from what is stated in the standard literature (Anderson and Nelgen, 2012a) (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c).

Keywords: spatial price transmission, staple crops, trade barriers, food price spikes
JEL Codes: F14, O24, Q11, Q17

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Introduction

The nature of international price transmission of agricultural commodities and the assessment of its determinants became a key issue in the course of the food crisis in 2007/2008 when food importing countries suffered from a significant increase in poverty due to food price shocks (Yang et al., 2015). As they predominantly feature economies based on agriculture, questions concerning the nature and characteristics of the transmission of prices and price information for agricultural products are especially crucial for sub-Saharan African countries.
Anderson and Nelgen (2012b), Anderson and Nelgen (2012c) and Yang et al. (2015) provide evidence that during the food price spike crisis several countries increased their taxes on agricultural exports, reduced import duties and introduced import subsidies. In case of upward price spikes, the most commonly stated objective of these measures was to safeguard the domestic food security of consumers (Anderson, Ivanic and Martin, 2014, 311). Governments also expressed the intention to reduce inflationary or balance-of-payments pressures resulting from an upward price spike (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c).

The present study is meant to assess the conjunctural impact of price insulating policies on spatial price transmission of maize, rice and wheat in Cameroon, Kenya and Tanzania in the period 2005-2015. In particular, our research question was whether price insulating policies were able to insulate the country from shocks on the international markets during the food price spike crisis. The three countries we selected are highly dependent on cereal imports, with maize, rice and wheat taking up a considerable share of their overall import of agricultural products. Moreover, since, within the last years, all three countries introduced tariff and non-tariff barriers and especially in the course of the food crisis 2007/2009, they appeared to be especially suitable for our analysis.
This paper is meant to improve the approach developed by Anderson and Nelgen (2012b) and Anderson and Nelgen (2012c) by estimating the impact of tariff and non-tariff trade policies on spatial price transmission in the agricultural markets not on a yearly basis, but with the help of monthly data. The use of monthly data allows for a more precise assessment of short-lived movements within the analysed series. These could, had we used a lower, i.e. yearly, frequency, have otherwise disappeared.

Since the Gauss-Markov conditions are not fully met by the time series we wanted to analyse, we further used some empirical methodologies which introduce some control factors for these violations: fractional integration, non-linear regime shifting in the time series as well as country time-invariant effects in the panel analysis. Thus the empirical strategy used provides a consistent and efficient estimation of the coefficients of the price insulating policies.

The indicator of trade policies covers a set of trade policies as large as the one included in the nominal rate of assistance introduced by Anderson and Nelgen (2012a), Anderson and Valenzuela (2008) and Anderson et al. (2008).

Trade policies are defined as a set of tariffs, para-tariff and non-tariff equivalent measures which governments introduce in order to influence the trade volume and relative prices in their respective countries.

The determination of the tariff rate is based on the tariff schedule and is extended to include the specificities of trade policies of each country, in order to take into account preferential trade agreements, border and behind-the-border trade measures.

In addition, the indicator we use covers the same set of trade policies included in the nominal rate of assistance introduced by Anderson and Nelgen (2012a), Anderson and Valenzuela (2008) and Anderson et al. (2008), like specific, ad-valorem, mixed tariffs, non-tariff barriers, standards and behind-the-border measures.

In particular, non-tariff barriers comprise technical measures such as sanitary or environmental protection activities as well as other measures traditionally used as instruments of commercial policy, e.g. quotas, price control, exports restrictions or contingent trade protective measures, as well as further behind-the-border measures, such as competition, trade-related investment measures, government procurement or distribution restrictions (UNCTAD, 2015).

Based on the prevalence of such trade policies with regard to agricultural products, Cameroon, Kenya and Tanzania were selected as country samples. In the last few years, these three countries enforced several trade-related policy acts to mitigate the adverse effects of the food crisis 2007-2009. In particular, during the period of the analysis, Kenya changed the tariff rates on wheat and maize several times and introduced some tariff-rate and import quotas. Similarly, Cameroon and Tanzania adjusted the import duties on rice and wheat (FAO, 2016b). Moreover, all three countries are important regional trade hubs and influence neighbouring countries through their policy-making.

Key aspects of this study concern the questions of how price shocks are transmitted and how trade policies affect the pass-through of price information. In this paper, the reference framework which is used to answer the research question consists of the “Law of One Price” and the Enke-Samuelson-Takayama-Judge spatial equilibrium models (Enke, 1951) (Samuelson, 1952) (Takayama and Judge, 1972). In this study, the results based on a time series approach are compared with the ones derived from the panel analysis. ARFIMA models, which do not take into account non-linearities in the DGP and time-invariant country heterogeneity, bias the effect of trade policies on spatial price transmission and their ability to offset the impact coming from the price shocks on the international markets.
Instead, both Markov switching and panel models provide evidence that trade policies play an important role in all market situations, but the presence of non-linearities in the DGP and time-invariant country heterogeneity affects the price transmission mechanism.

Overall, in this study it was possible to separately estimate the impact of trade policies within the two regimes of behaviour of the domestic price series: in the first regime the trend of domestic prices is increasing, in the second one it decreases. This highlights that trade policies play a role both in case of increasing and decreasing domestic prices. Nevertheless, price insulation policies are more relevant if prices are increasing, as the magnitude and the significance of the coefficients are larger within the regime of increasing trends of domestic prices.
We found that trade policies were indeed able to insulate the country from the price shocks on the international markets during the food price spike crisis, i.e. in times when insulation was needed most. It is noteworthy however, that, although the impact of these instruments could be proven to be relevant as counter-cyclical measures during the food price spike crisis, these policies cannot be regarded as structural solutions.

1. Literature review

While the question whether governments are able to effectively insulate the domestic economy from international price shocks has long been a matter of research, the practical relevance of the study of price transmission in agricultural markets again became evident in the course of the food crisis 2007/2008, when several countries introduced policy interventions in order to insulate themselves from price spikes at the international level. In the following, we briefly summarize the literature on price transmission and outline its specific relevance for agricultural markets. In general, the body of literature provides much information on the role of price insulating policies for agricultural markets (Johnson, 1975) (Lasco et al, 2008) (Ivanic and Will, 2008) (Bouët and Debucquet, 2010) (Timmer, 2010) (Anderson and Nelgen, 2012a) (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c) (Will and Anderson, 2012) (Chavas et al., 2014) (Do et al., 2014) (Gouel, 2014) (Gouel and Jean, 2015) (Jacoby, 2016).

1.1. Price transmission background

A complete, symmetric and quick transmission of prices is of high importance for the efficient allocation of resources. In this study, we focus on *spatial price transmission*, which is part of the *horizontal price transmission* and refers to cross-market price transmission which concerns the linkages between international and domestic prices and vice versa[3] (Esposti and Listorti, 2013). Spatial price transmission is an indicator for the integration of a country into the world market. The theoretical basis for spatial price transmission is the theory of spatial arbitrage. Assessment of the degree of price transmission and hence of the pass-through of price information relates to the theoretical hypotheses of the so-called law of one price and standard spatial price determination models (Enke, 1951) (Samuelson, 1952) (Takayama and Judge, 1972). Such approaches postulate that price transmission is complete with equilibrium prices of a commodity sold on competitive foreign and domestic markets differing only by transaction costs (when converted to a common currency). These models predict that changes in supply and demand conditions in one market will affect trade and therefore prices in other markets as equilibrium is restored through spatial arbitrage.

The absence of market integration or of complete pass-through of price changes from one market to another has important implications for economic welfare. Incomplete price transmission results in a reduction in price information available to economic agents and consequently may lead to decisions that contribute to inefficient outcomes. With the help of a concise study on price transmission, it is possible to analyse these characteristics (Rapsomanikis and Conforti, 2006).

In this regard, agricultural markets and the question of price pass-through are of particular importance. Since agricultural commodities are considered to possess high poverty leverage,

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[3] Another level of price transmission is *vertical price transmission,* which refers to the transmission of prices from consumers, triggered by demand shocks, to producers and vice versa. It describes price transmissions along a value chain (Swinnen and Vandeplas, 2014). Instead, a second part of horizontal price transmission is cross-commodity price transmission which refers to spillovers between prices of different commodities observed at the same position in the value chain (Esposti and Listorti, 2013).

the study of price transmission in the agricultural markets is of high relevance for the reduction of poverty in developing countries (Mosley and Suleiman, 2007).

Indeed, the inability of policy-makers to insulate the domestic economy from international price shocks could render other political acts aimed at market development and poverty reduction ineffective.

The wide welfare implications of price shocks of agricultural products for producers and consumers in developing countries became further evident in the course of the international food crisis 2007/2008, when agricultural markets were shocked by an increased volatility with a significant impact on the economies and national welfare of (developing) countries. In the course of the crisis, the question of what determines the international transmission of agricultural and food prices again became a key issue. Moreover, the increased number of policy interventions (so called price-insulating policies) in the course of the food crisis spurred the question of the influence of domestic policies on price transmission.

1.2. Impact of monetary policy and exchange rates on agricultural prices

The trend of the agricultural prices is also determined by monetary policy decisions and the exchange rate movements.

The relationship between monetary policy and real agriculture prices was analysed by the branch of research which addresses the non-neutral effects of monetary policy.

Such field was especially vivid in the 1970s: the link between monetary policy and agricultural prices was stressed by Schuh (1974), who applied a partial equilibrium model to analyse the US farming sector between the 1950s and the beginning of the 1970s. In particular, his research conclusions are different for small or large exporting countries because small countries face fixed world prices while large countries can indeed influence their terms-of-trade.

For a small exporting country, an overvalued exchange rate reduces the world price in domestic currency proportionately. In turn, lower prices imply an increase in the demand of crops and a reduction in total supply because mobile resources are moving away from the industry.

The final result for a small exporting country is that both export quantity and value are shifted to the domestic economy: the dependence of the agricultural sector from the domestic market grows stronger, the magnitude and speed of this change being determined by each crop's own price elasticity and the rate of the downwards shift of the supply curve (Orden, 2002) (Schuh, 1974, 2-3).

In the case of a large country, on the other hand, domestic and foreign prices diverge by the extent of overvaluation, while the elasticities of demand and supply of both trading partners affect the degree to which domestic prices are going to sink and foreign prices are going to soar (Orden, 2002) (Schuh, 1974, 2-3).

Depreciation raises inflation, increases export and reduces import quantities. Therefore, it has a larger impact on export than on import because the price and quantity effect has a reinforcing effect in the former case, while they work against each other in the latter (Orden, 2002, 308).

Another branch of the literature analyses how changes in exchange rates of a currency affect the domestic price of imported goods and services as well as the general domestic price level and inflation rate. The pass-through of exchange rate movements to domestic prices is higher in industries with homogeneous goods, such as raw materials, among which are also agricultural goods (Bouakez and Rebei, 2008) (Ca'Zorzi et al., 2007). For the purpose of our study, the relevance of exchange rate pass-through underlines the need to control for movements of the exchange rate when assessing the impact of policies on domestic agricultural prices.

1.3. Determinants of price transmission – policy-related trade costs

One major determinant of price transmission are trade costs, functioning as a wedge between domestic and international prices. Trade costs themselves are mainly driven by government policies which can thus affect spatial price transmission. Especially border and domestic policies (e.g. export subsidies, non-tariff barriers, quotas and prohibitive tariffs) can have a strong impact on the degree of spatial price transmission .The issue of policy-related trade costs is very relevant for African countries, where very high policy-related trade costs can reduce the long run pass-through of price information and increase the costs for importing and exporting. However, there has been some discussion about the exact nature of the relationship between specific policy measures and price transmission. In this field, research is still very limited and focuses mostly on advanced economies.

So far, research was not able to reach a common empirical stance towards the effect of policy intervention on agricultural markets on the extent of price transmission from world prices to domestic prices.

Looking at this empirical relation for 58 countries between 1968 and 1978, Mundlak and Larson (1992) find that domestic policies indeed affect prices, but that variations in world prices remain the dominant component in the variations of domestic prices. Barassi and Ghoshray (2007) stress that the reform of the European Common Agricultural Policy in 1992 increased the integration between the European and US wheat market. Thompson et al. (2002) stress the point that policy-liberalizing reforms contribute to a more rapid convergence of domestic and international prices.

Yang et al. (2015) scrutinize a worldwide sample of monthly food price indices from 147 countries: they find that the main determinants of the pass-through of food prices are the level of income and policy-related trade costs. While policy-related trade costs have a significantly negative impact, trade costs related to geography and infrastructure do not affect price transmission. For the rice market in Bangladesh, Goletti et al. (1995) conclude that especially trade-related food grain policies had a significant effect on price co-movements and price transmission. Generally, their impact can be either positive or negative. While seasonalities may be smoothed out by policies for price adjustment, resulting in stronger co-movements of prices, these policies meant to stabilize can also become unpredictable and indeed impede the transmission of prices.

1.4. Price insulating policy interventions on agricultural markets

In the field of analysing the processes related to the pass-through of price information and the determinants of price transmission, one major strand of literature focuses on the effects of policies which aim at insulating countries from international price shocks.

Price insulating policies are all those trade policies which can create a wedge between international and domestic prices and can be employed to insulate the domestic economies from price shocks. The particular aim which is pursued by policy-makers defines the set of price insulating policies. According to statements of most policy-makers, the objective of their actions is to reduce price transmission as well as to ensure social welfare and minimize the risk of losses for significant groups if international prices are determined as a result of imperfections within the world market or irrational speculation on the financial market. This observation is consistent with the behaviour of many governments, and it provides an economic rationale for the econometric estimation of price transmission elasticities (Will and Anderson, 2012, 8) (Freund and Özden, 2008).

These policies are thought to be able to reduce the conjunctural impact of imported shocks and cannot be regarded as structural trade policies as their focus is on the short term price transmission only.

Anderson and Nelgen (2012b) and Anderson and Nelgen (2012c) provide evidence that during the food crisis 2007/2008 several countries increased agricultural export taxes, reduced import duties and introduced import subsidies. In case of upward price spikes, the most commonly stated objective of these measures was to ensure the domestic food security of consumers. Governments also expressed the intention to reduce inflationary or balance-of-payments pressures from an upward price spike. Indeed, such price-insulating policies reduce the degree of perfect price transmission which can result in incomplete price transmission. Both large and small economies can enforce policies and increase domestic prices by introducing tariff and non-tariff barriers; however, the general equilibrium effects are different in the two cases. Indeed, large economies can influence international prices small economies are not able to do so.

1.5. Price insulation literature – effects of price insulating policies

Looking at the effects of price insulation policies, the empirical evidence is mixed.

Anderson and Nelgen (2012b) and Anderson and Nelgen (2012c) conclude that such policies were inefficient and ineffective: indeed, if all countries enforce these trade barriers at the same time, public interventions to stabilize agricultural prices remain without any impact. Finally, the larger the number of countries insulating their domestic markets, the more other countries perceive a need to do likewise: this suboptimal equilibrium implies a reduction of the stability, predictability of trade opportunities and decline of gains from trade (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c). Anderson et al. (2014) also show that price-insulation policies during the 2008 food crisis added to the spike in international prices for rice, wheat maize and oilseeds which actually diminished the benefits of price insulation. While these insulation policies resulted in a smaller increase of domestic prices for these commodities in some developing countries, other countries recorded an even higher increase in domestic prices than in the absence of such political acts.

Furthermore, Djuric et al. (2011) and Götz et al. (2013) conclude that Serbian, Ukrainian and Russian export restrictions on wheat and other cereals increased the instability of domestic markets. Cioffi et al. (2011), however, prove that the European price stabilization mechanism was able to insulate the European tomato and lemon markets against low import prices in fifty percent of the cases taken into account and claim that the mechanism was ineffective in a few other cases because of the insufficient integration of the European market with the market of the country of origin. Esposti and Listorti (2013) come to the conclusion that the suspension of EU import duties on cereals in 2008 was effective to offset the impact of a bubble of international cereal prices and claim that this relationship can be generalized to several markets and commodities.

In addition, Magrini et al. (2017) conclude that support policies aimed at the agricultural sector are effective and increase domestic food security.

In order to measure price distortions, these studies mainly rely on the usage of yearly data on the nominal rate of assistance (NRA), i.e. the percentage by which the policies that were implemented have raised the gross returns for farmers compared to the situation without any political intervention (Anderson, 2009). Thereby they are able to detect the comprehensive impact of price-insulation policies on spatial price transmission (Anderson and Nelgen, 2012a) (Anderson and Nelgen, 2012b). However, as it employs yearly data to compute the NRA, these studies on price-insulating policies were not able to detect short-lived movements of the price series.

This shortcoming implies that, up to now, the intra-annual impact of trade policies on spatial price transmission was not included in the analysis, even though it should be taken into account to give a comprehensive picture of the relationship between the above- mentioned variables. Intra-annual price variability is due to weather conditions, seasonality (e.g. harvesting times) and demand shifts over the year: and is thus highly relevant for investment, production and consumption decisions made by the economic agents.

Indeed, monthly observations provide much more information about domestic and border price series than yearly data. For instance, Figure 6 in the Annex shows how monthly data of the maize market provide richer information than the corresponding yearly observations. The situation is similar for both the rice and the wheat market, even though the time series graphs are not reported in the Annex.

2. Methodology

2.1. Identification strategy

In this study, the main aim is to assess the impact of price insulating policies on spatial price transmission of maize, rice and wheat in Cameroon, Kenya and Tanzania in the period of 2005 to 2015. In particular, the research question is whether price-insulating policies worked as counter-cyclical measures and if they were able to insulate the country from shocks on the international markets during the food price spike crisis.

Macroeconomic factors like exchange rates and all-commodity price inflation enable us to take into account the hypothesis of the non-neutrality of money, i.e. the assumption that monetary policy affects real agriculture prices.

It is furthermore expected that there could be differences in the results of the analysis of each crop market because policy-makers might adopt different trade policies for each of them. Indeed, domestic consumers and producers have distinct preferences towards each agricultural product and its specific cultivation properties, post-harvest preservation features and international integration of their respective markets determine whether a given trade measure will be effective.

In this paper, the evaluation of the impact of price insulating policies on monthly data is a key contribution to the existing body of literature, which has, so far, completely neglected the intra-annual impact of trade policies on spatial price transmission, as highlighted in the literature review (Anderson and Nelgen, 2012a) (Anderson and Nelgen, 2012b) (Anderson and Nelgen, 2012c).

Time series from monthly data allow for a more precise assessment of short-lived movements within the analysed series which could have disappeared because of a time aggregation bias at a lower yearly frequency. Monthly data provides a richer set of information about the time series than yearly observations (see also Figure 6 in the Annex).

The analysed time series violates the Gauss-Markov conditions as can be seen from the result of the specifications tests. Such tests identify fractional integration, non-linear regime shifting in the time series as well as country time-invariant effects in the panel analysis

The empirical methodologies adopted for this study introduce some factors into the estimation which control for these disturbances.

Nevertheless, these techniques do not allow for a separate identification of the estimate of these disturbances from the error term. Yet, the coefficient of the price insulating policies, which is the focus of this analysis, is consistent and can be properly identified.

The implementation of the empirical strategy follows a particular sequence: it starts from the least to the most sophisticated techniques to control for such confounders. The advanced econometric techniques we applied were the autoregressive fractional integration (ARFIMA), the Markov switching vector error correction (MSVECM) and a set of long panel models.[4]

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[4] A long panel is a panel database where T>N.

The ARFIMA model has the d parameter for fractional integration to handle long-run dependence and ARMA p and q parameters to handle short-run dependence (Baum, 2013).
The main strength of the ARFIMA is that this model is able to separate the fractionally-integrated long-run dependence, which cannot be expressed by a stationary ARMA model, from the short-run parameters p and q, which are the focus of interest of this analysis.
The added value of the MSVECM is that this approach allows us to take into account non-linear shifts in the general state of the trading system or of the surrounding economic and political environment.
Finally, the techniques for long panels have the advantage that they are able to control for the presence of time-constant omitted – because of failed measurements or non-existent observations – variables which are correlated with the explanatory variables as such panel databases contain information on both intertemporal dynamics and individual heterogeneity (Hsiao, 2007, 5) (Hsiao, 2014, 1-10) (Baltagi, 1998).
Additionally, if the behaviour of each observation-unit is similar, conditional on certain variables, panel data enables us to obtain a more accurate description of the behaviour of each observation-unit because they supplement observations of one unit with data from other units (Hsiao, 2007, 6) (Hsiao, 2014, 1-10). Panel datasets are also better able to study complex issues of dynamic behaviour (Baltagi, 1998).
Finally, if the data is non-stationary, long-panel methodologies provide a computational advantage as unit-root tests for long panels have a higher power than the ones for time series. Moreover, unit-root tests for long panels follow a Gaussian asymptotic distribution, while the ADF and the Philips-Perron converge to non-standard limiting distribution (Hlouskova and Wagner, 2006) (Lütkepohl, 2005) (Hlouskova and Wagner, 2006) (Hsiao, 2007, 7) (Hsiao, 2014, 1-10).
In addition the increase of efficiency in the estimation of long panels with respect to time series or cross-section samples is possible but not necessary as large datasets might imply a rise of heterogeneity in the sample and should be evaluated case-by-case.
A detailed explanation of the strengths and weaknesses of each approach is given in Annex II.
All those econometric approaches aim at giving the best description of the behaviour of the price series by assuming different effects of the confounders on the structure of the data-generating process of the price series.
This knowledge about the structure of the Data Generating Process (DGP) was then used to estimate consistently the impact of price-insulating policies on the price series.
The rationale of this empirical strategy is not to disregard less sophisticated techniques in

favour of more advanced ones, but to compare the results of different methodologies and, within the framework of a robustness analysis, to obtain a consistent and comprehensive interpretation of the relationship between price-insulating policies and prices.

2.2. Selection of the Sample

Maize, rice and wheat were chosen as sample crops because they are regarded as politically relevant by policy-makers in terms of trade, the generation of welfare for a society and food security. Furthermore, maize, rice and wheat are a significant part of the domestic food supply and their harvest is sold by producers on domestic markets to increase their income.

Cameroon, Kenya and Tanzania were selected as sample countries because their imports of maize, rice and wheat take up a large share of their overall agricultural imports. Furthermore, they implemented several price-insulating policies during the food price spike crisis.

From the following tables and graphs it is possible to see the relevance of the imports of maize, wheat and rice for Cameroon, Kenya and Tanzania.

In particular, the averaged absolute values of the international trade of maize, rice and wheat are summarized in the following table (ITC, 2016):

Table 1: Value of imported maize, rice and wheat in 2001-2015

Average 2001-2015 (ITC, 2016)	*Maize*	*Rice*	*Wheat*
Value of international trade	24,292,833	16,461,116	34,306,375
Value of imports to Africa	2,836,762	3,645,003	8,464,714
Value of import to Cameroon	3,618	184,350	118,078
Value of imports to Kenya	78,746	102,655	183,767
Value of imports to Tanzania	19,295	17,248	195,676

All figures are expressed in thousands of US dollars. Comma as thousand separator. Source: ITC (2016)

The focus of the analysis is on imports because a spatial price transmission analysis for the exporting sector would not be possible for this group of countries. Indeed, since they are small in terms of world trade[5], the "small open country hypothesis", stating that there is no transmission from domestic to international prices while transmission from international to domestic prices, holds for all African countries. Domestic prices are measured as the average of the values at different retail markets in several areas of each country and are taken as given.

[5] This implies that they only reveal a very small share in world exports and imports.

Domestic shocks to prices are not regarded in the analytical framework of this study.
This can be seen in Figure 1, Figure 2, Figure 3, which depict the import shares of wheat, maize and rice for Cameroon, Kenya and Tanzania. Evidently, the import share of these crops records fluctuations over the period of 1962-2013. However, it still represents considerable shares in overall imports especially in recent years, with an overall import share of the maize, wheat and rice of around 40% of overall agricultural imports for Cameroon and Tanzania and of around 30% for Kenya. Moreover, given the interest in the impact of tariff and non-tariff measures on spatial price transmission, the three selected countries are suitable for our analysis since, in the last few years, they all have enforced several trade-related policies in order to mitigate the adverse effects of recent food price spikes.
While Kenya's reduction of import tariffs points towards a trade liberalising policy, the imposition of a number of rules and regulations on food products illustrates the rise in non-tariff barriers. (FAO, 2016d). Similarly, Cameroon and Tanzania adjusted the import duties on rice and wheat (FAO, 2016b). Tanzania also reduced import tariffs for food products, but at the same time introduced periodic export bans on staple commodities, such as for example the temporary export ban on maize in 2008 which was later expanded to all cereals (FAO, 2014).
The significance of the analysis of these three countries is also amplified by the fact that these countries are regarded as highly competitive within the Sub-Sahara African region and are well integrated in the global trade.
This is underlined by the Global Competitiveness Index[6] 2015 (taking scores from 1 to 7, i.e. from a low degree of global competitiveness to a high degree of global competitiveness), where Kenya (score: 3.9) and Cameroon (score: 3.7) rank above the Sub-Saharan African average (score: 3.6) and Tanzania (score: 3.6) just within the Sub-Saharan African average (World Economic Forum, 2015). Tanzania is however above African average when considering its share in total value added exports worldwide, which is indicative for a country's participation in global value chains. In 2011, it accounted for 0.65 percent in total value added exports (African average: 0.52 percent). While Kenya and Cameroon account for a smaller share in total value added exports (around 0.4 percent and 0.37 percent), their value added exports are characterised by a relatively high backward integration. Backward integration represents the share of foreign value added in a country's exports. High backward integration hence means production and export at higher value added stages of the value chain

[6] The Global Competitiveness Index consists of sub-indices which comprise for example institutions, infrastructure, macroeconomic environment, health and education or financial market development (World Economic Forum, 2015).

(World Economic Forum, 2015). These characteristics render these countries samples of particular interest. As they can be considered small countries at the global level and on world markets, with regard to agricultural trade, it justifies their selection for the purpose of our analysis. However, their particular regional role adds further significance to the analysis of these three countries since they are crucial for the development in their respective Sub-Saharan African regions.

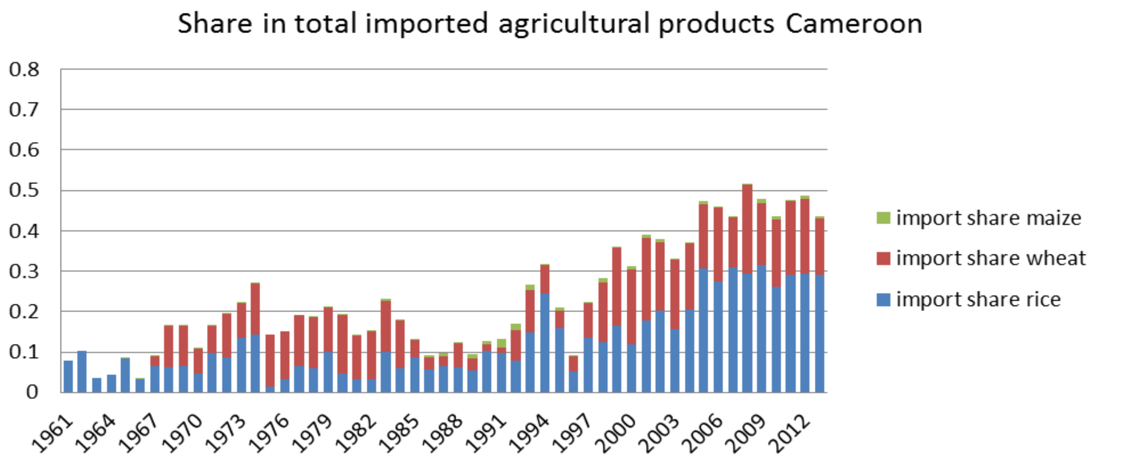

Figure 1: Import shares of maize, wheat and rice for Cameroon from 1961-2013 Source: (FAO, 2016c)

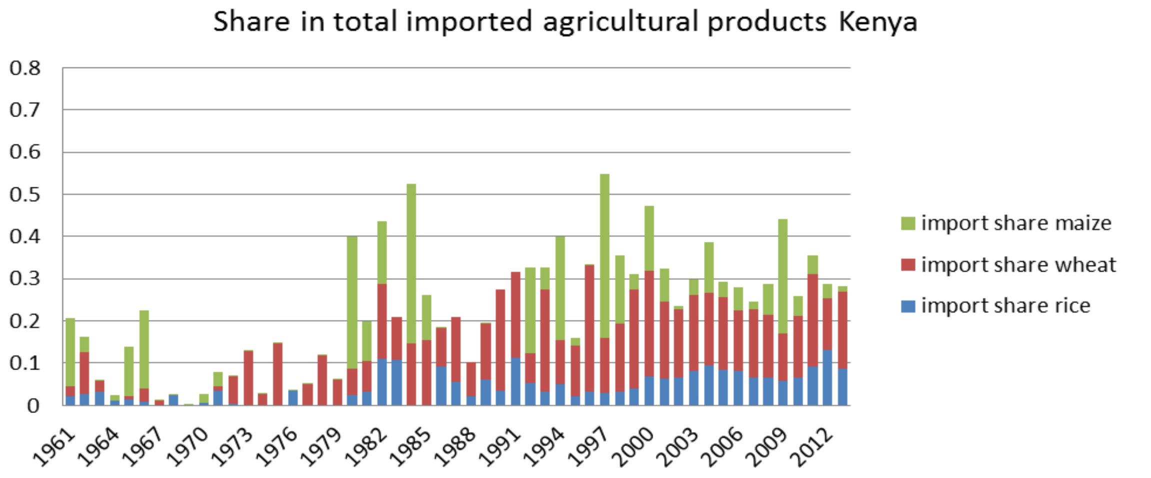

Figure 2: Import shares of maize, wheat and rice for Kenya from 1961-2013 Source: (FAO, 2016c)

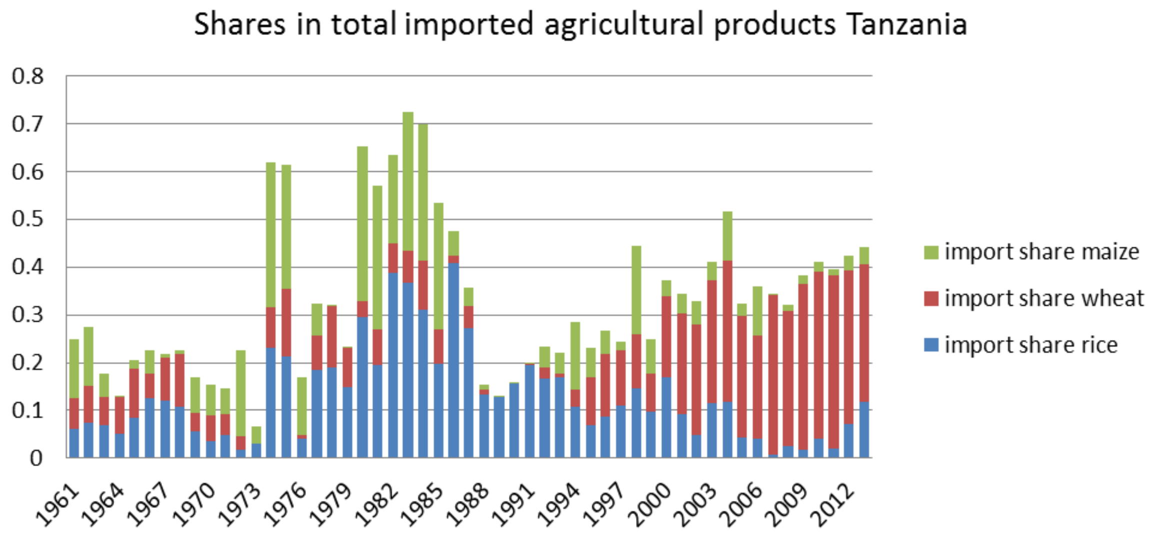

Figure 3: Import shares of maize, wheat and rice for Tanzania from 1961-2013 Source: (FAO, 2016c)

2.3. Econometric Model

In the following approach, the aim is to assess the impact of trade policies which have been enforced by the governments of Cameroon, Kenya and Tanzania in the period of 2005-2015 in order to insulate the countries from price shocks on the international markets. Indeed, all trade policies can create a wedge between international and domestic prices and can be employed to insulate the domestic economies from price shocks.

Some of them are discretional and are adopted for price-insulation on a case-by-case basis, some others are automatic and their insulating effect depends on the relationship between the changes in the policing instrument and international prices.

As these interventions are defined by the aim followed by policy-makers, there is no specific definition of price insulating policies in the literature. According to statements made by policy-makers, the objective of these actions is to reduce price transmission as well as to ensure social welfare and minimize the risk of losses for significant groups if international prices are determined as a result of imperfections in the world market or irrational speculation on the financial market, which has been regarded as relevant by several agricultural economists (Josling et al., 2010) (Sexton, 2012). This observation is consistent with the behaviour of many governments, and it provides an economic rationale for the econometric estimation of price transmission elasticities (Will and Anderson, 2012, 8) (Freund and Özden, 2008).

These policies are thought to be able to reduce the short-term impact of imported shocks and cannot be regarded as structural trade policies because they address just the short-term price transmission.

Furthermore, in this econometric approach, a partial equilibrium analysis is carried out. Indeed, the effect of price insulating policies on other countries or on the international prices is not addressed. Since all African countries are small in terms of world trade[7], the general equilibrium effect of price insulating policies is very limited and price transmission occurs just from international to domestic prices.

A general equilibrium analysis is interesting if it is applied to larger countries in terms of trade; this, however, will not be the scope of this study.

The main econometric strategy of this study consists in carrying out a robustness analysis by comparing the results of the different econometric approaches.

The econometric model is derived from an extended version of the law of one price, which can be expressed in the following way:

$$P_{dom,j} = (E_{dom/int}\, P_{int,\, j})$$

with $\boldsymbol{P_{dom}}$ as the (average) domestic price, $\boldsymbol{E_{dom/int}}$ the exchange rate and $\boldsymbol{P_{int}}$ as the international price.

It is possible to take the logarithmic form of the previous equation:

$$\ln (P_{dom,j}) = \ln(E_{dom/int}) + \ln(P_{int,\, j})$$

In this approach, the basic law of one price is extended by introducing the logarithm of the all-commodity inflation π. Furthermore, the international price is replaced by the logarithm of the border price $P_{border,\, j}$:

$$\ln (P_{dom,j}) = \ln(E_{dom/int}) + \ln(P_{border,\, j}) + \ln(\pi) + \varepsilon$$

The border price $P_{border,\, j}$ is the actual import price after the application of the ad-valorem equivalent tariff rate to the international price and is computed as $P_{border,\, j} = [(1+T_{t-1}) * P_{int,\, j})$, where T_{t-1} is the ad-valorem equivalent tariff rate at time t-1. This relationship is estimated by crop for each country.

[7] This implies that they only reveal a very small share in world exports and imports.

Inflation and border price have an impact on the price transmission process because international markets are not regarded as perfect and some frictions in the price formation of each crop are allowed.

If such variables are not taken into account within the regression, the error term ε has a structure. Their inclusion in the regression, however, renders the error term stochastic.

In particular, in this framework prices of other food items, materials, etc. included in the all-commodity price inflation index do not transmit completely and quickly to the international price of the crop j and are thus regarded as a separate control variable. Furthermore, the introduction of tariff and non-tariff barriers creates some distortions and reduces the degree of transmission between international and domestic prices. Such distortive effect is explicitly taken into account for the determination of the main explanatory variable, as explained in the section about the database building.

The introduction of exchange rate and all-commodity inflation in the econometric specification allowed us to control for the correlation between changes in money supply and variations of real agricultural prices, as assumed by the money non-neutrality hypothesis.

While there is no endogeneity between P_{int} and P_{dom} (small country assumption), ad-valorem the equivalent tariff rate could be endogenous since policy-makers set the rate according to the prevailing domestic price. The ad-valorem equivalent tariff rate T_{t-1} is used to avoid endogeneity. Since the model is log-log, the coefficient can be interpreted as elasticity.

Time series and panel econometrics aim at understanding the structure of the unknown Data Generating Process (DGP) and the price adjustment mechanism. On basis of such information, it is possible to disentangle some relationships among variables. The advantage of comparing several econometric approaches is to gain a complex and more robust and differentiated picture of the underlying price mechanism and transmission processes.

The main purpose of the econometric strategy is to control for some unknown, unobservable confounders which cannot be identified but the impact of which can be consistently estimated. After controlling for them it is possible to obtain a pure effect of the policy variable.

In particular, all the methodologies adopted allow to separately estimate the confounding factors and clean the estimates of the variables of interest from them. While the confounders cannot be identified, the coefficient of the variables of interest are consistent and can be properly identified, conditional on the estimate of the confounders.

Therefore, on the basis of such information it is possible to disentangle some relevant relationship among variables.

All operational decisions are based on the results of some preliminary specification tests,

which allowed us to understand the underlying Data Generating Process (DGP) and to estimate the most appropriate model.
We ran several tests for detecting unit roots, fractional integration or long memory, co-integration and non-linearities in the time series. The structure and the hypotheses of these tests as well as the logical strategy behind the empirical analysis are reported in detail in Annex II about the econometric theory and depicted in the flow charts for time series and panel analysis.
Since the time series exhibits fractional integration, an Autoregressive Fractional Autoregressive Moving Average (ARFIMA) model was chosen.
The ARFIMA model has the d parameter for fractional integration to handle long-run dependence and ARMA p and q parameters to handle short-run dependence (Baum, 2013).
The main strength of the ARFIMA is that this model is able to separate the fractionally-integrated long-run dependence, which cannot be expressed by a stationary ARMA model, from the short-run parameters p and q, which are the focus of interest of this analysis.

Since the Zivot-Andrews test verifies the presence of structural breaks, Markov Switching Error Correction Models (MSVECM) are computed. These approaches are able to mimic a DGP which shifts over a finite set of unobserved states, given that this transition follows a ergodic and irreducible Markov process. The MSVECM allows for taking into account the general state of the trading system or of the surrounding economic and political environment as well as to detect temporary discrete shifts of the transaction costs.
In addition, the panel analysis was carried out crop by crop and for all countries together because most economists acknowledge that the international economic events have a pervasive influence on agricultural domestic markets and policies and that specific price movements on the international markets are transmitted to domestic economies along the marketing channel of each single agricultural products (Josling et al., 2010). Cross-commodity price transmission is possible, but not explicitly modelled in this study.
For the panel analysis, several specification tests were run in order to detect serial correlation, unit roots, co-integration and cross-sectional dependence.
While the panel database for rice is stationary, the panel database for maize is non-stationary and non-cointegrated. A generalized Hausman test was run for both models: for the former the comparison was made between an OLS with panel-corrected standard errors (PCSE) and a FGLS/GLS approach, for the latter between a Prais-Winsten estimator with panel-corrected standard errors (PCSE) and a FGLS/GLS approach. The Generalized Hausman test allows for

choosing between the always consistent OLS/ Prais-Winsten estimator with PCSE against the FGLS/GLS estimator which is more efficient under the null hypothesis that the auto-covariance structure is correctly specified.

Additionally, the presence of cross-sectional dependence in both databases can be verified through the Cross-sectional Dependence (CD) test for large panels (Pesaran, 2015) and, if the test rejects the null hypothesis of no cross-sectional correlation, the Common Correlated Effect Mean Group (CCEMG) model can be estimated.

In both panels of this study there is no cross-correlation and we thus did not estimate the CCEGM. More details on the specifications tests we employed and the estimated models for the time series and panel analysis are to be found in Annex II.

3. Data

The database concerns three African countries: Cameroon, Kenya and Tanzania, which enforced several trade policies during the study period which covers approximately from January 2005 to December 2015. For each country, about 120 monthly price observations are available.

We obtained monthly ad-valorem equivalent tariff rates by a time disaggregation of the yearly effectively applied weighted average tariff rate from the WITS (World Bank Integrated Trade Solutions)/UNCTAD-TRAINS (Trade Analysis Information System) database through the monthly trade policies from the FAO-FADPA (Food and Agriculture Policy Decision Analysis) (UNCTAD, 2016) (FAO, 2016b) (World Bank, 2016a). The combination of these three datasets allows for the detection of discontinuous change of trade policies on a monthly basis and to build up a database of monthly ad-valorem equivalent tariff rates.

The FADPA database provides accurate information on the monthly policy changes applied by each country. Nevertheless, the FADPA database records just the ad-valorem equivalent tariff rata at the time of adoption and the termination of a given trade policy.

Therefore, the WITS/UNCTAD-TRAINS database is needed to build up a complete time series and to include data concerning the periods when trade policies were not changed.

This operation is accurate as FADPA and WITS databases provide equivalent results. Indeed, they employ a similar approach for the computation of tariff and non-tariff barriers. This time disaggregation is possible as tariffs and non-tariffs barriers as well as trade policies are quite constant over time. Monthly ad-valorem equivalent tariff rates consist of tariff, para-tariff and non-tariff measures: they are computed and compared using different methodologies in order to carry out a far-reaching sensitivity analysis (UNCTAD, 2016) (Basu et al., 2010) (UNCTAD, 2005) (Fugazza, 2013).

The sensitivity analysis consists of different approaches in order to give a reliable estimate of the ad-valorem equivalent tariff rate.

An initial analysis is carried out by computing the frequency index and the coverage ratio: while the former indicator summarizes the percentage of products to which one or more non-tariff measures (NTM) are applied and does not give any indication of the importance of the NTMs on overall import, the latter provides information about the relevance of the NTM because it computes the percentage of trade subjects to NTMs for the importing country j (Fugazza, 2013).

These indices are not able to give any indication about possible impacts of NTMs on price and quantities produced, consumed or traded; therefore, they are often employed as trade restrictiveness indicators in the framework of an estimation procedure of the impact of the NTMs on prices and quantities.

The effect of the NTMs on prices is obtained by regressing the domestic price on the border price. This is regarded to be free from the distortions induced by the NTMs after controlling for the systematic differences in non-traded goods prices (Dean et al., 2009) (Basu et al., 2010, 84).

The computation of the wedge between border and domestic price was challenging because it assumes that domestic and imported goods are perfect substitutes and because the identification of the appropriate domestic price might be difficult (Fugazza, 2013).

Furthermore, model-based approaches are employed to quantify the ad-valorem equivalent tariff rates, in particular the n-good n-factor general equilibrium model with log-linear utilities and log-linear constant returns to scale technologies, the gravity and applied general equilibrium models are estimated for this purpose. The first approach allows for the disentanglement of the effect of each single NTM, but would prevent us to control for the endogeneity of imports due to the presence of the NTMs and could bias elasticity estimates (Fugazza, 2013). Gravity models are generally corrected with a Heckman selection procedure because sunk costs to export affect the firm's capability to export and imply a large number of zeros in the bilateral trade relationship matrix. It is possible to investigate the effect of the NTM on price and quantity traded, produced and consumed, but it requires a large amount of information and can be carried out just for a few specific products and a limited range of countries. In addition, a cost-benefit analysis allows for the estimation of the “willingness to pay” of the economic agents and for a quantification of the costs and benefits for each group of actors. Nevertheless, the latter approach needs a large amount of information and to estimate accurately the willingness to pay could be burdensome.

In the UNCTAD/TRAINS database, the results of these different approaches are compared and weighted in order to obtain a realistic estimate of the ad-valorem equivalent tariff rates.

In particular, non-tariff barriers comprises technical measures, such as sanitary or environmental protection measures, as well as others traditionally used as instruments of commercial policy, e.g. quotas, price control, exports restrictions, or contingent trade protective measures, and also other behind-the-border measures, such as competition, trade-related investment measures, government procurement or distribution restrictions (UNCTAD, 2015). While not all of these instruments are used for price stabilization purposes, the whole trade-related policy framework is essential from the point of view of the policy-makers for the determination of effective price insulation policies.

The ad-valorem equivalent tariff rates computed take into account both automatic and discretional policy measures, since both the former and the latter contribute, even though by different mechanisms, to the outcome of insulating the country from price shocks on international markets. Nevertheless, in this analysis the single effects of discretional and automatic instruments cannot be regarded as separate issues.

Furthermore, in the computation of the ad-valorem equivalent tariff rate for each product several tariff lines which refer to several sorts of the same crop and different countries of destination with reduced rates – like members of a free trade area – or standard rates, are regarded and included in the indicator.

Information on non-tariff and para-tariff measures are also obtained on the basis of country-case studies and are collected from national and international databases as well as from business surveys. In particular, the main sources for non-tariff measures reported in the WITS/UNCTAD-TRAINS database are the national databases of the Ministries of Trade, Ministries of Agriculture, National Standards Bodies, as well as from international organizations, for example from the databases of the WTO notifications and the FAO CODEX Alimentarius. Furthermore, private sector data, which come from the questionnaires prepared by the UNCTAD and ITC for firm-level surveys and web-based portals, are included in the computation of the ad-valorem equivalent tariff rate.

Martinez et al. (2009) provide an approach to combine information about non-tariff measures from the EU market access database, the United States Trade Representative’s National Trade

Estimate, the WTO Trade Policy reviews and the Japanese Report on Compliance by Major Trading Partners with Trade Agreements (European Commission, 2016) (US Trade Representative, 2016) (WTO, 2016) (Ministry Economy, Trade and Industry of Japan, 2016).

Trade Policy Reviews are also based on the complaints by traders, which broadens the scope of the database because they take into account not only policies of concern, but also any difficulty traders may encounter in administering a policy (Basu et al., 2010, 82-83).

The average tariff rate is weighted according to the yearly/ monthly import share from partner countries. The monthly price series are given in the GIEWS database.

The yearly ad-valorem equivalent tariff rates are already provided in the WITS/UNCTAD TRAINS database, while we computed their time disaggregation by exploiting the information entailed in the FADPA database.

On the one hand, the indicators employed exhibit some disadvantages because their accuracy depends on the quality of the underlying data and the selection of the most appropriate weighting scheme. In addition, the weighted tariff rate does not allow for a differentiation between the dissimilar effect of trade policies on consumers and producers as well as for taking into account different elasticities between different products in the same country or the same product in different countries. This limitation, however, we regarded to be of minor relevance, since is not the main goal of this study to provide such a differentiated picture with respect to the groups of economic agents, crops and countries. It is important to be aware that unweighted average tariff rates tend to overstate the height of average tariffs because they include very high and prohibitive tariffs whereas weighted average tariff rates tend to be biased downwards because the import levels of high-tariff items tend to be low.

On the other hand, weighted tariff rates allow for the inclusion of some trade diversion/creation effects among countries which are due to regional trade agreements or similar areas.

A further issue in the computation of the weighted average ad-valorem equivalent tariff rates is that a problem of endogeneity could arise because prohibitive tariffs lead to zero import flows. In this regard, fixed weights and past period trade values are used to avoid such downwards bias of this indicator and soften the endogeneity problem (Fugazza, 2013).

The employment of the average ad-valorem equivalent tariff rate is preferred over the nominal rate of assistance (NRA) because of the lack of information needed for the computation of the latter (Anderson and Nelgen, 2012a) (Anderson and Valenzuela, 2008) (Anderson et al., 2008) (Basu et al., 2010) (UNCTAD, 2005). Indeed, the producer and border prices series are not available for the chosen crops in the analysed countries, therefore it is not possible to compute this indicator from the raw data.

In addition, the database about nominal rates of assistance provided by Anderson and Valenzuela (2008) and Anderson and Nelgen (2012a) is not adequate for the analysis carried out in this paper, because there are not all country-crop combinations useful for the comparison. Such data are at too low frequency, i.e. yearly instead of monthly, and the covered time period of the NRA dataset is too short to be relevant for this analysis: indeed, the database which can be used for this empirical estimation entails only 5 yearly observations from 2006 to 2010 for each country and crop.

The crops analysed are included in the 2017 Harmonized Commodity Description and Coding System under the chapter 10 (Cereals). They are identified with a three 4-digit code, i.e. 10.01. for wheat, 10.05. for maize and 10.06. for rice. Such level of detail in the product classification is enough to answer the research question addressed in this study[8] (Amjadi et al., 2011) (World Bank, 2016b).

Furthermore, the monthly all-commodity price-index for fuel and not fuel goods as well as the exchange rate (national currency per US dollar, period average) are derived from the IMF database (IMF, 2016).

Following the results of the preliminary tests on seasonality, the variables were seasonally adjusted through the X13 algorithm-based methodology.[9] Moreover, a logarithmic transformation was applied on all variables in order to interpret the coefficients of the regression as elasticities.

Monthly data on international and domestic prices of agricultural crops are taken from the FAO-GIEWS (Global Information and early warning system) Database (FAO, 2016a). Price data are collected by the FAO from national statistical authorities and harmonized in order to make possible cross-country comparisons. Although the collection and harmonization procedures carried out by the FAO is rigorous and this database is largely used for empirical

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[8] The 6-digit HS classification could provide more information about the trade flows of these crops than the 4-digit HS codes. Nevertheless, such level of detail is not available for all countries and crops. Moreover, the difference between maize in seed (1005.10) or in other form (1005.90) or between brow rice (1006.20) and broken rice (1006.40) is of minor relevance for the research question addressed in this study.

[9] The X13 algorithm-based methodology is an extension of the X12 and X11 ARIMA methods. In this approach, each time series Y_t is assumed to be the multiplicative composition of the three parts of trend-cycle (C_t), seasonal (S_t) and irregular component (I_t): $C_t \times S_t \times I_t$, The trend-cycle component is obtained by applying a trend moving average to the original series Y_t, which is then de-trended: $SI_t = S_t \times I_t = Y_t / \hat{C}_t$. Then, a quarterly or monthly seasonal moving average is applied to the de-trended series SI_t and a seasonally-adjusted time series is obtained: $SA_t = Y_t / \hat{S}_t$. The Henderson symmetric filter are applied to seasonally-adjusted time series SA_t to obtain the trend-cycle component and the process is iterated from the first step. Henderson (1916) minimize the sum of squares of the third difference of the moving average series, by applying symmetric filters in the middle of the time series and asymmetric weights at its end and at its start. This procedure removes all irregular variations shorter than 6 months and preserves cyclical patterns longer than one year (Ladiray and Quenneville, 2001).

analyses, readers should be aware of such a caveat.

Employment of monthly data reduces the number of available covariates, for instance data on GDP and trade flows are not collected on a monthly basis, but it improves the quality of the assessment of the short-lived movements of the time series, which cannot be detected at lower yearly frequency because of time aggregation bias.

A time series and an unbalanced as well as balanced panel databases were built and used for the estimation. In the unbalanced panel database there are some missing values because we did not implement an imputation strategy for the missing values. Indeed, all possible strategies were regarded as not being sound enough and not able to avoid biases in the database-building.

4. Results of the analysis

In this study we compared the behaviour of the price series in three sub-Saharan African countries: Cameroon, Kenya and Tanzania. The focus is on the analysis of the price behaviour of three major staple crops maize, rice and wheat in each of the countries.

During the food crisis 2007/2008, these three countries introduced several trade policies . The indicator employed for trade policies is the ad-valorem equivalent and includes both tariff and non-tariff measures. A purpose of these measures was to keep price transmission in check, given that these crops provide the bulk of caloric intake of the population of these three countries. Therefore, this analysis is very relevant from the point of view of policy design.

In the specific econometric approach of this paper, the value added comes from the use of high-frequency monthly data. If monthly data are used, there is a trade-off between the ability to detect short-lived movements and the limited availability of control variables. Indeed, high-frequency data significantly decrease the time aggregation bias of the estimation, but are not largely available for most of the macroeconomic variables: for instance, GDP and trade flows are not collected on a monthly basis.

In this insight, the advantage coming from the employment of high-frequency data is regarded as larger than the disadvantage of using further control variables because the monthly variables included in the regression allow for taking into account the main international factors, like all-commodity inflation and exchange rate which determine spatial price transmission (Orden, 2002) (Schuh, 1974).

In the first part of this study, each country was analysed separately by employing time series econometrics methodologies. Later on, a panel database was built from the series of the three countries and in this way time-invariant country effects were controlled for.

Panel databases were available only for rice (Cameroon and Tanzania) and maize (Cameroon, Kenya and Tanzania). Given the limited availability of tests and models for unbalanced long panels, the analysis was carried out only on balanced panels.

In order to properly mimic the Data Generating Process (DGP), the selection of the most appropriate econometric model was data-driven.

Therefore, several preliminary tests were run. In most of the cases the time series exhibited significant seasonal components. Seasonality in the agricultural sector is mostly supply-led because the availability and perishability of products strongly influence the market and vary across the year according to weather conditions. To get a consistent estimate of the effect of the variables of interest, seasonality was removed: in this paper the X13 algorithm-based methodology was used[10]. All standard preliminary tests were then applied to seasonally adjusted time series.

The specification tests provide evidence that the analysed time series violate the Gauss-Markov conditions. The factors to control for these violations, like fractional integration, non-linear regime shifting in the time series as well as country time-invariant effects in the panel analysis allow for a consistent and efficient estimation of the relationship between price insulating policies and prices within the framework of a robustness analysis.

Since most of the time series in the database are fractionally integrated, an Autoregressive Fractionally Integrated Moving Average (ARFIMA) model is computed

The ARFIMA model allows for the separation of the fractionally-integrated long-run dependence from the short-run response of the time series which are the focus of interest of this analysis.

In all ARFIMA models it is evident that the impact of the international macroeconomic framework is key to the determination of domestic price. In particular, both the coefficients of all-commodity price inflation and exchange rate or at least one of them are significant.

The ARFIMA models are appropriate to describe the DGP, the fractional integration parameter d being large (between 0.33 and 0.5) and highly significant. The analysed countries are highly integrated with the international economic environment. The outcome with regard to the importance of the trade policies is mixed. While the coefficients of trade policies were

[10] See footnote 9.

not significant for the maize market in all three countries as well as for the rice market in Tanzania, such measures played an important role in insulating the Cameroonian rice and wheat market from international price shocks. These results give rise to an ambiguous interpretation and suggest that more advanced tests and methodologies should be applied.

Since the Zivot-Andrews tests suggest the existence of structural breaks for many time series, a set of Markov Switching Models with a threshold and two regimes was estimated. All models were run without constant.

In particular, the results shown in Table 6 confirm that the DGP behaves differently in the two regimes. While the main divide between the two regimes for wheat market is the absolute value of the domestic prices, the key element for the maize and rice market for the definition of the two regimes is the increasing or decreasing trend of domestic prices.

The variables of interest exhibit different significance and magnitudes, depending if they lie in one or in the other regime.

The relevance of international drivers in spatial price transmission is confirmed: in particular, the coefficients of the exchange rate are positive, very large in magnitude and very stable in significance across all specifications.

Only if the trend of maize domestic prices decreases, the exchange rate in Kenya and Tanzania does not play a role. The opposite situation occurs for the rice market in Tanzania, where the increasing trend of domestic prices renders the exchange rate not significant.

Moreover, the all-commodity-price inflation is important in several specifications, but its coefficient level of significance is much more unstable. In some cases, the coefficient is positive, in some other cases it is negative.

From the estimation of the Markov switching models, which allow for taking into account the existence of non-linearities and the prevalence of different behaviours of DGP in the two regimes, the interpretation of the role of trade policies changes in a relevant way.

The prevalence of one or the other regime in the maize market determines the magnitude and significance of the coefficient for trade policies.

In the rice market, the coefficients of trade policies are highly significant for all countries and their magnitude is larger with increasing than decreasing domestic prices.

Moreover, the regimes of the wheat market in Cameroon are not determined by the trend of domestic prices, but by their absolute value. In the DGP of wheat domestic prices, there are two regimes: the former with high average domestic prices, the latter with low domestic prices. In both regimes, the coefficients of trade policies are highly significant.

Furthermore, such coefficients are positive for Cameroon and Tanzania if the DGP lies in the regime with the increasing trend of domestic prices, while they are negative or not significant if a decreasing trend of domestic prices is prevailing. In contrast to that, in Kenya the coefficient for trade policies is positive if the decreasing trend of domestic prices prevails, while it is negative if the trend of domestic prices increases.

If the sign of the coefficient is the same as for the trend of domestic prices and smaller than one, domestic prices grow less than international prices: trade policies are able to insulate the country from price shocks on the international markets during the food price spike crisis.

The price insulation effect of trade policies is stronger if the coefficient has the opposite sign of the direction of the trend because the trade policies are able not just to speed down the trend of domestic prices, but also to offset it.

Such offsetting effect takes place on the maize market in Tanzania and on the rice market of Cameroon and Tanzania if the trend of domestic price decreases.

Across all markets, countries and specifications, the states are very persistent: transition probabilities to be in a given state in the next period conditional on being in the same state in the current period are very high, ranging from 85% to 99%. Both the states with increasing or decreasing trend of domestic prices as well as with high or low domestic prices exhibit similar persistence. This matrix of transition probabilities means that the DGP is very unlikely to switch from one state to the other. The impact of trade policies on spatial price transmission in the maize and wheat markets is much larger if the DGP lies in the regime with increasing trend of domestic prices than in the case where the regime of decreasing trend of domestic prices prevails.

Important insights can be also obtained from the panel analysis. In particular, the markets of maize and rice look very different here. While the panels concerning the rice market are stationary, the database for maize is non-stationary and non-cointegrated. This implies the application of different estimation techniques for the two panels.

In this framework the significance of international macroeconomic factors is confirmed: either the all-commodity inflation or the exchange rate or both are highly significant. Nevertheless, the ability of governments to insulate the country from international shocks through trade policies is not similar between the two markets.

On the one hand, countries were able to insulate domestic economies from rice price shocks on the international markets in the analysed period, since the coefficient for trade policies in the rice market is highly significant, positive and smaller than one. On the other hand, the non-significance of the coefficient for trade policies in the maize market provides evidence that such instruments had no price insulation effect in this case.

At the same time, tests for dependence across countries in the database were computed. The CD test shows that there is no cross-sectional dependence between countries. The significance of the coefficients of the international macroeconomic variables and the output of the CD tests are a hint at the fact that the countries are strongly dependent on the development of the macroeconomic framework, but are not linked by contagion processes. In particular, the domestic variables of interest are not directly influenced by their value in the other countries of analysis but by the international environment.

The insulation effect of the trade policies analysed is quite relevant in terms of welfare of an average consumer. If the case of the Kenyan maize market is taken into account, such instruments are able to insulate the domestic markets from shocks on the international markets by allowing that less than 20% of the increase of the international price of maize is transmitted to the domestic market if a decreasing trend of domestic prices prevails.

On the other hand, if on the Kenyan maize market prices increase, trade policies allow that less than 25% of the international price of maize is transmitted to the domestic market.

A positive shock of 25% on the international maize price, if fully transmitted to the domestic market, implies an increase of the Kenyan domestic price by 77 USD each tonne since the Kenyan average domestic price for maize was 308 USD each tonne between January 2006 and February 2016. The enforcement of price insulation policies makes it possible that the domestic price increases less than the international price and, in particular, just by 15.50 and 14.50 USD each tonne if the trend of domestic prices is decreasing or increasing, respectively.

5. Conclusions

In this study an empirical model of spatial price transmission was developed and the questions how price shocks are transmitted and how trade policies affect the pass-through of price information were addressed. The selection of the different econometric methodologies is data-driven and based on the output of specification tests.

The analysis deals with the maize, rice and wheat markets in Cameroon, Kenya and Tanzania in the period 2005-2015.

These countries were chosen because they enforced several trade policies in order to influence the trade volume and relative prices and mitigate the adverse effects of the food crisis 2007/2009.

In this paper, the value added with respect to previous literature like Anderson and Nelgen (2012b) and Anderson and Nelgen (2012c) comes from the use of high-frequency monthly data, which allows for the detection of short-lived movements which could have disappeared because of a time aggregation bias at a lower yearly frequency. Monthly data provide more information than yearly data. In addition, the policy coverage of the ad-valorem equivalent tariff rate employed in this study is at least as good as the nominal rate of assistance introduced by Anderson and Nelgen (2012a), Anderson and Valenzuela (2008) and Anderson et al. (2008).

Although there are several distortions in the agricultural markets which determine the violation of the Gauss-Markov conditions in the Data Generating Process (DGP) of the price series, the adopted empirical methodologies provide a consistent and efficient estimation of the coefficients of the price insulating policies because they are able to control for such disturbances.

The results of the analysis shows that the price transmission process exhibits non-linearities and regime shifts in the markets of all three countries. Country heterogeneity is highly correlated with the set of international factors which determine the price transmission and induces a non-linear behaviour of price transmission mechanism. The introduction of country heterogeneity in the estimation of the panel model results in a better estimation for the rice market, but not for the maize market.

The comparison between the results of the Markov switching models and the panel analysis enables us to draw the conclusion about the characteristics of the non-linearities in the DGP.

The coefficients of the price insulation policies in the rice market keep their significance level both in the Markov switching estimation and in the panel analysis because the non-linearities of the DGP are due to time-invariant country specific effects which are controlled for in the panel models.

Whereas, coefficients of the price insulation policies in the maize market are significant in the Markov switching estimation but become non-significant in the panel models. This is due to the fact that time-invariant country specific effects are not relevant in the maize market. Very likely some other unknown factors play an important role in the DGP.

The application of such sophisticated econometric methodologies, which were chosen on basis of the results of several specification tests, was key to determine the mechanism of spatial price transmission in the maize, rice and wheat markets in Cameroon, Kenya and Tanzania in the period 2005-2015.

ARFIMA models, which do not take into account non-linearities in the DGP and time-invariant country heterogeneity, underestimate the effect of trade policies on spatial price transmission and their ability to reduce the negative impact coming from the price shocks on the international markets.

In contrast to that, both Markov switching and panel models provide evidence that trade policies play an important role in all market situations, while the presence of non-linearities in the DGP and time-invariant country heterogeneity affects the price transmission mechanism.

Overall, in this study it was possible to separately estimate the impact of trade policies within the two regimes of behaviour of the domestic price series: in the first regime the trend of domestic prices increases, in the second one the trend decreases. This highlights that trade policies play a role both in case of increasing and decreasing domestic prices, their relevance being much larger, however, if prices increase. The policy implication is that trade policies were able to insulate the country from price shocks on the international markets during the food price spike crisis, when it was mostly needed.

It is noteworthy, however, that, although the impact of these instruments has been proven to be relevant as counter-cyclical measures during the food price spike crisis, these policies cannot be regarded as structural solutions as this study does not provide any analysis of structural trade policies.

A discussion of the specific measures for the long term development of agricultural markets is beyond the scope of this paper but provides and interesting subject for further analysis.

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Annex I: Acronyms and Abbreviations

Acronym	Meaning
ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Aikake Information Criterion
ARDL	Autoregressive Distribute lag
ARFIMA	Autoregressive Fractional Moving Average
ARMA	Autoregressive Moving Average
BIC	Schwarz-Bayesian Information Criterion
CADF test	Cross-sectionally augmented Dickey Fuller test
CCE	Common Correlated Effect
CCEMG	Common Correlated Effect Mean Group
CD test	Cross-sectional Dependence test
CIPS test	Cross-sectionally Augmented Im–Pesaran–Shin test
COMESA	Common Market for Eastern and Southern Africa
DFE	Dynamic Fixed Effect
DGP	Data Generating Process
EAC	East African Community
ECCAS	Economic Community of Central African States
FADPA	Food and Agriculture Policy Decision Analysis
FGLS/GLS	(Feasible) Generalized Least square
FTA	Free Trade Area
GIEWS	Global Information and early warning system
GPH test	Geweke-Porter-Hudak test
Hadri LM test	Hadri-Lagrange multiplier test
HT	Harris–Tsavalis test (Harris and Tzavalis, 1999)
IPS	Im–Pesaran–Shin test (Im, Pesaran and Shin, 2003)
ITC	International Trade Center
LLC	Levin–Lin–Chu test (Levin, Lin and Chu, 2002)
MG	Mean Group
MSAR	Markov Switching autoregressive model
MSDR	Markov Switching Dynamic regression

MSVECM	Markov Switching Error Correction Models
NTM	Non-tariff measures
PACF	Partial autocorrelation function
PCSE	Panel corrected standard errors
PMG	Pooled Mean Group
PMLP	Phillips' Modified Log Periodogram
PP test	Phillips-Perron Test
REC.	Regional Economic Community
RLP	Robinson’s Log Periodogram
TRAINS	Trade Analysis Information System
TVECM	Threshold Vector correction model
VECM	Vector Error Correction Model

Annex II: Econometric Theory

6. Motivation

Time series and panel econometrics aim at understanding the structure of the unknown Data Generating Process (DGP) and the price adjustment mechanism. On the basis of such information it is possible to disentangle some relationships among variables. The advantage of comparing both econometric approaches is to gain a complex and more robust and differentiated picture of the concrete underlying price mechanism and transmission processes. In the specific econometric approach of this paper, the value added comes from the use of high-frequency monthly data and from advanced econometric techniques which take in account the existence of some unknown, unobservable confounders.

The monthly variables included in the regression allow to take in account the main international factors which determine spatial price transmission (Orden, 2002) (Schuh, 1974).

The main purpose of the econometric strategy is to control for some unknown, unobservable confounders, which cannot be identified, but the impact of which can be consistently estimated. After controlling for them it is possible to obtain a pure effect of the policy variable.

The implementation of the empirical strategy follows a logical sequence: it starts from the less to the most sophisticated techniques to control for such confounders.

All the outlined econometric approaches aim at describe at best the behaviour of the price series, by assuming different effects of the confounders on the structure of the Data Generating Process (DGP) of the price series.

Such a knowledge about the structure of the Data Generating Process (DGP) is employed to estimate consistently the impact of price insulating policies on the prices series.

The rationale of this empirical strategy is not to disregard the less sophisticated techniques in favour of the most advanced ones, but to compare the results of the different methodologies and to obtain in the framework of a robustness analysis a consistent and comprehensive interpretation of the relationship between price insulating policies and prices.

The operational steps in time series and panel econometrics depend on the result of preliminary tests. In the following part, the specific logical framework of both time series and panel analysis are outlined.

7. Time series analysis

The process to carry out a time series analysis is outlined in the following paragraphs and depicted in the flow chart about time series analysis.

2.1. *Preliminary tests*

Preliminary tests are needed to identify the structure of the DGP and select the most appropriate econometric model for inference. Tests and graphical tools which describe the structure of the DGP can explore the time domain (where the time series is viewed as a repetitive process over time) or the frequency domain of the series (i.e. spectral analysis with the spectrum of a time series as decomposition of the variance into components of various frequencies which contribute to it) (Brandes et al., 1968). The following preliminary tests of the time series are implemented.

2.2. *Trend and autocorrelation*

First evidence of the structure and characteristics of the time series is provided by the trend and the analysis of the existence of autocorrelation in the series. Knowledge about the presence of a non-zero constant or a trend and the number of significant lags is also important for designing the non-stationarity tests and the model to be estimated.

The presence of a trend or a non-zero constant is easily seen from the plot of the series. Information on the autocorrelation structure of the series is provided by computing information criteria such as the Aikake Information Criterion (AIC) or the Schwarz-Bayesian Information Criterion (BIC) which identify the number of lags for which the autocorrelation is significant[11]. In general, the information criteria gives the same result, in case of conflicting results, the AIC tends to produce the most accurate structural and semi-structural impulse response estimates for realistic sample sizes, if monthly data are available (Ivanov and Kilian, 2005).

To get a better picture of the structure of the DGP, an autocorrelation analysis is then carried

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[11] These tools are similar to the adjusted R^2: they compare the benefits and the costs due to the increase of the number of the lags. By increasing the lags, the residual variance is reduced, but the prediction interval widens and the estimates become inefficient (Ivanov and Kilian, 2005).

out. The aim is to detect the number of the lags for which there is a significant level of serial correlation. By including all lags with significant autocorrelation in the regression, the effect of such bias is controlled for. A first step to look at the existence of autocorrelation is to visualize the total and partial autocorrelation function.

While the total autocorrelation function computes the unconditional autocorrelation up to a given lag p, the partial autocorrelation function calculates such value, conditional on the autocorrelation up to the lag p-1. The ACF and PACF describe the memory of the process and explain if and how a series can be predicted from its own past. A white noise is described by the lack of significant ACF and PACF coefficients at a given lag. So far a given lag is significant, there is some autocorrelation up to this lag (Sjö, 2011).

In particular, for AR(p) process ACF tails off asymptotically and PACF cut off at lag p, while for MA(q) ACF cuts off at lag q and PACF tails off asymptotically. For ARMA processes ACF and PACS tails off asymptotically (Sjö, 2011).

2.3. Seasonality

Since time series data are raw, the presence of seasonality has to be checked. Seasonality is generally defined as *"the systematic, although not necessarily regular, intra - year movement caused by the changes of the weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by the agent of the economy"* (EUROSTAT, 2016) (Hylleberg, 1992).

The assessment of seasonality in the time series is first done with the help of graphical instruments like the cycle plot which is a seasonal subseries plot. The graph depicts the mean or the median of the time series of interest for the same month across different years with their values plotted against the relevant month. The seasonal subseries plot allows to identify in which month during the year such seasonality occurs. Seasonal subseries plot is drawn to study seasonality after decomposition of the series into frequency components (Cleveland et al., 1978). In addition to that, Friedman and Kruskal-Wallis tests are useful to detect instabilities in the time series and to identify cyclical components[12].

The null hypothesis is that the series do not exhibit any stable seasonality, i.e. all months have

[12] Further tools to detect seasonality are periodogram and spectral density. To draw such graphs, the time series are decomposed into a unique set of sinusoids of various frequencies and amplitude and each frequency is then plotted against its amplitude. It is possible to identify seasonal components , by computing the cycle of the series, which is the reciprocal of the peak frequency.

the same mean. Stable seasonality represents a recurring component, which is stable, systematic and predictable from one to the other year. For both tests the null hypothesis of no seasonality is rejected, if the p-value is smaller than 5% (EUROSTAT, 2016).

If both graphical representations and the aforementioned tests depict a significant level of seasonality, the series should be de-seasonalized.

In case of significant seasonality, the series can be seasonally adjusted through the seasonal dummies approach, seasonal differencing, model-based approaches like TRAMO/SEATS or filter-based ones like X11/X12/X13. Model-based methods assume that time series and their components can be described by an econometric model. In this case the model accuracy can be precisely evaluated, the underlying assumptions can be verified and a confidence interval can be built around the estimate. On the contrary, in the filter-based methods there is no reference to an explicit model. This is an empirical approach that decomposes time series into unobservable components using ad-hoc iterative procedure based on successive smoothing regardless the stochastic properties of the time series. For this reason the precision of the estimation cannot be rigorously checked. The underlying hypothesis of the filter-based methods is that each component can be described by the certain cycle lengths. Long cycles are attributed to the trend-cycle, the seasonal component is formed by seasonal frequencies and the irregular component is defined as the cycle that does not belong to the first two components (EUROSTAT, 2016).

On the contrary, the model-based philosophy assumes that the trend component, seasonal component and irregular component are present at all cycle lengths. Obviously, the share of each component in the given cycle is different, e.g. the trend component dominates in the longer cycles. The model-based approach describes the relationship between the components and assumes that irregular component is a white noise, i.e. is random, has zero mean and a constant variance and zero co-variances (EUROSTAT, 2016)[13].

In this paper all time series, which exhibit relevant levels of seasonality, were seasonally adjusted through the X13 algorithm-based methodology[14].

2.4. Stationarity/ unit root tests

A common characteristic of economic and financial time series is covariance non-stationarity, which means that the first and second moments of their distribution are not constant over

[13] In this paper, the seasonality tests and the de-seasonalisation procedure are carried out by the software Demetra+ and Stata *(EUROSTAT, 2016)*.

[14] See footnote 10

time. Main reason for non-stationarity is the existence of a non-zero constant, trend or structural breaks. If a series is non-stationary, standard econometric techniques for cross-section inference cannot be applied, because these methodologies produce biased standard errors and then inefficiency. Indeed, in time series there are high levels of autocorrelation, which lead to violation of the Gauss Markov assumptions of no serial correlation. Significant serial correlation does not imply biased and inconsistent coefficients but reduces the efficiency of the estimates. In this context, specific approaches are needed to describe accurately the behaviour of the series and then to draw conclusions about the relationship among variables.

Along with the above mentioned graphs for detecting autocorrelation, more formal tests for unit-root integration are run: Augmented Dickey-Fuller and Philips-Perron tests. Both tests are based upon the Dickey-Fuller (DF) test. The null hypothesis of the Dickey-Fuller test assesses whether the autoregressive coefficient is equal to one against the alternative that it is smaller than one. This corresponds to verify whether there is a unit root, i.e. whether the series is non-stationary (Sjö, 2011).

The Augmented Dickey-Fuller (ADF) is an extended version of the Dickey-Fuller, which includes more than one lag in the formula and then control for additional correlation deriving from lags higher than the first one. This test is valid, only if the residuals from the ADF regression are white noise (Sjö, 2011).

The Philips-Perron test suggests a non-parametric correction of the bias in the Dickey-Fuller test and can be used, even if the residuals of the ADF regression are not white noise. The empirical residual variance of the DF regression is adjusted by a non-parametric estimation of the residual variance, using Bartlett's triangular window. The Augmented Dickey Fuller (ADF) and Philips-Perron (PP) have the same null hypothesis as the Dickey-Fuller, i.e. that the series has a unit root (Sjö, 2011).

Depending on the results of the unit root tests, the model can be specified. If the series do not have any unit root, it is possible to run an OLS without any problem of inefficiency.

2.5. Fractional integration

However, price series of agricultural crops have shown in previous studies the presence of fractional integration or long memory. This implies that the series keeps the memory of a shock for a long period (Mohanty et al., 1998).If a series exhibits long memory, neither it is stationary I(0) nor it is a unit root I(1) process; it is an I(d) process (with d as a real number). A series exhibiting long memory, or persistence, has an autocorrelation function that damps hyperbolically, more slowly than the geometric damping exhibited by short memory ARMA processes. Thus, fractionally integrated processes may be predictable at long horizons (Baum, 2013) (Baillie, 1996).

To assess fractional integration the following tests can be used: the Geweke-Porter-Hudak (GPH) Test, Phillips' Modified Log Periodogram (PMLP) and Robinson's Log Periodogram (RLP).

The null hypothesis for the Geweke-Porter-Hudak, Phillips' Modified Log Periodogram and Robinson's Log Periodogram is that there is no fractional integration and that the series is then stationary. i.e. the degree of integration d=0. All tests are computed, using different powers in the framework of the robustness analysis (Geweke and Porter-Hudak, 1983) (Philipps, 1999a) (Phillips, 1999b) (Robinson, 1995). The three tests are compared, because each of them has some strengths and weaknesses.

The GPH method uses nonparametric methods - a spectral regression estimator - to evaluate d without explicit specification of the short memory ARMA parameters of the series. The power determines the number of harmonic ordinates to be included in the spectral regression. The regression slope is an estimate of the series' power spectrum in the vicinity of the zero frequency[15]. To evaluate the robustness of the GPH estimate, a range of power values is included (Geweke and Porter-Hudak, 1983) (Baum and Wiggings, 2000).

To distinguish unit-root behavior from fractional integration through the Geweke-Porter-Hudak test may be problematic, given that this estimator is inconsistent against the alternative hypothesis that the degree of integration d is larger than 1. This weakness of the GPH estimator is solved by Phillips' Modified Log Periodogram Regression estimator, which is based upon a modification of the Discrete Fourier Transform. In this way, it is possible to estimate the degree of integration d, so that its limiting distribution at d=1 is the same of the Geweke-Porter-Hudak estimator in the stationary case. This semiparametric test is then consistent against both $d < 1$ and $d > 1$ fractional alternatives (Baum, 2013) (Philipps, 1999a) (Phillips, 1999b).

An advantage of the Robinson's Log Periodogram Regression estimator is that it can be applied to more than one variable and that it is not restricted to using a small fraction of the ordinates of the empirical periodogram of the series. When applied to a set of time series, the

[15] If too few ordinates are included, the slope is calculated from a small sample. If too many are included, medium and high-frequency components of the spectrum will contaminate the estimate.

degree of integration d for each series is estimated from a single log-periodogram regression which allows the intercept and slope to differ for each series. The multivariate Robinson's Log Periodogram Regression is based on the assumption that different time series share a common differencing parameter and are normally distributed. Robinson claims that other conditions underlying his derivation are milder than those conjectured by GPH (Robinson 1995). The standard errors for the estimated parameters are derived from a pooled estimate of the variance in the multivariate case, so that their interval estimates differ from those of their univariate counterparts (Baum, 2013) (Robinson, 1995).

If at least one series in the regression is fractionally integrated, the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model is run. The ARFIMA model was proposed by Sowell (1992) and is computed through the full maximum likelihood estimation. The ARFIMA model has the d parameter for fractional integration to handle long-run dependence and ARMA p and q parameters to handle short-run dependence. Sowell has argued that using different parameters for different types of dependence facilitates estimation and interpretation (Baum, 2013).

In the ARFIMA model the degree of integration d is not an integer, but a real number. After the value of d is estimated form the data, the short-run effects is described by the behaviour of the fractionally differenced process, which is obtained by setting $d = 0$. Instead, the long-run effects are represented by the behaviour of the fractionally integrated process, which is modelled by using the estimated value of d.

Granger and Joyeux (1980) motivate the usefulness of the ARFIMA models by noting that their implied spectral densities for $d > 0$ are finite except at frequency 0, whereas stationary ARMA models have finite spectral densities at all frequencies. The ARFIMA model is indeed able to capture the long-run dependence, which cannot be expressed by stationary ARMA models (Baum, 2013).

2.6. Cointegration

If the Geweke-Porter-Hudak, Phillips' Modified Log Periodogram and Robinson's Log Periodogram are not able to reject the null hypothesis of no fractional integration as well as the ADF and Philips-Perron test are not able to reject the null hypothesis of unit-root, the series are unit-root, but not fractionally integrated. In this case, the existence of cointegration should be tested through the Johansen eigenvalue and trace tests (Sjö, 2011).

The Johansen test is checking sequential null and alternative hypotheses. It starts with the first null (rank=0) against the alternative (rank > zero), then it tests the null (rank =1) against the alternative (rank > 1) and so on. The rank points out the number of cointegrating relationships. If rank=0 the series are integrated, but not cointegrated. If there is full rank series are stationary (Lütkepohl, 2005).

If the series are integrated, but not cointegrated (rank=0) an Autoregressive Distribute lag (ARDL) model is employed. In this approach, the series has to be differenced in order to remove non-stationarity. On the contrary, if there is cointegration, a Vector Error Correction Model (VECM) is run. The VECM is a powerful tool, which allows disentangling the long-run equilibrium from the short-term deviations from this equilibrium. In particular, VECM directly estimates the speed at which a dependent variable returns to equilibrium after a change in other variables (Sjö, 2011).

2.7. Structural breaks

Sometimes the estimates could be not reliable because the time series could exhibit structural breaks. If there are structural breaks, the estimated parameters are computed as an average across different regimes and the hypothesis testing could be undermined because of too large standard errors. To increase reliability of the results, the hypothesis of the existence of structural breaks along the series is verified.

In particular, the Zivot-Andrews test has a null hypothesis of a unit root process with drift that excludes exogenous structural change against the alternative hypothesis of existence of one break in the trend or in the intercept or in both. If minimum t-statistics is smaller than critical value, the test is not able to reject the null hypothesis, it means that there are no structural breaks (Zivot and Andrews, 1992).

The Zivot-Andrews test is a sequential test which utilizes the full sample and uses a different dummy variable for each possible break date. The break date is selected where the t-statistic from the ADF test of unit root is at a minimum (most negative). Consequently a break date will be chosen where the evidence is least favorable for the unit root null (Zivot and Andrews, 1992) (Glynn and Perera, 2007) (Baum, 2004).

2.8. Markov Switching Model

If the Zivot-Andrews test verifies the presence of structural breaks, some Markov switching models are computed. These models belong to the class of the piecewise linear TAR models and allow a flexible specification: indeed, the relationship between some variables can be locally linear, but globally non-linear because of the existence of one or more structural breaks in the relationship. (Ihle and Cramon-Taubadel, 2008).

Threshold models are widely applied for the analysis of spatial and vertical price transmission and, in particular, to test the Law of one price in the Enke-Samuelson-Takayama-Judge spatial equilibrium models (Enke, 1951) (Samuelson, 1952) (Takayama and Judge, 1972). In the framework of threshold models, the assumption of perfect competition is removed and the existence of positive transaction costs is taken in account. The above mentioned threshold can be a function of the analysed price series or of external determinants which do not need to be observed (Ihle and Cramon-Taubadel, 2008).

In the first case a Threshold Vector correction model (TVECM) is applied: if the deviation of the process from its long-run equilibrium is at least as large as the transaction costs, the model adjusts and the price series tend to converge in the long term. On the contrary, if the deviation of the process from its long-run equilibrium is smaller than the transaction costs, no converge between the two prices takes place. Such feature implies the existence of a "band of inaction", where international and domestic prices or prices at different levels of the value chain do not converge in the long term, since transactions costs are larger than the price difference (Ihle and Cramon-Taubadel, 2008).

An alternative methodology is the Markov Switching Error Correction Model (MSVECM), which is able to mimic a DGP which shifts over a finite set of unobserved states, given that this transition follows a ergodic and irreducible Markov process. The MSVECM allows to take into account the general state of the trading system or of the surrounding economic and political environment as well as to detect temporary discrete shifts of the transaction costs.

While in the TVECM the price convergence occurs with certainty outside the "band of inaction", in the MSVECM the adjustment takes place with a given positive probability (Ihle and Cramon-Taubadel, 2008, 19).

While the time of transition from one state to another and the duration between changes in state is random and it is not possible to know with certainty in which state the process lies, the probability to be in each of them, conditional on the state where the process lay in the previous period, can be estimated. Moreover, in these models the process can evolve

differently in each state.
In the class of the MSVECM the two available econometric methodologies are the Markov Switching Dynamic regression (MSDR), which allows a quick adjustment after the process changes state, and the Markov Switching autoregressive model (MSAR), which describes a gradual adjustment after the process changes state. While the MSDR mimics accurately monthly and higher-frequency data, MSAR is more suitable for quarterly and lower-frequency data. Since monthly data are available in this study, the MSDR could be more adequate. Nevertheless, the two different methodologies are compared in order to check the robustness of the estimates (Ihle and Cramon-Taubadel, 2008).

8. Panel data analysis

The process to carry out a panel data analysis is outlined in the following paragraphs and depicted in the flow chart about panel data analysis.
In particular, all these methodologies allow to separately estimate the confounding factors and clean the estimates of the variables of interest from them. While the confounders cannot be identified, the coefficient of the variables of interest are consistent and they can be properly identified, conditional on the estimate of the confounders.

8.1. Preliminary tests

The described econometric analysis deals with long panels[16] which exhibit both serial and cross-correlation. Along with the results provided in the time series analysis, specific preliminary tests and estimation methodologies are applied to study the behaviour of long panels. Such approaches for long panels combine panel and time series analysis.
The techniques for long panels give the advantage that they are able to control for the presence of time-constant omitted – mismeasured or unobserved – variables which are correlated with the explanatory variables, because such panel databases contain information on both the intertemporal dynamics and the individual heterogeneity (Hsiao, 2007, 5) (Hsiao, 2014, 1-10) (Baltagi, 1998).
Moreover, if the behaviour of each observation unit is similar conditional on certain variables, panel data allow to obtain a more accurate description of the behaviour of each observation

[16] A long panel is a panel database where T>N.

unit supplementing observations of this unit with data on other units (Hsiao, 2007, 6) (Hsiao, 2014, 1-10). Panel datasets are also better able to study complex issues of dynamic behaviour (Baltagi, 1998).

Finally, long panel methodologies provide a computational advantage, if there is non-stationarity: indeed, unit-root tests for long panels have higher power than the ones for time series. Moreover, unit-root tests for long panels follow a Gaussian asymptotic distribution, while the ADF and the Philips-Perron converge to non-standard limiting distribution (Hlouskova and Wagner, 2006) (Lütkepohl, 2005) (Hlouskova and Wagner, 2006) (Hsiao, 2007, 7) (Hsiao, 2014, 1-10).

Instead, the increase of efficiency in the estimation of long panels with respect to time series or cross-section samples is possible, but not necessary, because large datasets could imply the rise of heterogeneity in the sample and should be evaluated case-by-case. The preliminary checks concern the existence of serial correlation and unit-root in panel databases.

8.2. Serial correlation

Serial correlation in linear panel-data models biases the standard errors and causes the results to be less efficient, therefore it is important to identify serial correlation in the idiosyncratic error term. In this insight, there is a trade off between robustness and power of the tests for detecting serial correlation (Drukker, 2003) (Wooldridge, 2002).

A first category of tests like the Baltagi–Wu test derived in Baltagi and Wu (1999) are based on very specific assumptions about the nature of the individual effects or assess individual-level effects jointly. Therefore, these tests are very powerful against this specific assumption, but not robust against different specifications. These tests for serial correlation are highly parametrized and based upon many assumptions and then they represent optimal tests within each class.

Instead, the Wooldridge's procedure is a more general test, which is based upon fewer assumptions, and then more robust, but less powerful against a specific set of assumptions than the previous tests. In the Wooldridge test, the following first-difference regression is run and the presence of serial correlation between the first-differenced errors is tested (Drukker, 2003) (Wooldridge, 2002):

$$\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta\varepsilon_{it}$$

The main observation made by (Wooldridge, 2002) is that corr(Δ_{ε}, $\Delta_{\varepsilon,\, t-1}$) is equal to 0.5, if the residuals are not serially correlated. Therefore, the Δ_{ε} is regressed on its lags and the coefficient of the first lag of the differenced residuals is tested to be equal to 0.5. In this procedure, it is also possible to account for the within-panel correlation in the regression and to design a test, which is also robust to conditional heteroscedasticity (Wooldridge, 2002).

8.3. Unit root tests

A second type of preliminary checks concerns the existence of a unit root. Such tests in long panel have to take in account that the database could exhibit both serial and cross-correlation. The main unit-root tests for long panels are described in Levin, Lin and Chu (2002), Harris and Tzavalis (1999), Breitung (2000), Breitung and Das (2005), Im, Pesaran and Shin (2003), Choi (2001) and Hadri (2000).

In particular, the null hypothesis of the Levin–Lin–Chu test (LLC) (Levin, Lin and Chu, 2002), Harris–Tsavalis test (HT) (Harris and Tzavalis, 1999), Breitung test (Breitung, 2000) (Breitung and Das, 2005), Im–Pesaran–Shin test (IPS) (Im, Pesaran and Shin, 2003) and Fisher test (Choi 2001) is that all the panels contain a unit root (Hlouskova and Wagner, 2006).

On the contrary, the null hypothesis of the Hadri-Lagrange multiplier (LM) test is that all the panels are stationary or trend stationary versus the alternative hypothesis that at least some of the panels contain unit roots (Hadri, 2000) (Hlouskova and Wagner, 2006).

The LLC, HT and Breitung tests make the simplifying assumption that all panels share the same autoregressive parameter so that $\rho_i=\rho$ for all i. Such restriction implies that the rate of convergence would be the same for all countries, an implication that is too restrictive in most of the applications. The IPS and the Fisher-type tests, however, allow the autoregressive parameter to be panel specific (Hlouskova and Wagner, 2006).

All these tests are not perfectly equivalent, because they behave asymptotically in a different way. According to the specific sample, it could be more appropriate to choose one rather than the other. If a dataset has a small number of panels and a large number of time periods, then a panel unit-root test that assumes that N is fixed or that N tends to infinity at a slower rate than T will likely perform better than one that is designed for cases where N is large. For the database in this study LLC, Breitung, IPS, Fisher-type and Hadri-LM tests are the most suitable ones. Moreover, HT, Breitung and LLC work only for balanced panels, while IPS, Fisher-type tests can be also computed on unbalanced panel.

In particular, the Hadri-LM test can be used just on the balanced panels and test whether the series is stationary against the alternative of unit root. In this approach, the following equation is estimated (Hlouskova and Wagner, 2006):

$$y_{it}=r_{it}+\beta_{it}+\varepsilon_{it}$$

where r_{it} is a random walk component of the series. In particular, $r_{it}= r_{it-1}+u_{it.}$ ε_{it} and u_{it} are zero-mean i.i.d. normal errors. The Hadri-LM test verifies the following null hypothesis:

$$\lambda: \sigma_u/\sigma\varepsilon=0 \text{ against } \lambda>0$$

If σ_u is zero, r_{it} collapses to a constant and the series y_{it} is stationary.

HT-test assesses directly whether the autoregressive parameter is equal to 1, while LL-test is based on the same transformation as in the ADF. Furthermore, while HT-test and LLC-test adjust the autoregressive parameter and its t-statistics after running the fitting regression, the Breitung test pre-whiten[17] the data, before running the regression for verifying the null hypothesis of non-stationarity (Hlouskova and Wagner, 2006).

In the IPS-test the regression is fitted to each panel separately and the resulting t-statistics is averaged, whereas in the LLC-test data are pooled before fitting the regression. Therefore, in LLC-test a common autoregressive parameter is imposed, since the t-statistics is computed on the result of the pooled regression (Maddala and Wu, 1999).

8.4. Cointegration

If the series have a unit root, they could be also co-integrated. To assess the existence of co-integration in panel databases, the tests of Westerlund are run. Westerlund (2007) provides four co-integration tests for long panels, i.e. G_a, G_t, P_a and P_t, based on the error correction approach. The underlying idea is to test for the absence of co-integration by determining whether the error correction term for individual panel members or for the panel as a whole is significant. Westerlund (2007) defines an error-correction model where a_i is the error correction parameter.

In this framework, the G_a and G_t statistics test H_0: $a_i = 0$ for all i versus H_1: $a_i < 0$ for at least one i. These statistics start from a weighted average of the individually estimated a_i and their t-ratio respectively. Rejection of H_0 should therefore be taken as evidence of co-integration of at least one of the cross-sectional units.

Instead, the P_a and P_t statistics pool information over all the cross-sectional units to test H_0: $a_i = 0$ for all i versus H_1: $a_i < 0$ for all i. Rejection of H_0 should therefore be taken as evidence of

[17] A whitening transformation is a linear transformation that transforms a vector of random variables with a known covariance matrix into a set of new variables whose covariance is the identity matrix meaning that they are uncorrelated and all have variance 1. The transformation is called "whitening" because it changes the input vector into a white noise vector (Kessy et al., 2015)

co-integration for the panel as a whole. Such tests allow the computation of robust critical values through bootstrapping, if there is some cross-sectional correlation (Persyn and Westerlund, 2008)

8.5. Model specification

If there is no serial correlation and no unit-root in the panel, a simple OLS model with panel corrected standard errors (PCSE) can be run. The standard random and fixed effects estimators as well as GLS estimators for balanced panel as developed in Baltagi and Li (1991) and for unbalanced panels as provided in Baltagi and Wu (1999) are not suitable for long panels, because they converge to their limiting distribution, if the number of countries N converges to infinity. These estimators are more useful when there are many panels relative to time periods (Hlouskova and Wagner, 2006). On the contrary, the OLS estimator with panel corrected standard errors is consistent for long panels, because it converges to the limiting distribution, when the number of time periods T approaches infinity. (Hlouskova and Wagner, 2006).

Instead, if there is serial correlation and unit root, but no co-integration, a Prais–Winsten estimator with the panel corrected standard errors is computed. The Prais-Winsten estimator controls for serial correlation and converges to its asymptotic distribution, when the number of time periods T approaches infinity. Moreover, OLS and Prais-Winsten estimator with PCSE take in account disturbances, which can be either heteroskedastic across panels or heteroskedastic and contemporaneously correlated across panels (Hlouskova and Wagner, 2006).

A further approach for estimation in long panels is the GLS or FGLS estimator, which allows heteroscedasticity, but no cross-sectional correlation. This methodology can be applied to both serially correlated and not serially correlated data. In particular, full FLGS variance–covariance estimates are very optimistic, if the database consists of 10–20 panels with 10–40 periods per panel, while the OLS or Prais–Winsten estimates with PCSEs have coverage probabilities that are closer to nominal ones (Beck and Katz, 1995) (Hlouskova and Wagner, 2006).

The alternative choice between OLS/Prais-Winsten with PCSE and GLS/FGLS estimators could be evaluated with a Generalized Hausman test. The null hypothesis is that the covariance structure is correctly specified. Under the null hypothesis both estimators OLS/Prais-Winsten with PCSE and GLS/FGLS are consistent, but GLS/FGLS estimates are more efficient. While the OLS/Prais-Winsten with PCSE is always consistent but less efficient under null hypothesis (covariance structure correctly specified), GLS/FGLS are more efficient under the null hypothesis, but inconsistent under the alternative (covariance structure not correctly specified). For the computation of the confidence intervals of both estimators the FGLS estimate of the covariance matrix is employed, because this is asymptotically superior under the assumed covariance structure of the disturbances (Hlouskova and Wagner, 2006).

Finally, if the Westerlund tests reject the null hypothesis and the panel exhibit then co-integration, the approach by Pesaran, Shin and Smith (1999) is applied. Pesaran, Shin and Smith (1999) introduce a generalized framework, which takes in account three strategies to model the behaviour of a dynamic co-integrated panel: Mean Group, Pooled Mean Group and Dynamic Fixed Effect estimator. The difference between these approaches concerns the poolability of the estimated parameters. On the one hand, in the mean group approach the parameters of each equation are estimated by group and the relative distribution is analysed. The mean group estimator is then a consistent estimate of the average heterogeneous parameters (Pesaran and Smith, 1995). On the other hand, the Dynamic Fixed Effect estimator assumes the same slope across all individuals (Pesaran, Shin and Smith, 1999).

An intermediate solution is the pooled mean group (PMG) estimator proposed by Pesaran, Shin and Smith (1999). This approach is very flexible, because intercepts, error variance and short term parameters are different, while the long run parameter is the same across all individuals. The PMG estimator can be applied to both stationary and non-stationary covariates and describes the pooled long run effects without implausible common dynamics. In particular, the estimator can converge towards a MG or towards a PMG approach, according to introduced specifications. The approach can be tested through a Hausman-type poolability test (Hausman, 1978).

Hausman-poolability test assesses the null hypothesis that the parameters are homogenous across the individuals and compares MG and PMG. Under the null hypothesis that the parameters are homogenous across the individuals, both MG and PMG are consistent, but PMG is more efficient. Under the alternative, PMG is not consistent because the parameters are heterogeneous across the individuals (Maddala and Wu, 1999) (Pesaran, 2007) (Eberhardt, 2011) (Hausman, 1978).

8.6. Panel data with cross-sectional dependence

A further concern in the analysis comes from the presence of cross-correlation in the panel data, which leads to the violation of the Gauss Markov conditions. Significant cross-correlation does not imply biased and inconsistent coefficients but it reduces the efficiency of the estimates. Therefore, standard techniques for panel data like fixed and random effects are not suitable. Cross-correlation among individuals can be due to the fact that there is some deterministic or stochastic common factor in the panel. If there is cross-correlation in the panel database, all the above mentioned estimators could be seriously biased in size.

In order to test the presence of cross-sectional dependence, Pesaran (2015) extends the Cross-sectional Dependence (CD) test, introduced in Pesaran (2004), to large panels. In the CD test the null hypothesis is that there is no cross-sectional correlation, i.e. the coefficient of the unobserved common factor is zero.

If there is cross-sectional dependence and unit-roots in the long panel, the Common Correlated Effect Mean Group (CCEMG) estimator is computed. This estimator is based upon the Common Correlated Effect (CCE) originally developed in Pesaran (2006) for short panels. Pesaran (2006) shows that the CCE can be consistently estimated, if the unobserved common factor in a short panel is approximated by the cross-sectional mean $\overline{x_t}$ under strict exogeneity of $x_{i,t}$. This estimator is robust to different types of cross-sectional dependence of errors, possible unit roots in the common factor and slope heterogeneity (Chudik and Pesaran, 2015) (Ditzen, 2016).

Nevertheless, the CCE is not consistent in dynamic panels, because dynamic panels include lagged dependent and weakly exogenous variables as regressors (Chudik and Pesaran, 2015). Therefore, the aim of Chudik and Pesaran (2015) and Pesaran (2015) is to derive an estimator for long panels, which is consistent in presence of cross-sectional dependence. In order to address this issue, Chudik and Pesaran (2015) extend the CCE model into the Common Correlated Effect Mean Group (CCEMG) estimator. They propose the following equation to be estimated:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i x_{i,t} + \delta_i \overline{x_{i,t}} + \theta_i \overline{y_{i,t-1}} + e_{i,t}$$

They conclude that the CCEMG is asymptotically valid in dynamic panels under the condition that the lags of cross-sectional averages to be included in the regression should be large enough and at least as large as the number of unobserved common factors. Generally it is suggested to introduce $\sqrt[3]{T}$ cross-sectional averages in order to control for cross-sectional dependence and to warrant consistency of the estimator (Ditzen, 2016) (Chudik and Pesaran, 2015) (Pesaran, 2015).

Flow Chart for time series analysis

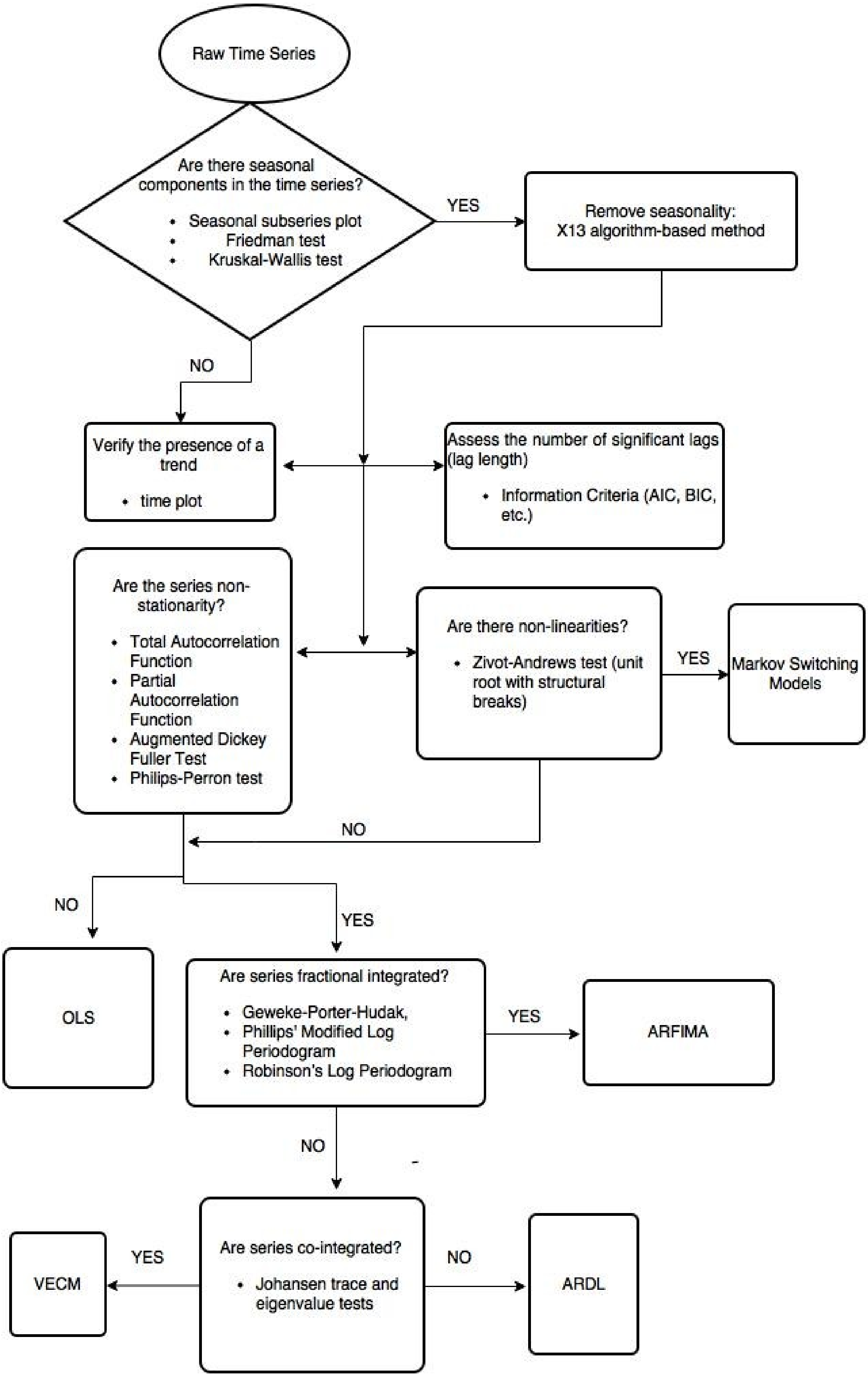

Figure 4: Flow chart for time series analysis

Flow Chart for panel analysis

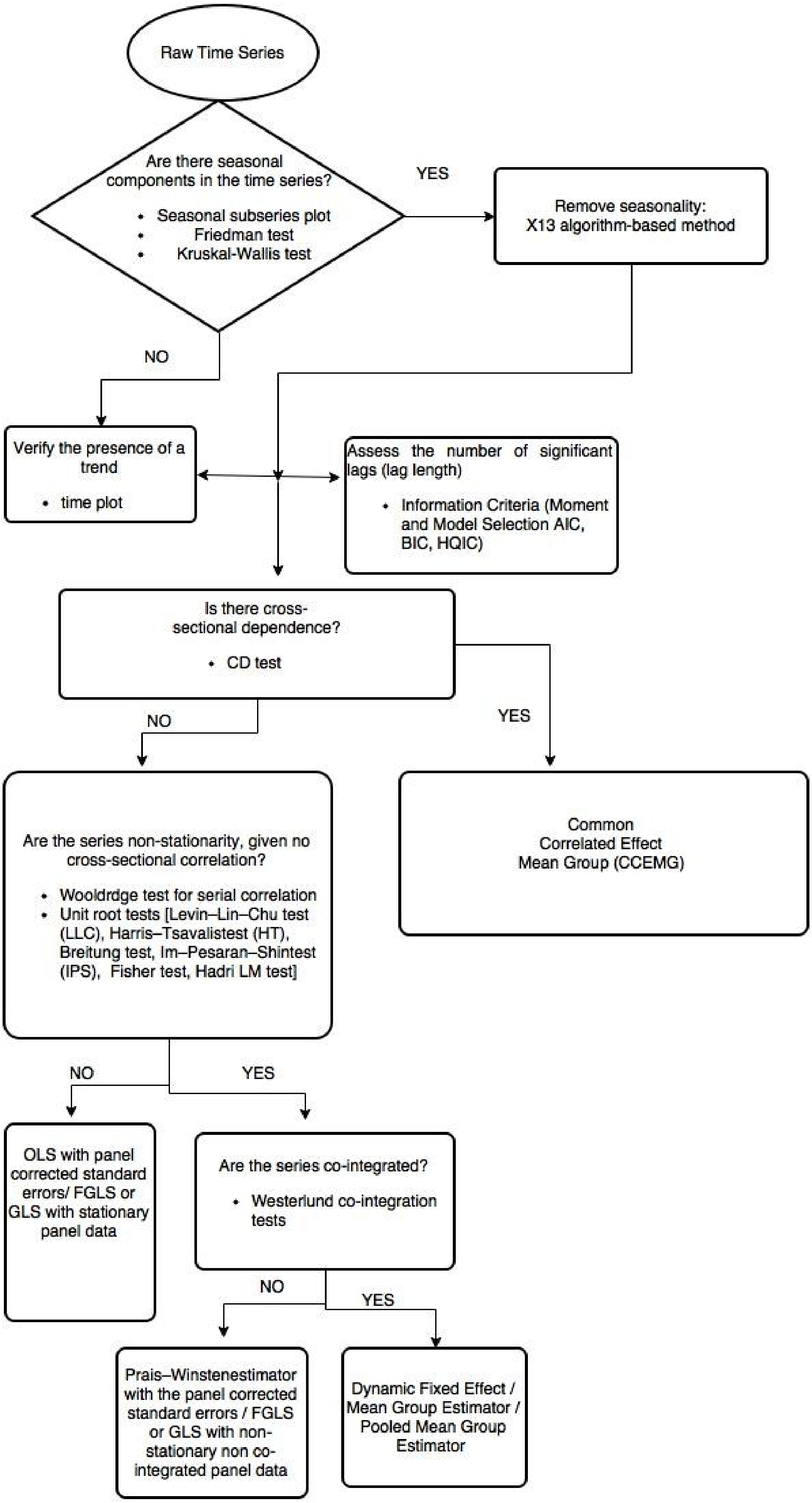

Figure 5: Flow chart for panel analysis

Annex III: Results

9. Time series Analysis

Preliminary tests and graphs

Figure 6: Comparison among graphs of monthly and yearly time series (Maize: Tanzania, Cameroon, Kenya


Cameroon: Maize Border price (Monthly)
USD/tonne
Maize Border price (monhtly)
Cameroon: Maize Border Price (yearly)
USD/tonne
Maize Border price (yearly)
Kenya: maize average Domestic Price (Monthly)
USD/tonne
Maize Average Domestic Price (Monthly)
Kenya: maize average Domestic Price (yearly)
USD/tonne
Maize Average Domestic Price (yearly)
Kenya: Maize Border price (Monthly)
USD/tonne
Maize Border price (monhtly)
Kenya: Maize Border Price (yearly)
USD/tonne
Maize Border price (yearly)

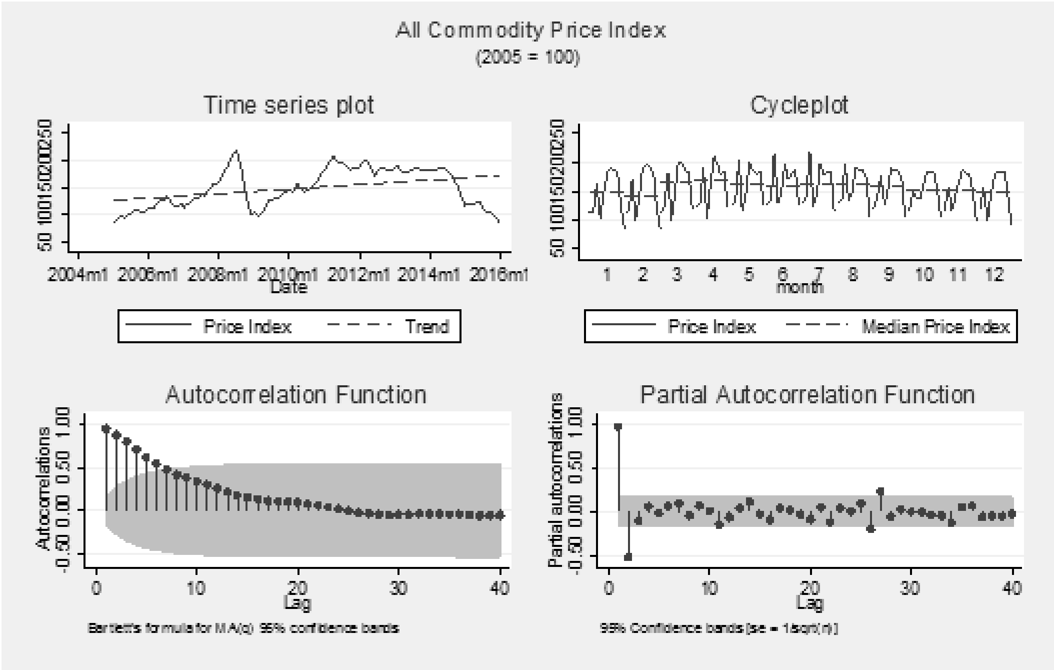

Figure 7: Time series plot, Seasonal subseries plot, autocorrelation function and partial autocorrelation function for All-Commodity Price Inflation (same for all countries and all crops)

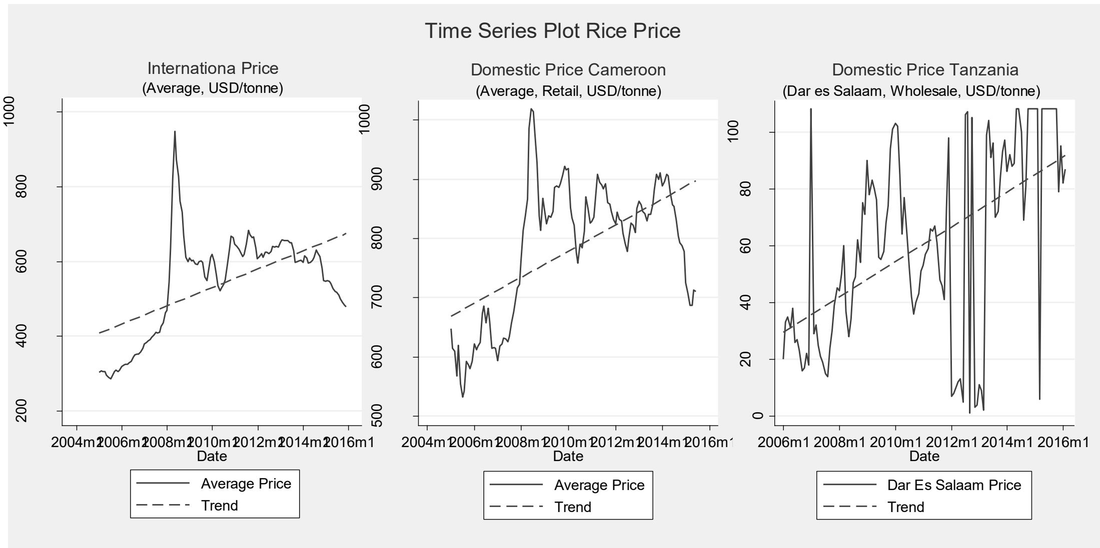

Figure 8: Trend analysis with time series plots for rice for international price and domestic prices in Cameroon and Tanzania

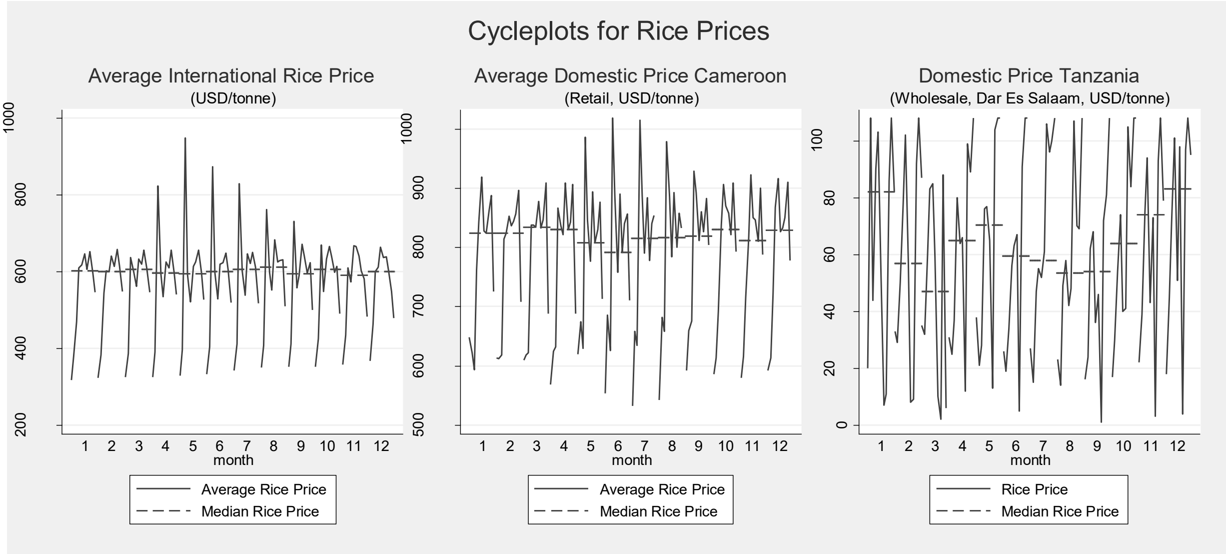

Figure 9: Seasonality analysis with seasonal subseries plot for rice for international price and domestic prices in Cameroon and Tanzania

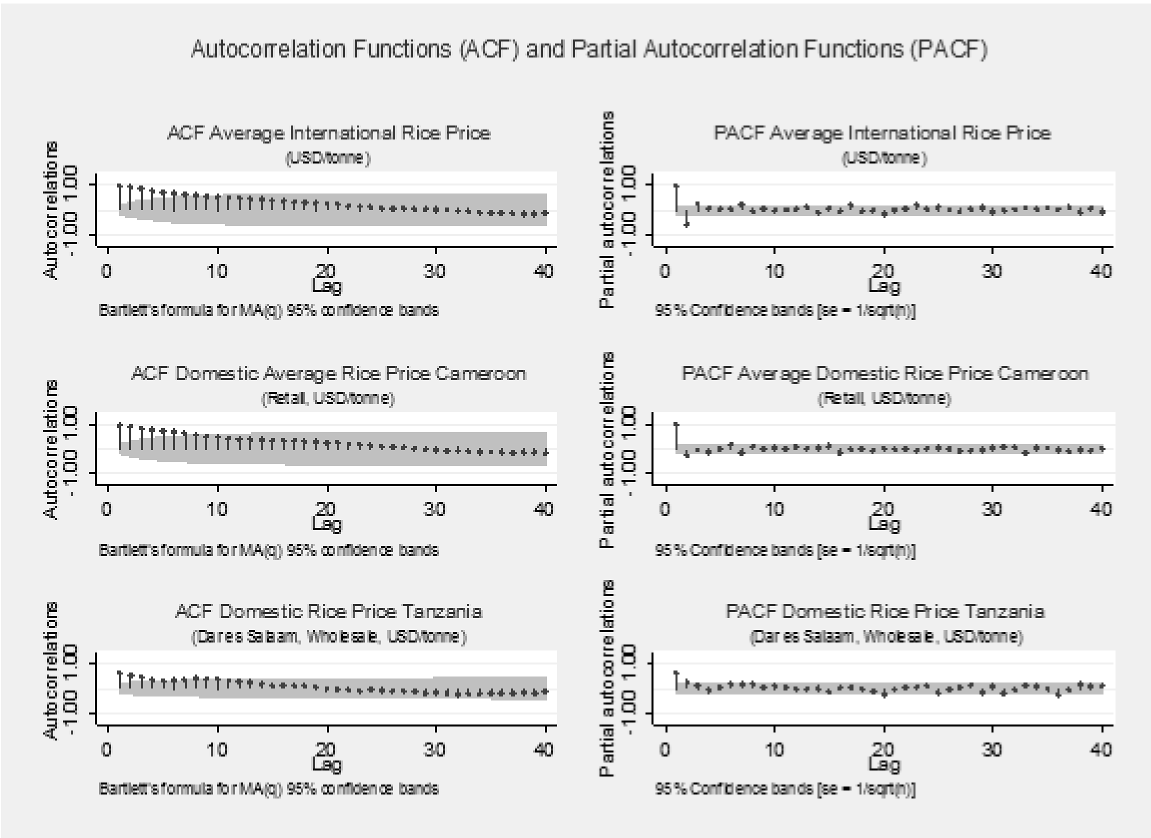

Figure 10: Autocorrelation functions and partial autocorrelation functions for rice for international price and domestic prices in Cameroon and Tanzania

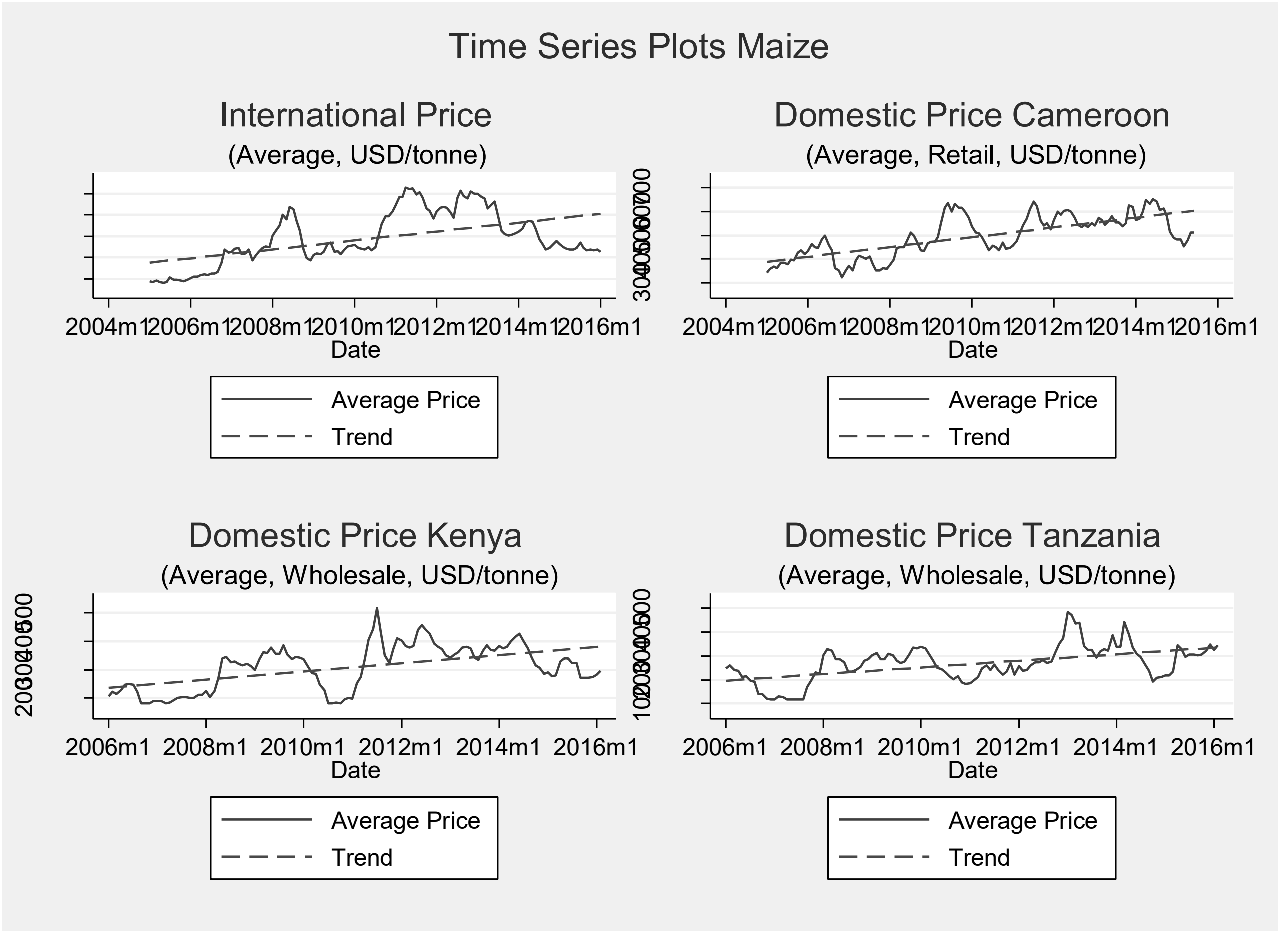

Figure 11: Trend analysis with time series plots for maize for international price and domestic prices in Cameroon, Kenya and Tanzania

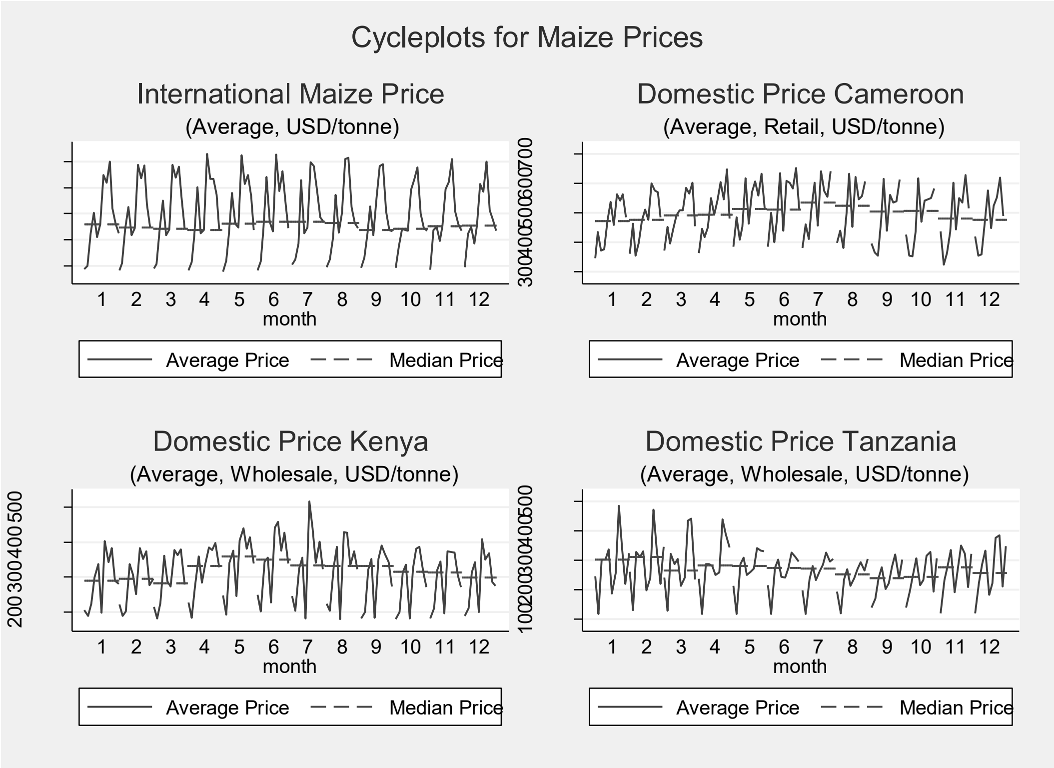

Figure 12: Seasonality analysis with seasonal subseries plot for maize for international price and domestic prices in Cameroon, Kenya and Tanzania

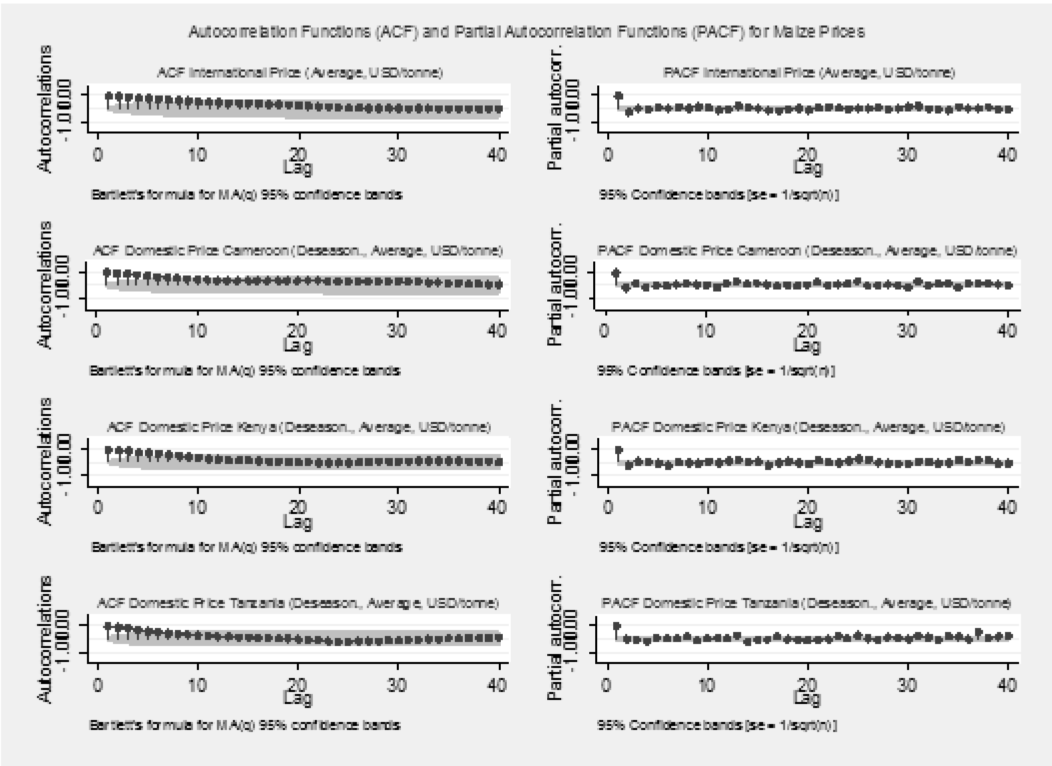

Figure 13: Autocorrelation functions and partial autocorrelation functions for maize for international price and domestic prices in Cameroon, Kenya and Tanzania

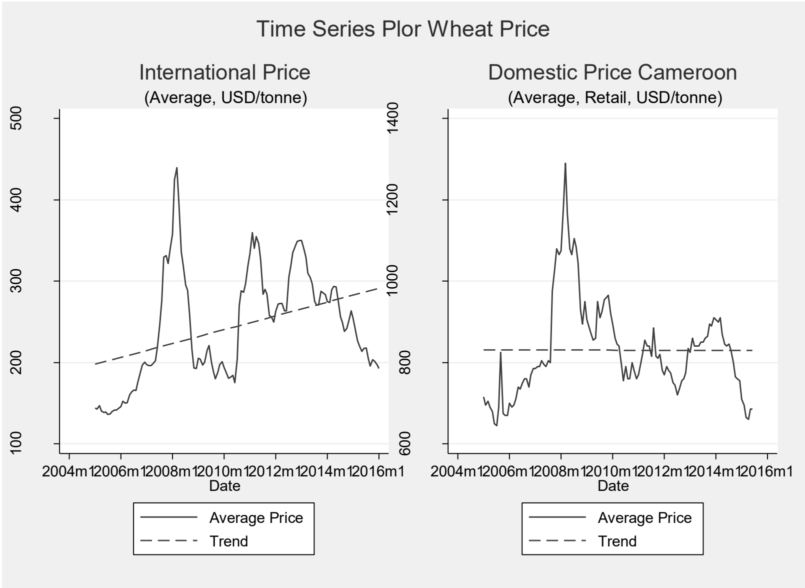

Figure 14: Trend analysis with time series plots for wheat for international price and domestic price in Cameroon

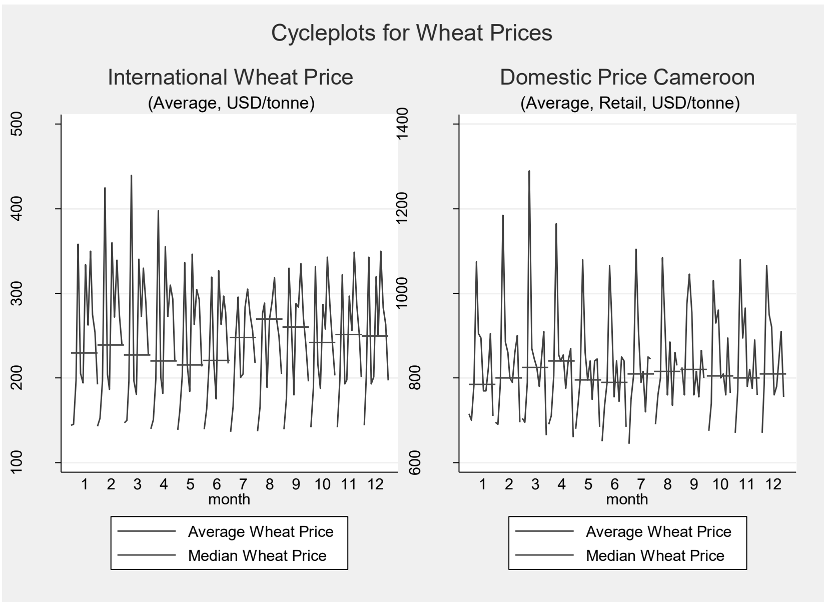

Figure 15: Seasonality analysis with seasonal subseries plots for wheat for international price and domestic price in Cameroon

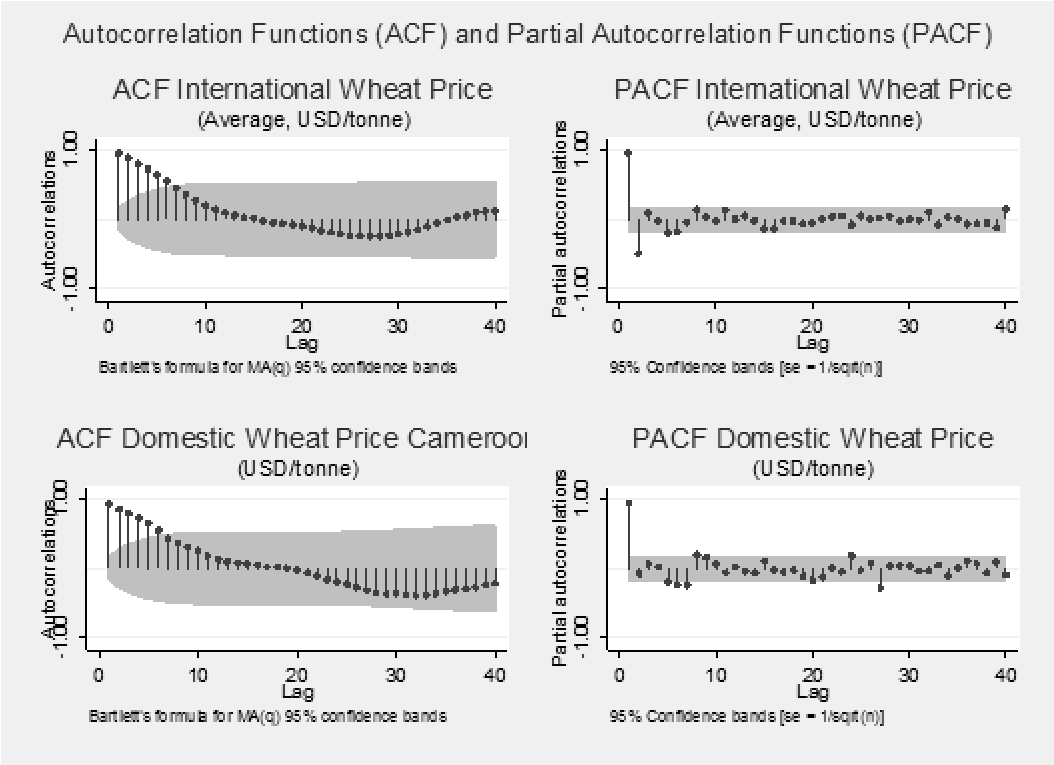

Figure 16: Autocorrelation functions and partial autocorrelation functions for wheat for international price and domestic prices in Cameroon

Table 2: Results for stationarity tests for all variables (general, country- and crop-specific variables)

Results Stationarity Tests[1]

[1] **if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.**

	Augmented Dickey-Fuller Test[a]			Phillips-Perron Test			
Variables	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
General variable (same for all crops and countries)							
All Commodity Price Index	-1.862	-3.446	0.674	-1.321	-3.446	0.883	Yes

	Augmented Dickey-Fuller Test[b]			Phillips-Perron Test			
Country-specific variables	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Cameroon							
Exchange Rate	-1.538	-3.446	0.816	-1.629	-3.446	0.781	Yes
Kenya							
Exchange Rate	-3.039	-3.449	0.122	-2.791	-3.449	0.200	Yes
Tanzania							
Exchange Rate	-0.849	-3.448	0.961	-0.686	-3.447	0.974	Yes

Results Stationarity Tests for Rice

Crop-specific variable (same for all countries)							
Average International Price	-1.998	-3.446	0.602	-1.848	-3.446	0.681	Yes
Note: While All Commodity Price is the same for all countries and crops and Average International Price for all countries, the respective length of the time series varies depending on the remaining variables for the analysis. We depict here the results for the time series covering most of the months (January 2005-December 2015).							
	Cameroon						
	Augmented Dickey-Fuller Test[b]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-1.722	-3.447	0.741	-1.593	-3.447	0.795	Yes
Interaction International Price and Tarif Rate	-3.909**	-3.446	0.012	-3.700**	-3.446	0.022	No
	Tanzania						
	Augmented Dickey-Fuller Test[c]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-2.601	-3.447	0.280	-2.754	-3.447	0.214	Yes
Interaction International Price and Tarif Rate	-3.129*	-3.448	0.100	-4.244***	-3.447	0.004	No

***p-value < 0.01; **p-value < 0.05: *p-value < 0.10

[a] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : All Commodity Price Index (2); Average International Price (3)*

[b] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (2), Exchange Rate (2), Interaction International Price and Tarif Rate (3)*

[c] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (1), Exchange Rate (2), Interaction International Price and Tarif Rate (1)*

Results Stationarity Tests for Wheat

	Augmented Dickey-Fuller Test[a]			Phillips-Perron Test			
Variables	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Crop-specific variable (same for all countries)							
Average International Price	-2.151	-3.446	0.517	-1.957	-3.446	0.625	Yes
	Cameroon						
	Augmented Dickey-Fuller Test[b]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-2.028	-3.447	0.586	-1.913	-3.447	0.648	Yes
Interaction International Price and Tarif Rate	-3.018	-3.446	0.127	-2.642	-3.446	0.261	Yes

***p-value < 0.01; **p-value < 0.05: *p-value < 0.10

[a] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Average International Price (2)*

[b] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (1), Exchange Rate (2), Interaction International Price and Tarif Rate (2)*

Results Stationarity Tests for Maize

	Augmented Dickey-Fuller Test[a]			Phillips-Perron Test			
Variables	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Crop-specific variable (same for all countries)							
Average International Price	-1.707	-3.446	0.748	-1.556	-3.446	0.809	Yes
	Cameroon						
	Augmented Dickey-Fuller Test[b]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-2.967	-3.447	0.142	-2.350	-3.447	0.407	Yes
Interaction International Price and Tarif Rate	-3.018	-3.446	0.127	-3.064	-3.446	0.115	Yes
	Kenya						
	Augmented Dickey-Fuller Test[c]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-2.256	-3.447	0.459	-2.168	-3.447	0.508	Yes
Interaction International Price and Tarif Rate	-2.250	-3.448	0.462	-2.071	-3.447	0.563	Yes
	Tanzania						
	Augmented Dickey-Fuller Test[d]			Phillips-Perron Test			
	Test Statistic	5% Critical Value	P-value	Test Statistic	5% Critical Value	P-value	Non-stationarity
Country-specific variables							
Domestic Price	-3.229	3.448	0.079	-2.765	-3.447	0.210	Yes
Interaction International Price and Tarif Rate	-1.74	-3.448	0.733	-1.679	-3.447	0.760	Yes

***p-value < 0.01; **p-value < 0.05: *p-value < 0.10

[a] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Average International Price (2)*

[b] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (4), Exchange Rate (2), Interaction International Price and Tarif Rate (3)*

[c] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (2), Exchange Rate (2), Interaction International Price and Tarif Rate (1)*

[d] *lag length specification (based on tests for lag-order selection statistics for VARs and VECMs) : Domestic Price (4), Exchange Rate (2), Interaction International Price and Tarif Rate (2)*

Table 3: Results for structural break tests for all variables (general, country- and crop-specific variables)

Results Structural Break Test, Zivot Andrews Test [1]

[1] **if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.**

Variables	Minimum t-statistic	5% Critical Value	Time of structural break
General variable (same for all crops and countries)			
All Commodity Price Index	-3.764	-5.08	December 2013

Results Structural Break Test Rice, Zivot Andrews Test

Crop-specific variable (same for all countries)			
Average International Price	-5.980	-5.080	no break

series varies depending on the remaining variables for the analysis. We depict here the results for the time series covering most of the months (January 2005-December 2015).

	Cameroon			Tanzania		
	Minimum t-statistic	5% Critical Value	Time of structural break	Minimum t-statistic	5% Critical Value	Time of structural break
Country-specific variables						
Domestic Price	-4.995	-5.08	January 2008	-5.695	-5.08	no break
Exchange Rate	-3.418	-5.08	September 2007	-3.115	-5.08	April 2014
Interaction International Price and Tarif Rate	-5.619	-5.08	no break	-3.958	-5.08	January 2012

Results Structural Break Test Wheat, Zivot Andrews Test

Variables	Minimum t-statistic	5% Critical Value	Time of structural break
Crop-specific variable (same for all countries)			
Average International Price	-3.523	-5.080	April 2008
	Cameroon		
	Minimum t-statistic	5% Critical Value	Time of structural break
Country-specific variables			
Domestic Price	-3.838	-5.08	September 2008
Exchange Rate	-3.418	-5.08	September 2007
Interaction International Price and Tarif Rate	-4.691	-5.08	May 2008

Results Structural Break Test Maize, Zivot Andrews Test

Variables	Minimum t-statistic	5% Critical Value	Time of structural break
Crop-specific variable (same for all countries)			
Average International Price	-4.293	-5.080	August 2010

	Cameroon			Kenya			Tanzania		
	Minimum t-statistic	5% Critical Value	Time of structural break	Minimum t-statistic	5% Critical Value	Time of structural break	Minimum t-statistic	5% Critical Value	Time of structural break
Country-specific variables									
Domestic Price	-3.665	-5.08	November 2008	-3.780	-5.08	February 2011	-4.114	-5.08	January 2010
Exchange Rate	-3.418	-5.08	September 2007	-3.115	-5.08	April 2014	-3.115	-5.08	April 2014
Interaction International Price and Tarif Rate	-4.459	-5.08	July 2013	-4.758	-5.08	July 2010	-4.568	5.08	July 2010

Table 4: Results for fractional integration tests for all variables (general, country- and crop-specific variables)

Results Fractional Integration Tests[1]

[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.

Variables	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
General variable (same for all crops and countries)					
	0.4	0.010	0.041	0.001	
	0.5	0.000	0.001	0.000	
All Commodity Price Index	0.6	0.000	0.001	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	

Results Fractional Integration Test Rice

		Cameroon				Tanzania			
	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
Crop-specific variable (same for all countries)									
	0.4	0.016	0.104	0.005					
	0.5	0.001	0.004	0.000					
Average International Price	0.6	0.000	0.000	0.000	Yes				
	0.7	0.000	0.000	0.000					
	0.75	0.000	0.000	0.000					
Country-specific variables									
	0.4	0.093	0.101	0.049		0.046	0.004	0.005	
	0.5	0.001	0.005	0.001		0.001	0.000	0.001	
Domestic Price	0.6	0.000	0.000	0.000	Yes	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000		0.000	0.000	0.000	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000	
	0.4	0.226	0.811	0.205		0.009	0.000	0.000	
	0.5	0.022	0.153	0.017		0.000	0.000	0.000	
Exchange Rate	0.6	0.001	0.010	0.000	Yes	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000		0.000	0.000	0.000	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000	
	0.4	0.136	0.022	0.113		0.832	0.073	0.483	
	0.5	0.020	0.000	0.016		0.078	0.003	0.070	
Interaction International Price and Tarif Rate	0.6	0.001	0.000	0.000	Yes	0.059	0.004	0.057	Yes
	0.7	0.000	0.000	0.000		0.001	0.000	0.001	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000	

Results Fractional Integration Test Wheat

Variables	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
Crop-specific variable (same for all countries)					
	0.4	0.038	0.040	0.023	
	0.5	0.002	0.001	0.001	
Average International Price	0.6	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	
		Cameroon			
Country-specific variables	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
	0.4	0.071	0.111	0.027	
	0.5	0.001	0.001	0.000	
Domestic Price	0.6	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	
	0.4	0.226	0.811	0.205	
	0.5	0.022	0.153	0.017	
Exchange Rate	0.6	0.001	0.010	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	
	0.4	0.164	0.613	0.142	
	0.5	0.007	0.029	0.004	
Interaction International Price and Tarif Rate	0.6	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	

Results Fractional Integration Test Maize

Variables	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
Crop-specific variable (same for all countries)					
	0.4	0.043	0.034	0.027	
	0.5	0.006	0.003	0.004	
Average International Price	0.6	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000	
	0.75	0.000	0.000	0.000	

		Cameroon				Kenya				Tanzania			
Country-specific variables	Powers	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration	P-values Geweke/Porter-Hudak Test	P-values Phillips' Modified Log Periodogram Regression	P-values Robinson's Log Periodogram Regression	Fractional integration
	0.4	0.143	0.116	0.033		0.030	0.032	0.014		0.047	0.912	0.013	
	0.5	0.003	0.005	0.002		0.001	0.006	0.000		0.002	0.053	0.001	
Domestic Price	0.6	0.000	0.000	0.000	Yes	0.000	0.002	0.000	Yes	0.000	0.001	0.000	Yes
	0.7	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	
	0.4	0.226	0.022	0.205		0.009	0.000	0.000		0.009	0.000	0.000	
	0.5	0.022	0.000	0.017		0.000	0.000	0.000		0.000	0.000	0.000	
Exchange Rate	0.6	0.001	0.000	0.000	Yes	0.000	0.000	0.000	Yes	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	
	0.4	0.159	0.256	0.137		0.071	0.102	0.116		0.002	0.001	0.005	
	0.5	0.019	0.026	0.014		0.019	0.018	0.006		0.005	0.001	0.001	
Interaction International Price and Tarif Rate	0.6	0.001	0.000	0.000	Yes	0.000	0.000	0.000	Yes	0.000	0.000	0.000	Yes
	0.7	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	
	0.75	0.000	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000	

Estimated Models

Table 5: Results for autoregressive fractionally integrated moving average (ARFIMA) models

Autoregressive fractionally integrated moving average

Maize

Dependent variable	Cameroon ln(Domestic Price)			Kenya ln(Domestic Price)				Tanzania ln(Domestic Price)			
Model	containing a constant		containing no constant	containing a constant		containing no constant		containing a constant		containing no constant	
	Coefficient	p-value[a]		Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]
Constant	9073***	0.000	*no convergence of the Broyden–Fletcher–Goldfarb–Shanno algorithm*	1.275	0.452			1.716	0.515		
ln(Interaction International Price and Tarif Rate)	0.0004	0.983		0.084	0.370	0.0804	0.393	-0.232	0.441	-0.267	0.369
ln(lnAll Commodity Price Index)	0.1117	0.190		0.269**	0.042	0.318***	0.006	0.27*	0.055	0.317***	0.009
ln(Exchange Rate)	-0.556***	0.005		0.59*	0.055	0.789***	0.000	0.352	0.244	0.531***	0.000

Rice

Dependent variable	Cameroon ln(Domestic Price)			Tanzania ln(Domestic Price)			
Model	containing a constant		containing no constant	containing a constant		containing no constant	
	Coefficient	p-value[a]		Coefficient	p-value[a]	Coefficient	p-value[a]
Constant	11.418***	0.000	*no convergence of the Broyden–Fletcher–Goldfarb–Shanno algorithm*	-0.215	0.981		
ln(Interaction International Price and Tarif Rate)	0.054***	0.000		-0.0144	0.875	-0.0144	0.875
ln(lnAll Commodity Price Index)	0.076*	0.069		-0.385	0.487	-0.391	0.412
ln(Exchange Rate)	-0.864***	0.000		0.828	0.446	0.803**	0.015

Wheat

Dependent variable	Cameroon ln(Domestic Price)		
Model	containing a constant		containing no constant
	Coefficient	p-value[a]	
Constant	14.205***	0.000	*no convergence of the Broyden–Fletcher–Goldfarb–Shanno algorithm*
ln(Interaction International Price and Tarif Rate)	0.026**	0.024	
ln(lnAll Commodity Price Index)	0.007	0.883	
ln(Exchange Rate)	-1.231***	0.000	

*[a] ***p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*

Table 6: Results for Markov-switching regression models

Markov-switching regression model (estimation without a constant)

Maize

Dependent variable	Cameroon ln(Domestic Price)				Kenya ln(Domestic Price)				Tanzania ln(Domestic Price)			
Regime	Regime 1		Regime 2		Regime 1		Regime 2		Regime 1		Regime 2	
	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]
ln(Interaction International Price and Tarif Rate)	0.582*	0.06	-0.245***	0.000	0.195***	0.002	-0.247***	0.005	0.603***	0.000	0.227	0.409
ln(lnAll Commodity Price Index)	-0.432	0.123	1.066***	0.000	0.132*	0.057	0.752	0.000	-0.281***	0.002	0.459	0.259
ln(Exchange Rate)	0.838***	0.000	0.351***	0.000	0.931***	0.000	0.685	0.000	0.526***	0.000	0.233	0.074

Transition probabilities

	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1	0.967	0.013	0.972	0.027	0.959	0.065
Regime 2	0.033	0.987	0.028	0.973	0.041	0.935
Regime determination	**Regime 1: increasing trend of domestic prices is prevailing**		**Regime 1: decreasing trend of the domestic pricesis prevailing**		**Regime 1 increasing trend of domestic trends is prevailing**	
	Regime 2: decreasing trend of domestic prices is prevailing		**Regime 2: increasing trend of the domestic prices is prevailing**		**Regime 2 decreasing trend of domestic prices is prevailing**	

Rice

Dependent variable	Cameroon ln(Domestic Price)				Tanzania ln(Domestic Price)			
Regime	Regime 1		Regime 2		Regime 1		Regime 2	
	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]	Coefficient	p-value[a]
ln(Interaction International Price and Tarif Rate)	0.522***	0.000	0.673***	0.000	0.482***	0.000	0.175**	0.031
ln(lnAll Commodity Price Index)	0.177**	0.03	0.043	0.21	-0.187***	0.000	-0.151	0.877
ln(Exchange Rate)	0.39***	0.000	0.03***	0.000	0.600	0.000	0.777***	0.000

Transition probabilities

	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1	0.898	0.093	0.918	0.113
Regime 2	0.102	0.907	0.082	0.887
Regime determination	**Regime 1: decreasing trend of domestic prices is prevailing**		**Regime 1: increasing trend of domestic prices is prevailing**	
	Regime 2: increasing of domestic prices is prevailing		**Regime 2: decreasing trend of domestic prices is prevailing**	

Wheat

Dependent variable	Cameroon ln(Domestic Price)			
Regime	Regime 1		Regime 2	
	Coefficient	p-value[a]	Coefficient	p-value[a]
ln(Interaction International Price and Tarif Rate)	0.151**	0.016	0.213***	0.000
ln(lnAll Commodity Price Index)	0.207***	0.005	0.333***	0.000
ln(Exchange Rate)	0.77***	0.000	0.662***	0.000

Transition probabilities

	Regime 1	Regime 2
Regime 1	0.989	0.034
Regime 2	0.011	0.967
Regime determination	**Regime 1: very high domestic prices are prevailing**	
	Regime 2: low or average domestic prices are prevailing	

*[a] ***p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*

10. Panel Data Analysis

Preliminary tests and graphs

Table 7: Results for Wooldridge test for autocorrelation for balanced panel data for Maize and Rice

Balanced Panel Maize (Cameroon, Kenya and Tanzania)			
Wooldridge test for autocorrelation in panel data[1]			
[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.			
H_0 = no first-order autocorrelation			
	F statistics	**p-value**	**Is there first-order autocorrelation?**
Test joint significance of:			
Domestic Price	F(1,2)= 142.551	0,0069	**YES**
Interaction International Price and Tarif Rate			
All Commodity Price Index			
Exchange Rate			
****p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*			

Balanced Panel Rice (Cameroon and Tanzania)			
Wooldridge test for autocorrelation in panel data[1]			
[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.			
H_0 = no first-order autocorrelation			
	F statistics	**p-value**	**Is there first-order autocorrelation?**
Test joint significance of:			
Domestic Price	F(1,1)= 4.663	0,2761	**NO**
Interaction International Price and Tarif Rate			
All Commodity Price Index			
Exchange Rate			
****p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*			

Table 8: Results for panel unit root tests for balanced panel data for Maize and Rice

Balanced Panel Maize (Cameroon, Kenya and Tanzania)

Results Panel Unit Root Tests[1,2]

[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.

[2] The tests include non-zero constants and time trend, if they were detected from the graphs or the tests.

				Domestic Price			Interaction International Price and Tarif Rate			All Commodity Price Index			Exchange Rate		
Test[a]	Null hypothesis	Alternative Hypothesis	Asymptotics	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome
Fisher ADF (Inverse Chi-squared)	All panels contain unit roots	At least one panel is stationary	T→ Infinity	6.594	0.3601	All panels contain unit roots	3.8176	0.7014	All panels contain unit roots	7.0985	0.3118	All panels contain unit roots	11.0625*	0.0865	All panels contain unit roots
Fisher Philips-Perron (Inverse Chi-squared)	All panels contain unit roots	At least one panel is stationary	T→ Infinity	3.993	0.6776	All panels contain unit roots	1.6677	0.9476	All panels contain unit roots	1.1271	0.9803	All panels contain unit roots	5.8583	0.4393	All panels contain unit roots
IPS	All panels contain unit roots	Some panels are stationary	T, N → Infinity, sequentially	-0.5338	0.2968	All panels contain unit roots	0.1196	0.5476	All panels contain unit roots	-0.8127	0.2082	All panels contain unit roots	-1.4172*	0.0782	All panels contain unit roots
LLC	Panels contain unit roots	Panels are stationary	N/T→ 0	0.4312	0.668	Panels contain unit roots	-0.9198	0.1788	Panels contain unit roots	-0.231	0.4087	Panels contain unit roots	-1.7799**	0.0375	Panels are stationary
Breitung	Panels contain unit roots	Panels are stationary	T, N → Infinity, sequentially	0.0135	0.5054	Panels contain unit roots	0.5787	0.7186	Panels contain unit roots	2.8747	0.998	Panels contain unit roots	-0.6418	0.2605	Panels contain unit roots
Hadri LM	All panels are stationary	Some panels cointains unit root	T, N → Infinity, sequentially	13.0787***	0.000	Some panels cointains unit root	39.341***	0.000	Some panels cointains unit root	14.4595***	0.000	Some panels cointains unit root	28.12***	0.000	Some panels cointains unit root

[a] lag length specification (based on Moment and Model selection Aikake Information Criterion for Panel VARs and Panel VECMs) : 1 lag

[b] ***p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05

Balanced Panel Rice (Cameroon and Tanzania)

Results Panel Unit Root Tests[1,2]

[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.

[2] The tests include non-zero constants and time trend, if they were detected from the graphs or the tests.

				Domestic Price			Interaction International Price and Tarif			All Commodity Price Index			Exchange Rate		
Test[a]	Null hypothesis	Alternative Hypothesis	Asymptotics	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome	Test Statistic	p-value[b]	Outcome
Fisher ADF (Inverse Chi-squared)	All panels contain unit roots	At least one panel is stationary	T→ Infinity	112.288***	0.000	At least one panel is stationary	141.652***	0.000	At least one panel is stationary	89.9196***	0.000	At least one panel is stationary	82.0179***	0.000	At least one panel is stationary
Fisher Philips-Perron (Inverse Chi-squared)	All panels contain unit roots	At least one panel is stationary	T→ Infinity	95.303***	0.000	At least one panel is stationary	114.601***	0.000	At least one panel is stationary	113.5888***	0.000	At least one panel is stationary	93.914***	0.000	At least one panel is stationary
IPS	All panels contain unit roots	Some panels are stationary	T, N → Infinity, sequentially	-12.261***	0.000	Some panels are stationary	15.523***	0.000	Some panels are stationary	10.2823***	0.000	Some panels are stationary	-9.5565***	0.000	Some panels are stationary
LLC	Panels contain unit roots	Panels are stationary	N/T→ 0	-12.163***	0.000	Panels are stationary	15.353***	0.000	Panels are stationary	10.0244***	0.000	Panels are stationary	-8.2628***	0.000	Panels are stationary
Breitung	Panels contain unit roots	Panels are stationary	T, N → Infinity, sequentially	-6.553***	0.000	Panels are stationary	-6.772***	0.000	Panels are stationary	-7.9532***	0.000	Panels are stationary	-5.6295***	0.000	Panels are stationary
Hadri LM	All panels are stationary	Some panels cointains unit root	T, N → Infinity, sequentially	-1.662	0.952	All panels are stationary	-1.789	0.963	All panels are stationary	1.378	0.916	All panels are stationary	-0.961	0.832	All panels are stationary

[a] lag length specification (based on Moment and Model selection Aikake Information Criterion for Panel VARs and Panel VECMs) : 1 lag

[b] ***p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05

Table 9: : Results for Westerlund test for co-integration for balanced panel data for Maize and Rice

Balanced Panel Maize (Cameroon, Kenya and Tanzania)

Westerlund test for co-integration in panel data[1]

[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.

H_0 = no co-integration

Statistics	Value	Z-value	p-value (robust)	Is there co-integration?
Group Mean Statistics				
G_a	-2.603	0.202	0.49	NO
G_t	-12.596	0.632	0.59	
Panel Statistics				
P_t	-4.546	-0.297	0.38	
P_a	-12.664	-0.113	0.39	

Table 10: Results for cross-sectional dependence (CD) test for balanced panel data for Maize and Rice

Balanced Panel Maize (Cameroon, Kenya and Tanzania)			
Cross-Sectional Dependence Test	**Statistics**	**p-value**	**Is there weak cross-sectional dependence?**
H_0= errors are weakly cross-sectional dependent	-7.244***	≈0	NO
****p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*			

Balanced Panel Rice (Cameroon and Tanzania)			
Cross-Sectional Dependence Test	**Statistics**	**p-value**	**Is there weak cross-sectional dependence?**
H_0= errors are weakly cross-sectional dependent	-10.39***	0,000	NO

Estimated Models

Table 11: : Results for non-stationary non-cointegrated panel model for maize

Non-stationary non-cointegrated panels (FGLS/GLS vs. Prais Winsten with PCSE)[1]						
[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.						
Balanced Panel Maize (Cameroon, Kenya and Tanzania)						
AR(1) term	*Common to all panels*			*Panel-specific*		
Panel structure	*Hetersoschedastic with cross-sectional correlation*			*Hetersoschedastic with cross-sectional correlation*		
Generalized Hausman test	H_0= FGLS/GLS and Prais-Winsten with Panel Corrected Standard Errors (PCSE) estimator both consistent, but GLS/FGLS more efficient					
	Chi square	***p-value***	***Outcome***	***Chi square***	***p-value***	***Outcome***
Prais-Winsten w. PCSE vs. GLS	0,39	0,9413	GLS more efficient	1,69	0,639	GLS more efficient
Prais-Winsten w. PCSE vs. GLS	0,74	0,8642	FGLS more efficient	1,96	0,5801	FGLS more efficient
Model	***GLS on panel data***			***GLS on panel data***		
Dependent variable	***ln(Domestic Price)***			***ln(Domestic Price)***		
	Coefficient		**p-value**	**Coefficient**		**p-value**
Constant	5.939***		0,000	5.485***		0,000
ln(Interaction International Price and	0,0084		0,88	0,011		0,837
ln(lnAll Commodity Price Index)	0.2**		0,015	0.1988**		0,015
ln(Exchange Rate)	-0.1633*		0,053	-0.1683**		0,028
Model	***FGLS on panel data***			***FGLS on panel data***		
Dependent variable	***ln(Domestic Price)***			***ln(Domestic Price)***		
	Coefficient		p-value	Coefficient		p-value
Constant	6.06***		0,000	5.5***		0,000
ln(Interaction International Price and Tarif Rate)	0.006		0,914	0,011		0,845
ln(lnAll Commodity Price Index)	0.199**		0,014	0.198**		0,015
ln(Exchange Rate)	-0.175**		0,037	-0.17**		0,027
****p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*						

Table 12: Results for stationary panel model for rice

Stationary panels (FGLS/GLS vs. OLS with PCSE)[1]						
[1] if seasonality was detected in the time series, the series were de-seasonalized. Therefore, all series are seasonally adjusted.						
Balanced Panel Rice (Cameroon and Tanzania)						
AR(1) term	*Common to all panels*			*Panel-specific*		
Panel structure	*Hetersoschedastic with cross-sectional correlation*			*Hetersoschedastic with cross-sectional correlation*		
Generalized Hausman test	H_0= FGLS/GLS and OLS with Panel Corrected Standard Errors (PCSE) estimator both consistent, but GLS/FGLS more efficient					
	Chi square	***p-value***	***Outcome***	***Chi square***	***p-value***	***Outcome***
OLS w. PCSE vs. GLS	59.95***	0,000	GLS inconsistent, OLS with PCSE consistent	59.14***	0,000	GLS inconsistent, OLS with PCSE consistent
Model	***OLS with PCSE***			***OLS with PCSE***		
Dependent variable	***ln(Domestic Price)***			***ln(Domestic Price)***		
	Coefficient	**p-value**		**Coefficient**	**p-value**	
Constant	4.4***	0,000		4.4***	0,000	
ln(Interaction International Price and Tarif Rate)	0.41***	0,000		0.41***	0,000	
ln(lnAll Commodity Price Index)	0.09	0,096		0.09	0,113	
ln(Exchange Rate)	-0.13***	0,000		-0.13***	0,000	

****p-value < 0.01; **p-value < 0.05: *p-value < 0.10: critical value for hypothesis testing is 0.05*

Third chapter

Shocks, price transmission and Food consumption with changes in Price risk aversion

Shocks and Food consumption with changes in Price risk aversion

Lodovico Muratori

This paper aims to answer the following key research questions: i) does household price risk aversion change over time? ii) and, eventually, does a time-varying risk aversion affect production and consumption pattern of farm households? To this end, I apply to the Ugandan Living Standard Measurement Study (LSMS) three-wave panel data for the period 2009-2012 the risk aversion parameter introduced by Bellemare et al. (2013b), which analyses the effect of the market imperfections and the institutions which facilitate risk-bearing on the household behaviour towards risk. Unlike Bellemare et al. (2013b) I develop a microfounded empirical model, where the risk aversion parameter is allowed to change over time and not just across households, and estimate it by a two-stage structural approach. The empirical results show that the risk aversion parameter is not constant over time and that peasants prefer to increase their income with the sale of the harvested crop instead of directly consuming it, because the reduction of dietary energy consumption derived from the giving up the harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained.

Keywords: commodity prices, risk aversion, panel data, Uganda

JEL codes: D13, D81, O12, Q12

Introduction

Since 795 million of people are undernourished worldwide, food security is still a relevant problem in many countries and represents a primary policy goal from a social and economic point of view (FAO et al., 2015).

Prolonged under-nutrition reduces ability to work, endangers country's human capital and can imply large health care costs in the medium and long term. Children under 5 years of age are particularly vulnerable and inadequate nutrient intake has long-term negative impact on their cognitive skills and health, then on the long-term development potential of the country.

Household food consumption depends on the available supply, prevailing food prices and household income. If the households produce and consume crops at the same time, their optimization decisions are more sophisticated than the ones of standard consumers, because the opportunity costs to sell one unit of harvested crop on the market is represented by the giving up the consumption of this unit of self-produced crop. In order to address this issues, farm household models were introduced and applied firstly to the rural sector in Japan (Kuroda and Yotopoulos, 1978).

The major innovation of the farm household models is that the production and consumption decisions of farm households are interlinked, because the latter consume and produce crops at the same time, while in the standard microeconomic theory consumers and producers are separate agents (Mas-Colell et al., 1995) (Singh et al., 1986) (Taylor and Adelman, 2003).

Given the objective of the farm households to increase their own welfare and make sure their own food security, the farmers face a major trade-off between the consumption of their own harvested crop and the sale of it on the market (Taylor and Adelman, 2003).

The main peculiarities of these models is that the budget of farm households is not fixed, as it is the case of standard consumers, but endogenously determined by positive farm profit component which is to be added to negative elasticity between price and consumer's demand (Mendola, 2007) (Taylor and Adelman, 2003, 36).

Indeed, farm household models encompass the dual role of the households as producers and consumers of the regarded crops and allow to summarize at the microeconomic level demand-side and supply-side factors into a single variable, the marketable surplus. The marketable surplus is defined as the difference between produced and consumed quantities of a given crop by the household.

This variable allows to take into account the household heterogeneity, because households can be net sellers, net buyers or autartik as well as they can switch over time (Bellemare et al., 2013b, 879) (Singh et al., 1986).

The past few decades have witnessed renewed interest from the scientific community with respect to the analysis of the behaviour of farmers: the neoclassical farm household models, which describe these economic agents as both producers and consumers, were extended to include the risk analysis, which allows to understand why farmers prefer low-risk and low-return over high-return and high-risk strategies (Mendola, 2007) (Nielsen and Zeller, 2013) (Dercon, 1996) (Lybbert and McPeak, 2012) (Morduch, 1994) (Rosenzweig and Binswanger, 1993).

While income risk aversion has been widely documented by the literature, price risk aversion, which is the focus of this study, has aroused just more recently researchers' interest (Finkelshtain and Chalfant, 1991) (Barrett, 1996) (Bellemare et al., 2013b).

The question whether the risk aversion parameter is constant or changing over time has been often neglected, while it should be systematically addressed.
In this paper, it is investigated whether the occurrence of exogenous shocks change price risk aversion and which is the impact of a time-varying price risk aversion on household food consumption.
Risk assessment by the farm households depends on both the psychological risk preferences of each household and the existing institutional framework, i.e. the existence of market imperfections and the availability of institutions which facilitate risk-bearing (Mendola, 2007) (Bellemare et al., 2013b).
If there are incomplete markets and only a partial possibility for farmers to insure themselves against food consumption risk, the only available food consumption smoothing strategy is preucationary saving, which consists of storing some portions of the harvest in response to uncertainty regarding future food availability (Thomson and Metz, 1999, 65-66).
Food storage allows to make crops available along the year, but several farmers do not have appropriate storage facilities and they are not able to store properly in their houses or granaries: they need to sell their harvest to traders or wholesaler, who own appropriate storage facilities and demand for a remuneration for the use of their capital (Thomson and Metz, 1999, 65-66).
Therefore, storage can imply some costs and households are not likely paying additional costs to store very small excess supply. Some of these costs are indirect, because farmers sell most of their product in the post-harvest period, in order to avoid that the harvest spoils: this behaviour leads to a temporary surplus and low farm gate prices (Thomson and Metz, 1999, 65-66).
Moreover, it is very likely that household will shift consumption from one month to other, but less likely that the food intertemporal consumption decisions will extend from one year to the other. Indeed, several crops are highly perishable: they are bought not long before their actual consumption and their harvest is sold within a reasonable interval of time before crops perish (FAO, 1997).
Traders and wholesalers can also opt for inter-annual storage, but such an activity has a speculative purpose. For food security reasons, inter-annual storage is carried out by the government, but not by the private economic agents. Finally, to store some commodities like fruits and vegetables for more than few weeks can be very expensive and these items are traded just on seasonal basis (Thomson and Metz, 1999, 65-66).
For the above mentioned reasons, in the empirical two-stage structural model developed in this study, precautionary savings in food and storage are not included.
Data are obtained, by combining the Uganda Living Standard Measurement Study (LSMS) and the calories intake for kilogram is taken from the International Network of Food Data Systems (World Bank, 2015) (FAO, 2015). Data are prepared in order to make them available for estimation of the magnitude and the sign of the variables of interest.
The panel database concerns 3284 households which consumed or produced the major staple crops in Uganda, like beans, cassava, maize, plantains, rice and sweet potatoes during three survey waves 2009-2010, 2010-2011 and 2011-2012.
Two different databases, a balanced and an unbalanced panel, were built and used for the analysis. In the unbalanced panel database all 3284 households are taken into account for the estimation, while the balanced one consists of 2491 households, since some observations are missing for one or two years. Information employed for the empirical analysis are the market and farm gate

prices of the crops, dietary energy consumption, quantity supplied and consumed of crops by the households, income of the household, a set of household features taken from the literature (Dohmen et al., 2011), (Moscardi and Janvry, 1977) (Nielsen and Zeller, 2013) (D'Souza and Tandon, 2015, 14). A survey wave dummy variable allows to assess whether the risk aversion parameter is changing over time.

The results of the empirical analysis suggest that the risk aversion parameter is not constant over time and that households can become more risk averse, if they face adverse market conditions in the previous periods.

This study provides evidence that peasants prefer to increase their income with the sale of the harvested crop instead of directly consuming it, because the reduction of dietary energy consumption derived from the giving up the harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained.

Furthermore, the attendance of the primary school by the household head reduces the psychological risk aversion, while all other household features have just an impact on the strategy how households employ the risk-bearing institutions. In particular, attendance of the primary school provides confidence and skills to the household heads to face some of the challenges, which there are in a risky environment.

Knowledge of the importance of the exogenous shocks for the determination of the time-varying risk aversion parameter is useful for design of development policies. Finally, awareness of the key contribution of the harvest sale on the market to the farm household food security could stress the relevance of measures for the development of agricultural markets in developing countries.

Literature Review

In the context of agricultural business, farmers face several forms of business risk: it includes personal, institutional, production and price risk[1]. The "personal risk" is due to death or illness of the firm owners, whereas the "institutional risk" refers to "political risk", i.e. the implementation of unfavourable policy changes. The latter can be further decomposed into "relationship risk", i.e., the breach of contracts between business partners in the value chain, and "sovereign risk", i.e., the inability by the government to honour its commitments like the enforcement of trade agreements (Hardaker, 2004, 6-7) (Hardaker et al., 2015, 5-6). Production risk concerns the harvest shortfall due to unexpected bad weather conditions and to the impact of pests and diseases on crops and livestock. Price risk is linked to volatility of the input, output prices and of the exchange rates. Both production and price risks are assumed to be particularly relevant in agriculture because production decisions have to be made long before the time the harvest is sold, so that the market price for the output is not known at the time these decisions have to be made (Hardaker, 2004, 6-7) (Hardaker et al., 2015, 5-6). In several models concerning production decisions, peasants are assumed to carry out mostly subsistence production for self-consumption; therefore, output and input prices, if included in the approach, are treated as exogenous variables (Janvry et al., 1991, 1400-1401).

Before the contribution by Finkelshtain and Chalfant (1991), the assessment of the impact of risk

[1] A separate issue concerns "financial risk". It refers to the way the firm is financed and is due to debt leverage, it means the ratio between debt capital and total capital, which makes the business dependent on lenders, or to changes in interest and inflation rates as well as to the anticipated calling-in of a loan by a lender (Hardaker, 2004, 6-7) (Hardaker et al., 2015, 5-6).

and uncertainty on welfare was carried out separately for consumption and production decisions (Bellemare and Lee, 2016).

Producers

Concerning the welfare analysis of producers, Oi (1961) challenged the conventional wisdom that price instability is undesirable for firms, which can obtain larger profits under price uncertainty. Oi (1961) came to this conclusion because of his assumption that firms can predict future prices perfectly or can adjust their output instantaneously.
Instead, if this hypothesis is dropped, the expected profit is smaller with price instability than with price stability, and that the expected profit declines as price variability increases (Tisdell, 1963). Unlike Oi (1961) and Tisdell (1963), who deal with risk-neutral firms, McCall (1967) introduces risk aversion and shows that a risk-averse firm will produce less than a risk-neutral and even less than a risk-loving firm.
These approaches evaluate how price stabilisation influences the level of output, while Schmitz et al. (1981) assessed the benefit of price stabilisation to producers by directly addressing its effect on preferences. In particular, Schmitz et al. (1981) showed that Oi (1961)'s results hold if the firm is profit risk-loving, while a risk-averse firm may prefer price stability.
Baron (1970) and Sandmo (1971) applied different approaches but both found that a risk averse producer will produce less when price is a matter of chance than when it is certain and known. In particular, Baron (1970) regards price uncertainty as given and analyses the impact of price risk aversion on the firm's output, while Sandmo (1971) considers profit risk-aversion as given and focuses on the impact of price uncertainty on output.
The Sandmo (1971)'s predictions about lower productivity of the risk-averse producers were empirically confirmed by Appelbaum and Ullah (1997), who applied non-parameteric methods to estimate the first four moments - mean, variance, skewness, and kurtosis - of the price distribution in the printing and publishing industry as well as in the stone, clay and glass industries. In this approach, the output under price certainty cannot be observed from the data, therefore the authors obtained it by introducing some restrictions on the parameters derived from duality and compared it with actual output level under price uncertainty.
Leland (1972), Turnovsky (1973) and Epstein (1978) extended the approach of Baron (1970) and Sandmo (1971) by modelling firms as risk-averse agents, which can set both supply price and quantities as well as they are able to change at extra cost their ex-ante decisions after the actual selling price is realised. From these studies, Leland (1972), Turnovsky (1973) and Epstein (1978) concluded that a change from risk-neutrality to risk-aversion does not necessarily decrease output and can actually increase the planned output depending upon the shape of the cost function.
Batra and Ullah (1974) extended also the models by Baron (1970) and Sandmo (1971) and introduced the decision-making process of farmers about the amount of capital and labour. By exploiting such a framework, Batra and Ullah (1974) came to the conclusion that - under the assumption that absolute risk aversion is decreasing - a risk averse producer will use less of all inputs if output prices are uncertain than in the case these prices are certain and known.
Hartman (1975) disputes the Batra and Ullah (1974)'s result and pointed out that their conclusions hold only if labour and capital are complements (i.e., increasing one input increases the marginal productivity of the other input and the production function is concave).

A different approach is followed by Feldstein (1971), who developed a model based on the Jensen inequality, where production outcomes rather than output prices are matter of chance. Feldstein (1971) found that a risk-neutral producer should produce more than a risk-averse one and that risk affects not just risk-averse, but also risk-neutral producers.
Ratti and Ullah (1976) extended the approach by Feldstein (1971) with the introduction of a proportional random shock. Their result is that a risk averse producer produces less than a risk neutral producer and use less of capital and labour, if these input are complements. Pope and Just (1978) and Pope and Kramer (1979) argued that the implications derived by Ratti and Ullah (1976) do not correspond to the available empirical evidence. Indeed, several risk averse producers over-employ rather than under-employ some production factors and that some inputs like irrigation can reduce risk rather than increase it. By allowing that the chance outcome can negatively affect the productivity of an input, Pope and Just (1978) and Pope and Kramer (1979) prove that risk averse producer may use more rather than less inputs than a risk neutral producer. Finally, Ratti (1978) develops a more sophisticated model as reply to the latter critiques by Pope and Just (1978) and Pope and Kramer (1979) as well as he provides evidence that risk-averse producers use fewer inputs and in a less intensive way.

Consumers

Waugh (1944) was the first to analyse the issue of price instability and risk aversion from the point of view of the consumers and argued that consumers are better off under price variability than under a price stabilized at its mean, given the assumption that consumption can be allocated freely among different time periods.
Nevertheless, the Waugh (1944)'s approach does not take into account the concept of the price risk aversion, which was later introduced in this field by Stiglitz (1969). In particular, Stiglitz (1969) highlighted the link between risk neutrality and linearity: if an economic agent is risk-neutral at all income and price ratios, its income-consumption curves are linear and its cardinal utility can be represented by a function, which is linear in income.
Turnovsky et al. (1980) showed that the consumers' preference for price stabilization is a function of the income elasticity of demand for the commodity, the price elasticity of demand for the commodity, the budget share allocated for consumption of the commodity and the coefficient of relative risk aversion. Since the desirability of price stabilization is positively correlated with income risk aversion and negatively correlated with price and income elasticities, consumers can be price risk-loving if the budget share is small and the income risk aversion is low.
Hanoch (1977) investigated the relationship between income risk preference and price risk preference. In particular, he showed that a necessary condition for a consumer to be price risk-loving is that relative risk aversion over income be less than 2 and that a consumer can never be price risk-averse with respect to all commodities.
In all these models farm gate output prices, if included, are taken as exogenous and household farms are not able to give up own consumption or reduce quantity sold on the market or to replace consumption of one crop with the other and sell the crops with the highest farm gate prices, in order to make sure their food security.

Farm households

The rigid separation between consumption and production in the analysis of the impact of risk on the welfare was overcome by Finkelshtain and Chalfant (1991), who realized that both the prices of the commodities the farm household consumes and its income are random. Finkelshtain and Chalfant (1991) provided evidence that the relationship betwen risk aversion and output is ambiguous: production under price uncertainty can be greater or equal to or smaller than the certainty output.

Indeed, the conclusions of Sandmo (1971) represent a special case of the Finkelshtain and Chalfant (1991)'s more general approach: they depend on the fact that the wealth effect of price dominates the consumption effect. In the Finkelshtain and Chalfant (1991) model the farm household maximizes its expected utility over the consumption of a portion of the farm output, an aggregate market good and leisure. In this framework, the decision-making process involves two-periods: in the first one, the household makes its leisure and output decisions, and in the second one, after the uncertain prices are realized, it makes its consumption decision. The risk premium developed by Finkelstaink generalizes the Arrow-Pratt risk premium (Pratt, 1964): in the Pratt (1964)'s approach the risk premium is defined as the maximum amount of income an individual is willing to pay to stabilize his income at its expected value, given that income is the only random variable, while the one employed by Finkelshtain and Chalfant (1991) is the maximum amount of income an individual is willing to pay to stabilize his income when both income and price are random.

Barrett (1996) combined the approach of Turnovsky et al. (1980) and Finkelshtain and Chalfant (1991) and provided evidence that, in the case of a farm household which produces and consumes a single commodity, the inverse farm size-productivity relationship holds true.

The Barrett (1996)'s approach was extended by Bellemare et al. (2013b) to the production and consumption of several crops: the latter article showed that the Ugandan farm households are risk-averse and willing to give up about 18% of its income to stabilize the commodity prices. More recently, McBride (2016) highlighted that the results by Bellemare et al. (2013b) about the computation of the willingness to pay depend on the way missing data are dealt with.

In the reply to McBride (2016), Bellemare et al. (2016) explained that both the assumptions for the replacement of missing data made by Bellemare et al. (2013b) and McBride (2016) are ad-hoc and that additional empirical research is needed in this field, since the change of a single assumption leads to very different results. Therefore, Lee et al. (2015) and Bellemare and Lee (2016) stressed the importance to integrate previous reseach on the price risk aversion with the results provided by the experimental and behavioural economics.

Moreover, for simplicity's sake, in the analysis of the household behaviour in a risky environment the risk aversion parameter has been taken as constant over time by the standard economic theory and the question, whether this parameter can change over time, has been long ignored (Stigler and Becker, 1977). In this field, the most updated contributions addressed the possibility of variation of the psychological risk aversion over time - proxied by the Arrow Pratt coefficient of risk aversion. However, they do not reach a consensus whether individuals become more risk-averse or risk-tolerant after the occurrence of a shock or a major life event of psychological, social or economic nature (Hanaoka et al., 2015; Decker and Schmitz, 2015; Görlitz and Tamm, 2015;

Malmendier et al., 2011; Cohn et al., 2015; Andersen et al., 2008; Schurer, 2015)[2].
Also, more recently, scholars extended the concept of risk aversion pointing out that two sets of factors influence the decisions of the farm households in a risky environment: their psychological risk preferences and the availability of institutional arrangements to mitigate the risk, which they face (Bellemare et al., 2013b). This because the Arrow-Pratt coefficient of relative risk aversion proxies just psychological risk preferences and it is not able to describe alone the prevailing risk faced by the households in the economy, since it is independent from market imperfections and availability of institutions which facilitate risk-bearing. Analysis of the socio-economic context is also important to determine household risk profile because households could exercise caution and forfeit expected profit in order to protect themselves and reduce risk, if institutions provide incomplete insurance (Mendola, 2007).

The Model

The developed model lies in the research tradition related to the standard expected utility theory under uncertainty (Neumann and Morgenstern, 1947) and assumes that households prefer lower smooth consumption streams to fluctuating ones (Morduch, 1994).
While in the classical microeconomic theory consumers and producers are separate agents, in the farm household models production and consumption decisions are interlinked, because the economic actors consume and produce crops at the same time (Singh et al., 1986; Taylor and Adelman, 2003)[3]. This feature implies that the budget of farm households is not fixed, as it is the case of standard consumers, but endogenously determined by positive farm profit component which is to be added to negative elasticity between price and consumer's demand (Taylor and Adelman, 2003, 36). Sources of non-separability can be high transaction costs - due to transports expenditures, distance from the market or excessive marketing margins - and thin, remote markets with very few buyers and sellers as well as prevalence of risk in the economic environment (Singh et al., 1986).
Several studies give proof that firms forego expected profits to hedge against risk in presence of output price uncertainty (Sandmo, 1971; Schmitz et al., 1981; Baron, 1970). In this respect, risk analysis can help explaining why farmers prefer low-risk and low-return over high-return and high-risk strategies (Mendola, 2007; Nielsen and Zeller, 2013; Dercon, 1996; Lybbert and McPeak, 2012; Morduch, 1994; Rosenzweig and Binswanger, 1993). Instead, individual consumers are price risk-loving for a specific commodity when the budget share of that commodity is not too large, given the quasi-convexity of their indirect utility function (Deschamps, 1973; Hanoch, 1977; Newbery and Stiglitz, 1979; Turnovsky et al., 1980; Finkelshtain and Chalfant, 1991; Barrett, 1996; Bellemare et al., 2013b).
In our model we present a farm household model where each household h faces in each period t the following optimization problem of its direct utility function with respect to non separable production and consumption decisions on crop j (Singh et al., 1986; Bellemare et al., 2013b)[4]:

[2] There is some evidence that a change in risk aversion occurs over the life cycle, but it was shown by some authors that the trend of its variation depends on the socioeconomic group of the individuals (Dohmen et al., 2011; Cohen and Einav, 2007; Schurer, 2015). In particular, risk aversion soars for all socioeconomic groups from late adolescence until the agents reach the middle age, afterwards it decreases for individuals, who are in a good socioeconomic position, while it continues to increase with age - at the same rate as observed before middle age - for the more disadvantaged people (Schurer, 2015).

[3] For a more technical reference see Mas-Colell et al. (1995).

[4] In order to keep simple the notation, the index h is omitted in the mathematical derivation, but it should be always

$$\max E[U(\sum_j MS_{jt})] \tag{1}$$

subject to

$$\sum_j P^P_{jt} MS_{jt} = E[Y_t(A_{ijt})] \tag{2}$$

where MS_{jt} is the marketable surplus, i.e. the difference between quantity harvested and quantity consumed of the crop j, P^P_{jt} is the farm gate price, Y_t is the full income and A_{ijt} is the price risk aversion coefficient, given the correlation between the prices of the crop i and j. The equal sign in the budget constraint equation 2 is due to the fact that all off-farm activities are disregarded in this empirical model. The home consumption of self-produced food is not included in the model too, because the focus is on market price risk aversion.

Through Epstein (1975)'s duality result, I can derive the maximization of indirect utility function which is equivalent to the maximization of the direct one, as follows[5]:

$$\max E[V(P^P_{jt}, Y_t)] \tag{3}$$

subject to

$$\sum_j P^P_{jt} MS_{jt} = E[Y_t(A_{ijt})] \tag{4}$$

where MS_{jt}, P^P_{jt}, Y_t and A_{ijt} are the same variables of the equations 1 and 2.
Optimization of indirect utility function provides advantages over direct one, since it is homogenous of degree zero in prices and income and measurement unit for prices and income do not matter (Bellemare et al., 2013b).
Note that precautionary saving is omitted in this empirical model, which uses average annual values net of the shift of intertemporal food consumption from one month to the other. Indeed, the bulk of storage activity for food security purposes is carried out by private economic agents on intra-annual basis, because inter-annual storage activity is expensive and carried out for speculative purposes as well as several crops are highly perishable: they are bought not long before their actual consumption and their harvest is sold within a reasonable interval of time before crops perish (Thomson and Metz, 1999, 65-66) (FAO, 1997).

I assume that equation 1 can be represented by a Cobb-Douglas direct utility function over N crops:

$$U(MS_{jt}) = \prod_{j=1}^{N} MS_{jt}^{\alpha_j} \tag{5}$$

given $\sum \alpha_j = 1$.

Along the lines of the derivation of the model entailed in the Annex II, the indirect utility

regarded that the optimization is carried out at household level.

[5] Optimization of direct utility, equation 1, consists in maximization of consumption of goods given income and prices, while optimization of indirect utility, equation 3, minimizes total expenditure with fixed prices given a certain target utility level (Mas-Colell et al., 1995, 50-60). Indirect utility function can be obtained by replacing optimal marketable surplus MS^*_{jt} into direct utility function (Mas-Colell et al., 1995, 50-60)

function for N crops is the following one:

$$\ln V(P^P_{jt}, Y_t, A_{ijt}) = \alpha_j \ln \alpha_j - \alpha_j \ln P^P_{jt} + \ln Y_t + \ln A_{ijt}$$
$$\forall j \qquad \sum_i^N \alpha_j = 1 \tag{6}$$

In this approach, the price risk aversion coefficient A_{ijt} plays a relevant role. A_{ijt} takes into account that some families are both producers and consumers of crops and was developed by Turnovsky et al. (1980), Barrett (1996) and Bellemare et al. (2013b):

$$A_{ijt} = \frac{MS_{jt}}{P^C_j}\left[\beta_{jt}\left(\eta_j - R\right) + \epsilon_{ij}\right] \tag{7}$$

where MS_{jt} is the marketable surplus of commodity j, P^C_j the consumer market price of commodity j, $\beta_{jt} = \frac{P^P_{jt} MS_{jt}}{Y_t}$ is the budget share of marketable surplus of commodity j, η_j the income elasticity of marketable surplus of commodity j, R the Arrow-Pratt coefficient of risk aversion as well as ϵ_{ij} the cross-price elasticity between the marketable surplus of the crops i and j.

The derivation of the price risk aversion matrix A_{ijt} is entailed in the annex I.

The geometric meaning of A_{ijt} is similar to the one of the Arrow-Pratt coefficient of risk aversion. Specifically, A_{ijt} indicates the concavity of the utility function: if A_{ijt} is negative, the farm household is price risk averse, since the minus sign provides evidence that the utility function is concave down; if $A_{ijt} = 0$ the household is price risk-neutral; if A_{ijt} is positive, the farm household is risk-loving, since the plus sign provides evidence that the utility function is convex. The components of A_{ijt} have the following interpretation: the marketable surplus MS_{jt} or the share of the sale revenues over the household income β_{jt} are positively correlated with the A_{ijt}, because the larger β_{jt} and MS_{jt}, the larger is the loss of the farmer household if an adverse price shock occurs. $(\eta_j - R)$ is an adjustment factor for the marketable surplus MS_{jt}, which deducts the psychological risk preferences proxied by the Arrow-Pratt risk aversion coefficient from η_j, the income elasticity of marketable surplus. Namely, $(\eta_j - R)$ represents the elasticity of the utility function due to the variations in the marketable surplus net of the changes in the risk psychological preferences. P^C_j is negatively correlated with A_{ijt}, because low consumer market prices P^C_j provide an alternative to sale revenues for farm households to obtain enough calories from the market, in case of adverse producer price shock. Finally, the cross-price elasticity ϵ_{ij} is positively correlated with A_{ijt}, because a high level of crop cross-correlation reduces the efficacy of any farm household diversification strategy.

The empirical strategy

The aim of the empirical analysis is to investigate whether the household price risk aversion coefficient is changing over time and then how time-varying price risk aversion affects the household food consumption pattern. This study provides an original contribution with respect to Bellemare et al. (2013b), because the empirical analysis is microfounded and the price risk aversion parameter is allowed to change over time. To this end, the following empirical regression, which is derived from the above micro model, is used for estimation:

$$\ln DEC = c - \alpha_j \ln P_{jt}^P + \ln e_t + \ln \widehat{A_{ijt}} \tag{8}$$

where the log of the indicator of dietary energy consumption ($lnDEC$), i.e. the amount of calories a representative farm household is assuming during the year, is employed as empirical counterpart of the indirect utility function (Ramasawmy, 2012, 17), $\widehat{A_{ijt}}$ is the estimated household price risk aversion (see below), e_t is the total expenditure, which proxies for the full income Y_t of the equation 6.

To control for possible sources of endogeneity between price risk aversion coefficient A_{ijt}, and dietary energy consumption, DEC (e.g., it is possible that households with higher level of DEC, i.e. richer in terms of calories consumption, are less risk-averse toward food shortfall), the price risk aversion coefficient A_{ijt} is not directly introduced as explanatory variable in the equation 8. Rather, a 2SLS approach is applied by first instrumenting the risk aversion parameter ($\widehat{A_{ijt}}$) through a first stage regression, equation 9, and then including it as explanatory variable in the equation 8.
In order to instrument $\widehat{A_{ijt}}$, the following first-stage equation is estimated:

$$\ln \widehat{A_{ijt}} = \gamma_j \ln P_{j,t-1}^C + \ln H + W_{1112} + \nu \tag{9}$$

where $\widehat{A_{ijt}}$ is the empirical counterpart of the price risk aversion parameter introduced by Bellemare et al. (2013b), $P_{j,t-1}^C$ is the lagged value of the market price of the crop j, H a set of household control variables and W_{1112} is equal to 1 if the observation refers to the survey wave period 2011-2012, 0 if it refers to the waves 2009-2010 or 2010-2011. ν the error term.
The lagged value of the market prices $P_{j,t-1}^C$ is employed to control for the contemporaneous endogeneity between the market prices, $P_{j,t}^C$, and the price risk aversion coefficient, A_{ijt}.
Further instruments are the market prices of plantains, beans, cassava, maize, rice and sweet potatoes as well as the household size, the number of children and daughters, the literacy indicator, the attendance of the school, the gender and age of the household head (Dohmen et al., 2011; Moscardi and Janvry, 1977; Nielsen and Zeller, 2013) (D'Souza and Tandon, 2015, 14). The literacy of the household heads is proxied by a dummy, which is equal to 1, if they are literate, 0 otherwise. School attendance is defined by two dummy variables: the first one refers to primary school, which is equal to 1 if the household head attended primary school, 0 otherwise; the second dummy concerns the attendance of secondary school, which is equal to 1 if the household head attended secondary school, 0 otherwise. The dummy variable for the gender of the household heads is equal to 1 if they are male, 0 if they are female.
The selection of instruments is based on a far-reaching literature and the relevance of the instruments has been tested by various techniques: microeconomic models, econometric regression-based techniques, lottery-based, game-theoretical experiments, etc. (Dohmen et al., 2011; Moscardi and Janvry, 1977; Nielsen and Zeller, 2013; D'Souza and Tandon, 2015).
Take also into account that the equation 8 captures the impact of time-varying price risk aversion on household food consumption pattern, while the equation 9 allows to disentangle the variation of the price risk aversion coefficient over time and to understand which household features have

a major impact on the price risk aversion coefficient.

In this study, approaches of the previous literature are extended to detect the impact of these variables on the price risk aversion coefficient, which assesses the relationship between the underlying market conditions and the household behaviour towards risk (Bellemare et al., 2013b). To this end, survey wave dummy variables are also introduced to detect changes of the price risk aversion over time. The inclusion of such time dummy allows to disentangle whether there was some break in the risk aversion parameter during the time period of the survey.

Note that in this empirical framework farm gate price P_{jt}^{P} and market price P_{j}^{C} are included as two different variables, because they are assessed at the different levels of the value chain of the crop j. The difference between them depends on the structure of the value chain and can be due to several factors, like transport and transaction costs as well as market distorsions, which are not specifically addressed in this study (Muratori, 2016). As it can be seen in the graph 1, high volatility of food prices occurred between 2009 and 2012. This situation allows to assess the impact of very volatile prices on the behaviour of farm households and, in particular, to study the changes of their risk aversion parameter over time in a comprehensive fashion.

Be also aware that in the price risk aversion matrix A_{ijt} (Bellemare et al., 2013b), the Arrow Pratt coefficient of risk aversion, R, which proxies psychological risk preferences, is deducted. Therefore, A_{ijt} does not provide any information whether the household psychological risk preferences change over time after the occurrence of some price shocks. Nevertheless, it is possible to have an insight in the variations of the psychological risk preferences due to the occurence of price shocks, by analysing the residuals ν of the first-stage regression 9. Indeed, the residuals ν are the left-over, after the relationship between price risk aversion parameter A_{ijt} and a set of variables, which proxy the availability and efficiency of risk-bearing institutions, is estimated. Therefore, although the residuals ν entail much noise, they represent a rough indicator of the empirically estimated household psychological risk aversion, $\widehat{R}$, as well as they can be employed as dependent variable in the following regression, which is estimated within a fixed effect model:

$$\widehat{R} = H + W_{1112} \tag{10}$$

This approach allows to investigate whether the household psychological risk preferences, R change over time and which factors determine such a variation. The above described model includes both the behaviour of net sellers and net buyers. Nevertheless, it is likely that the behaviour of two groups of farm household is different after the occurrence of a price shock. To deal with this issue, the equation 9 is extended with a market position dummy variable, MP_{hjt}, which is equal to 1, if the farm household is a net seller of a given crop j, 0 otherwise:

$$\ln \widehat{A_{ijt}} = \gamma_j \ln P_{j,t-1}^{C} + \ln H + W_{1112} + MP_{hjt} \tag{11}$$

The equation 11 allows to disentangle whether there is difference in the reaction to price shocks between net seller and net buyer farm households.

Data

The approach is based on the data collected by the Ugandan Statistical Office and the World Bank team within the framework of the Living Standard Measurement Study (LSMS) (World Bank, 2015).

Such database applied to this method allows to draw consistent conclusions, which can be generalized to the population of Uganda, because its sampling design warrants representativeness at national and sub-national level (Himelein, 2012). Moreover, the database is integrated with data on calories intake of food, which are collected from International Network of Food Data Systems (FAO, 2015).

The panel database concerns households which consumed or produced the major staple crops in Uganda, like beans, cassava, maize, plantains, rice and sweet potatoes during three survey waves, taking into consideration the following years 2009-2010, 2010-2011 and 2011-2012.

Data were prepared to allow the estimation of the magnitude and the sign of the variables of interest. Due to the particular structure of the agricultural survey data, several sheets of the Living Standard Measurement Study were merged in order to obtain necessary information for the analysis.

The collected database provides information about consumption and production behaviour of 3284 households which harvested or consumed the above mentioned staple crops during the LSMS survey waves 2009-2010, 2010-2011 and 2011-2012 or at least in one of them.

This leads to the construction of two different databases, a balanced and an unbalanced panels which are both used for the analysis. In the unbalanced panel database all 3284 households are taken into account for the estimation, while the balanced one consists of 2491 households, since some observations are missing for one or two years.

In order to compute dietary energy consumption (DEC), calories intake for kilogram is taken from the International Network of Food Data Systems (FAO, 2015). In particular, I distinguished calories data between the different food items and their processing status, for instance if they are dry or fresh.

Another important issue with respect to data preparation concerns the conversion of non-standard measurement units, like cups, buckets, etc., widely used in the context of rural agriculture, into kilograms. Conversion factors were taken from (World Bank, 2011) and (Woittiez et al., 2013).

The reported farm gate and market prices, given for the specific measurement units provided by the respondents (for instance, a sack or a cup), were converted in prices per kilogram of crop.

If market prices were missing, they were replaced by the average market price of the specific crop. Instead, farm gate prices were not imputed and therefore there are many missing values for this variable. The reason of the different approach with respect to the missing values of the two prices is due to the fact that the farm gate price received by the farmers can vary in a significant way across regions, along seasons and due to the market access available to the farm household. Farmers cannot easily switch from one buyer to the other, because they are quite dispersed across the country and live often in remote areas. On the contrary, consumers, mostly living in urban environment, can more easily switch from a seller to the other in order to obtain a better price for kilogram of crop, given the same quality level of the purchased product.

The kilogram-equivalent quantities and the calories intake for kilogram are also used for the

computation of the yearly dietary energy consumption.
Moreover, information about actual income earned by the household members is difficult to obtain because of the reticence of respondents to declare such data and the prevalence of informal business activities. In order to have a reliable estimate of the household income, the expenditure approach is followed. Household financial capability is based on total expenditures, i.e. all expenses for consumption, non-durable, durable goods and for taxes and other fees. Such outlays are reported for different time horizons and therefore all of them are converted on a 365-days basis to get total yearly expenditures.
In order to develop comparison some controls were introduced. Such dummies indicate whether the household head is male, whether he or she is literate and attended primary or secondary school. The number of children (members younger than 18 years) in each household and their gender, household size and the age of the household head were also computed and included in the panel database.
Following the equation 7, all parameters for the calculation of the the price risk aversion coefficient A_{ijt} were separately computed.
By merging the household production and consumption database for the above mentioned crops and taking the difference between the yearly kilogram-equivalent harvested and the kilogram-equivalent consumed quantity, the yearly marketable surplus for each crop and household was obtained.
If quantity produced and consumed of a given crop were missing and then the marketable surplus could not be computed, it is not straightforward, whether the missing values are due to zero production and consumption or whether the respondent was not able to reply to the question. To avoid to spoil the dataset, in this case missing values of marketable surplus were not replaced.
The budget share of marketable surplus of commodity $\beta_{jt} = \frac{P_{jt}^P M_j}{Y_t}$ was also added to the database. The price risk aversion matrix evaluates the impact of the underlying market conditions on the household behaviour towards risk: in particular, it includes the amount of the marketable surplus, the value of the market prices, the budget share of the revenues from the sale of each commodity, the cross-price elasticity between the marketable surplus of different commodities, the income elasticity of marketable surplus and the Arrow-Pratt coefficient of relative risk aversion (Turnovsky et al., 1980) (Bellemare et al., 2013b).
The Arrow-Pratt coefficient of relative risk aversion is estimated from the data, by computing the second derivative of the dietary energy consumption with respect to the quantity of consumed crops (Arrow, 1971). The Arrow-Pratt coefficient is estimated by a two-steps static panel model: in the second stage the quantity of consumed crops is regressed on the fitted value of DEC, derived from the first stage computation. The choice of the fixed or random effects strategy is based upon the results of the Hausman test. Result of the estimation with respect to the Arrow-Pratt coefficient of relative risk aversion is 1.0277, which is within the range of credible values found in the literature (Bellemare et al., 2013b, 886) (Friend and Blume, 1975) (Chavas and Holt, 1990) (Hansen and Singleton, 1983) (Saha et al., 1994).
In this empirical analysis the utility function $V(P_{jt}^P, Y_t, A_{ijt})$ is given by the dietary energy consumption (DEC). This function turns quantity of crops consumed into calories available to the household.
Besides, a specific database is created to estimate the income and cross-price elasticity of the marketable surplus of each commodity. The elasticities are computed through a static panel

model, which used the results of the Hausman test also in this case.
With all information included in the database, the price risk aversion coefficient A_{ijt} is computed for each combination of household, crop and year. Then, this parameter was added to the database.
Since endogeneity between risk aversion coefficient and dietary energy consumption was detected in several specification tests, a set of instruments to be employed in the IV regression was derived from the microfounded model or taken from the literature: some of the instrumental variables are the market prices of plantains, beans, cassava, maize, rice and sweet potatoes. Moreover, there are some instruments which describe the main household features like the household size, the number of children and daughters, the literacy indicator, the attendance of the school, the gender and age of the household head (Dohmen et al., 2011), (Moscardi and Janvry, 1977) (Nielsen and Zeller, 2013) (D'Souza and Tandon, 2015, 14).
The literacy of the household heads is proxied by a dummy, which is equal to 1, if they are literate, 0 otherwise. The attendance of the school is defined by two dummy variables: the first one refers to primary school, which is equal to 1 if the household head attended primary school, 0 otherwise; the second dummy concerns the attendance of secondary school, which is equal to 1 if the household head attended secondary school, 0 otherwise.
Moreover, the dummy variable for the gender of the household heads is equal to 1 if they are male, 0 if they are female. Finally, a survey wave dummy variable was introduced, which assumes value 1 over the 2011-2012 period, and value 0 if the wave is 2009-2010 or 2010-2011. The inclusion of such time dummy allows to disentangle whether there was some break in the risk aversion parameter during the time period of the survey. A summary of the dummy variables is provided in table 2.
The selection of the instruments is based on a far-reaching literature: indeed, several articles verify the relevance of the above mentioned variables as determinants of risk preferences, by applying microeconomic models, econometric regression-based techniques, lottery-based and game-theoretical experiments (Dohmen et al., 2011), (Moscardi and Janvry, 1977) (Nielsen and Zeller, 2013) (D'Souza and Tandon, 2015).
All variables other than the dummy indicators were converted in logarithms, so that the coefficients of the all estimated regressions can be directly interpreted as elasticities.

Estimation Results

Specification tests

The most appropriate econometric technique for the estimation has been chosen after having conducted several specification tests.
With respect to the alternative between an OLS and an IV estimator is assessed through a set of Lagrange Multiplier tests. The tests of Breusch and Pagan, Honda, King and Wu, Gourieroux, Holly and Monfort follow a normal or chi-square asymptotic distribution under the null hypothesis that individual and time effects are not significant (Breusch and Pagan, 1980) (Gouriéroux et al., 1982) (Honda, 1985) (King and Wu, 1997).
If the p-value of these tests is smaller than 5%, the null hypothesis is rejected and the IV estimator is consistent, since time and individual effects are significant.

The output of these tests is reported in the table 3. The tests by Breusch and Pagan (1980), Gouriéroux et al. (1982) and Honda (1985) reject the null hypothesis, while the test by King and Wu (1997) is not able to reject it.
Moreover, a Wu-Hausman test between the IV and the OLS estimator is conducted. In this case, the null hypothesis is that both instrumental variable and OLS estimators are consistent, but OLS is more efficient against the alternative hypothesis that the OLS estimator is inconsistent, while the instrumental variable estimator is consistent (Hausman, 1978) (Wu, 1973).
The Wu-Hausman test reported in table 4 rejects the null hypothesis and therefore the instrumental variable model is estimated.
In order to overcome the simultaneity bias between market price and risk aversion in the first stage regression, the first lag of the market price variables is used. The introduction of the one lag-price variables allows to introduce some dynamics in the model, taking into account that households do not change immediately their behaviour and need one period to adjust their expectations to the new prevailing economic environment.
The instrumental variables are tested in order to verify whether they satisfy the inclusion and exclusion restrictions.
Sargan-Hansen test for overidentifying restrictions allows to assess the exclusion restriction, i.e. the joint exogeneity of the instruments. A necessary requirement to apply the test is the overidentification of the model, it means that the number of instruments has to be larger than the number of the endogenous variables. The null hypothesis of the Hansen-Sargan test is that the instruments are jointly exogenous against the alternative that at least one of them is endogenous. If the p-value is smaller than 5%, the null hypothesis is rejected (Sargan, 1958) (Hansen, 1982). As shown in table 6, the null hypothesis of joint exogeneity of all above mentioned instruments was rejected both for the balanced and unbalanced panel.
If the null hypothesis is rejected, it is not possibile to identify which instrument is endogenous, unless all instruments are excluded one by one from the regression and the test is re-run.
By excluding one by one the instruments from the test, it was possible to conclude that the market price of plantains is endogenous. Therefore, this variable was removed and a second Hansen-Sargan test was re-run. In this case, the test was not able to reject the null hypothesis of joint exogeneity of all instruments as shown in table 6.
After evaluating the exogeneity restriction, the relevance of this reduced set of instruments is tested. For this purpose I used the F-test for weak instruments in the first-stage regression is computed (Stock and Yogo, 2005).
As indicated in the table 7, all instrumental variables are relevant and satisfies the inclusion restriction.
Furthermore, the IV model on panel data can be run with fixed or random effect.
In order to select between the two alternatives, the Hausman test between random and fixed effect estimators was computed. In this test, the null hypothesis is that both random and fixed effect estimators are consistent, but the random effect is more efficient against the alternative that random effect is inconsistent (Hausman, 1978) (Wu, 1973).
As indicated in table 5, the Hausman tests confirms that the random effect estimator is not consistent and then a fixed effect estimator should be computed. Only in the case of the balanced panel, the Hausman test is not able to reject the null hypothesis. Therefore, for completeness' sake both the random and fixed effect models are estimated only for balanced panel and compared

with each other.

Estimated models

Several instrumental variable fixed and random effects models are estimated, because endogeneity between the risk aversion parameter and the dietary energy consumption was detected by the specification tests.
Although the Wu-Hausman test provides evidence that there is some endogeneity, a panel FGLS is also estimated as benchmark model and compared with the IV models. This comparison allows to assess the relevance of endogeneity in the dataset.
The FGLS is an extension of the OLS model: both the FGLS and the OLS approaches do not take into account endogeneity, but the FLGS is more robust than the OLS against heteroschedasticity and autocorrelation of the error term (Wooldridge, 2002) (Baltagi, 2008).
All results of the FGLS, fixed and random effect models are reported in tables 8, 9 and 10. The conclusion of the FGLS model is that all coefficients - apart the one of the farm gate price of rice - are highly significant as shown in table 8: the most important factors for the determination of the dietary energy consumption of the households are their risk aversion parameter and their income. The farm gate prices of the regarded crops play also an important, but smaller role on the level of dietary energy consumption of the households. Nevertheless, the results of the FGLS are not trustworthy, because this model disregards the endogeneity between price risk aversion coefficient A_{ijt} and dietary energy consumption, DEC, which exists in the data.
In particular, it is possible that households with higher level of DEC, i.e. richer in terms of calories consumption, are less risk-averse toward food shortfall.
Both the Wu-Hausman test and the results of the two-step IV panel models in tables 9 and 10 confirm that the endogeneity problem is a serious issue in the estimation of the above mentioned empirical approach. Given the joint exogeneity and high relevance of the instruments employed, the results of the IV panel models in tables 9 and 10 are indeed more reliable.
From the second stage IV regression in table 9, it is possibile to see that only the farm gate prices for beans and rice, the income as well as the risk aversion parameter are significant.
The IV panel models confirm that the income and the risk aversion parameter of the households are the most important factors in the determination of the household dietary energy consumption. The coefficient of the income lies between 0.64 and 0.56 and it is significant at 5% in all cases, while the one of the risk aversion parameter lies between 0.45 and 0.51 and significant at 0.01%.
The relevance of the estimates of the farm gate prices is more ambiguous. The coefficient of the farm gate price of beans is significant at 0.01 % in the random effect model and at 10 % in the fixed effect model. Instead, the estimate of the farm gate price of rice is significant at 5% only in the fixed effect model.
In general, the estimated coefficients of the IV panel models are larger in absolute value than the ones from the panel FGLS regression. This suggests that the endogeneity of the model leads to a downward bias, i.e. the explanatory are negatively correlated with the error term.
The introduction of the instrumental variables to control for endogeneity make a striking changes in the estimates of farm gate prices. While all farm gate prices - apart the one of rice - are highly significant in the FGLS regression, in the panel IV model only the coefficient for the rice farm

gate price is significant at 5 % and the relevance of the farm gate price of beans is ambiguous. Moreover, the estimate of the elasticity of the farm gate price of rice is large in magnitude, i.e. it amounts to 0.5.

The second-stage IV regression confirms the hypothesis, that income and dietary energy consumption are positively correlated, it means that the richer a household, the larger its consumption of calories will be.

The farm gate price for rice is therefore negatively correlated with the dietary energy consumption. It means that households reduce their dietary energy consumption, if the farm gate price of rice increases. Farm households give up consumption of rice, if they think that they can sell it on the market at high prices.

Farm households prefer to increase their income instead of directly consuming the harvested rice, because the reduction of dietary energy consumption derived from the giving up the rice harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained. Indeed, the elasticity of DEC with the respect to income is much higher in absolute value than the one of DEC with respect to the rice farm gate price. Since rice is a crop with large market potential, which is facing an increasing demand mostly by urban households, in this way farmers make sure their food security in the medium term.

This outcome is also confirmed by the fact, that risk aversion parameter is positively correlated with the dietary energy consumption and highly significant.

While rice contributed to the caloric intake of urban households, which seem to prefer it over other food items, it generated income for rural households, which were so able to purchase more traditional crops like cassava, plantains, beans, etc. on the market and improve their food security.

Such interpretation seems consistent with the evolution of the rice market in Uganda. Indeed, rice does not belong to the traditional staple crops in Uganda both for consumers and producers, but its production and consumption soared in a significant way in the last few decades (Ahmed, 2012) (Kikuchi et al., 2013).

In particular, between 2006 and 2011 rice was the crop, the export of which grew at most with an annual growth rate of 20.49%. Moreover, it was the second fastest growing in production after cocoa beans with an annual growth rate between 2006 and 2011 of 8.63% (Kikuchi et al., 2013, 2).

This change of trend is due to the fact that in the early 2000s a massive campaign was launched by the Africa Rice Center, the West African Rice Development Association, to promote rice production and consumption (Kikuchi et al., 2013, 2). In 2008 the Government of Uganda released the Uganda National Rice Development Strategy, by stressing that the rice is the key to food security and poverty reduction in Uganda. In the following years a significant effort was made to train farmers in rice cultivation (Kikuchi et al., 2013, 2).

The farm gate price of beans is also negatively correlated with the household dietary energy consumption, but the estimates of its coefficient are not very reliable, because they are very unstable. These parameters are highly significant only in the random effect model, but their p-value is larger than the critical value of 5% in the fixed effect model. From this output some doubts can be cast on the relevance of beans for food security.

Indeed, the direct contribution of beans to caloric intake is very important for rural households, while its market potential and its ability to generate income for farm household is very limited.

Beans are a traditional crop, but more recently they have been socially regarded as an inferior good. Several Ugandan consumers consider them as the "poor man's meat" and they are not at ease preparing and eating them, because of the long cooking time needed and the discomfort due to the effects of flatulence (Kilimo Trust, 2012, 7). This opinion is mostly widespread within the urban households.
Moreover, the results of the model in table 9 are confirmed by the fact that beans production increased only by 2% in this period after a sharp decline in 2006, although population grew steadily between 2006 and 2010 (Kilimo Trust, 2012, 7-12).
The slightly increasing production was then used for self consumption of the producer households and export, although the income generating ability of this business is still very small. In particular, farm households consume 68% of the harvested beans, while the remaining 32% is split in two parts, one is sold to domestic consumers (12%), and the other one, which is exported (20%) to Kenya, South Sudan, Democratic Republic of Congo, Tanzania, Burundi, UK and USA (Kilimo Trust, 2012, 7-12).
Therefore, the little impact of beans farm gate price on dietary energy consumption are due to the fact that some farm households gave up their consumption to sell them to other rural household or for export. Nevertheless, the conclusions concerning the beans cannot be regarded as very strong, because the instability of the significance level of the estimates makes them not reliable.
All models are in log-log form, therefore the coefficient estimates can be interpreted as elasticities.
In particular, an increase by 1% of the risk aversion parameter leads to a surge by between 0.45% and 0.51% of the DEC: since the overall rise of the price risk aversion coefficient between 2009 and 2011 was about 21.5 % - after a large drop by 72.5 % between 2009 and 2010 and a positive recover in the following year - the increment of the yearly median dietary energy consumption in the analysed period lies within the range of 47,522 and 53,860 calories for each household.
Instead, if the household income grows by 1%, the DEC soars by betweeen 0.56% and 0.64%. Between 2009 and 2011 the household income rose by 14 %, which corresponds to an increase of 267,000 UGX. Such an income variation implies a surge of the median yearly dietary energy consumption between 38,500 and 44,000 calories for each household.
Among the analysed crops, the most relevant one in terms of DEC is rice. If the farm gate price of rice rises by 1%, the dietary energy consumption decreases by 0.5%.
The overall increase of the rice farm gate price between 2009 and 2011 was about 11% - after a very high spike in 2010 and a reduction in the following year - this rice price change implies a reduction of the household dietary energy consumption by 5.5%, which corresponds to a yearly median decrease of about 27,000 calories for each household.
The instruments, which were proved as exogenous and relevant, were used in the first stage regression to control for the endogeneity of the risk aversion parameter in the second-stage regression. Therefore, from the first stage IV regression, it is possible to see the impact of the instruments on the endogenous variable, the risk aversion parameter.
In order to overcome the simultaneity bias between market price and risk aversion in the first stage regression, the first lag of the price variables is used. The introduction of the one lag-price variables allows to introduce some dynamics in the model, taking into account that households do not change immediately their behaviour and need one period to adjust their expectations to

the new prevailing economic environment.
As shown in the results in table 10, only the market prices of cassava and sweet potatoes are significant in the first-stage IV regression. The coefficient of the market price of cassava is -0.13 and significant at 0.1%, while the one of the market price of sweet potatoes is 0.048 and significant at 5%. The different sign of the two market prices suggests a different reaction by the households in building up their expectation with respect to the variations of the two above mentioned prices.
It is noteworthy that in the first stage regression the elasticity of the risk aversion parameter with respect to the cassava market price is both larger in magnitude and more significant that the one of risk aversion parameter with respect to the market price of sweet potatoes.
Given the different magnitude of the two estimates, it is possible to conclude that their difference is negative and that the comprehensive effect of increasing market prices is the reduction of the risk aversion parameter of the farm households.
In spite of this general conclusion, it is valuable to investigate the reasons of the difference of signs between the coefficients of market price of cassava and sweet potatoes.
Both cassava and sweet potatoes represent an important contribution to the diet of Ugandan households, but they are dissimilar in terms of their cultivation properties, post-harvest preservation features and their marketing potential (Haggblade and Dewina, 2010, 2-4).
Firstly, cassava is very tolerant to drought and arid weather, while sweet potatoes are not so. Therefore, cassava is grown as a form of insurance against drought and the failure of other staple crops. Moreover, cassava can be stored in the ground for longer period and harvested as needed, while sweet potatoes are very perishable (Haggblade and Dewina, 2010, 2-4).
Cassava is produced by the farm households for their own consumption, but an increasing share of the harvest is sold on the market. Nevertheless, cassava is mostly sold on domestic markets within Uganda, because the high water content makes very difficult to trade this crop in large volumes across international borders. On the contrary, sweet potatoes are largely a subsistence crop with little commercialization due to their perishability and their low value-to-bulk ratio (Haggblade and Dewina, 2010, 2-4). The difference among the signs of the coefficients of cassava and sweet potatoes is based upon the discrepancy between the expectations built up by the farm households concerning the farm gate and market prices of the two crops at time t.
High market prices in the period t-1 induce the expectation in the farm households that the market price in period t will be high as well. High market prices at time t can have two major implications on the welfare of the households at time t. On the one hand, high market prices at the time t imply high farm gate prices at the same time, everything else equal. On the other hand, high market prices at the time t make more expensive the purchase of crops by the consumers at the same time t.
For farm households the decision-making process is more straightforward, because the immediate overall effect on them is definitively positive, because these households do not need to purchase staple crops on the market.
Concerning the functioning of this mechanism the difference between cassava and sweet potatoes can be highlighted. While cassava has a relevant marketing potential and high farm gate prices increase the potential income and then the food security of the farm household, the marketing potential of sweet potatoes is very limited and the above outlined relation between high market prices at time t-1 and risk aversion parameter at time t does not work properly.
Since farm households are well aware that the production of sweet potatoes is not able to gen-

erate a relevant income to them, the expectation that the market price of sweet potatoes will be high at the time t increases slightly the risk aversion of the farm households. Indeed, high market prices of sweet potatoes could put at risk the household food security, because they make more expensive to purchase enough quantity of this food at time t, if all other sown crops fail.
On the contrary, the market prices of beans, rice and maize play no role in the determination of the risk aversion parameter. The reasons of the limited relevance of the crop market prices other than the ones of cassava and sweet potatoes is due to the specific features of the market of beans, rice and maize.
Indeed, beans are important for the consumption of the producers, but they are very little traded. Their price is also very volatile from one year to the next, therefore it cannot be used for forecasting next year prices (Haggblade and Dewina, 2010, 8-9).
Instead, rice is not a traditional crop and it is mostly imported. Therefore, changes in its market price cannot lead to expectation of future higher profits for the farm households.
The fact, that the coefficient for maize market price is not significant, is puzzling, because maize can be easily dried, stored and sold formally and informally for cash domestically and across the Uganda-Kenya border (Haggblade and Dewina, 2010, 4). The commercial ties between Uganda and Kenya are very tight, because Uganda, which is self-sufficient in maize, exports a sizeable share of its maize production to Kenya. This strong link with Kenya leads to the fact that Ugandan maize domestic price is strongly influenced by the regional prices (Haggblade and Dewina, 2010, 7-8).
Therefore, an explanation of the lack of sensitivity of the risk aversion parameter to the changes in maize market price could be the occurence of political turmoils in Kenya during 2007 and 2008, which increased the Kenyan demand of maize import from Uganda and then the domestic price in Uganda. Most of consumers reacted to the increasing market price of maize, by replacing it with some less price-sensitive rootcrops and perennials (Haggblade and Dewina, 2010, 7-8).
Because of this change of behaviour with respect to the consumers, the farm household probably regarded this increase of prices very transitory. Therefore, the elasticity of the risk aversion to the market price of maize is not significant.
Some household control variables are also important in the regression: the estimate of the literacy dummy is significant at 1%, while the one of the primary school dummy is significant at 5%. Both coefficients are large and similar in magnitude, but they have opposite signs. The ability to read and write increases the risk aversion of the households, because it makes the household heads aware of the existing risks. Instead, the attendance of the primary school provides the household heads confidence and skills to face some of these risk and leads to a reduction of the risk aversion parameter. The attendance of the secondary school does not have any impact on the risk aversion parameter.
The coefficient of the household size is -0.076 and the one of the age of the household head is -0.0022; both are significant at 5%. The larger the household the lower the risk aversion: it means that to live in the same household represents an insurance mechanism against the risk that one of the members is temporarily not able to make a living.
Similarly, an increasing age of the household head can be associated with more experience, which reduces the risk aversion parameter. Both the coefficient of household size and head age are very small and their effect is therefore of minor importance.
The coefficient of the dummy variable of the survey wave is 0.87, very large in magnitude and

significant at 0.1%. This results means that the household risk aversion grew much in 2011-2012 with the respect to the average of the former waves 2009-2010 and 2010-2011. Such conclusion gives a hint, that the risk aversion parameter is not constant over time and that househols can become more risk averse, if they face adverse market conditions in the previous periods. Indeed, very volatile food prices between 2009 and 2012 - as depicted by the graph 1 - induced such an outcome.
All other household control variables, like the number of children and daughters as well as the gender of the household head, play no role in the determination of the risk aversion parameter.

Since the price risk aversion matrix A_{ijt} does not provide any information whether the household psychological risk aversion changes over time after the occurence of some price shocks, the residuals ν of the first-stage regression 9 can be employed as proxy of the empirically estimated Arrow Pratt coefficient of risk aversion, $\widehat{R}$ in the fixed effect model, equation 10.

This approach allows to investigate whether the household psychological risk preferences, R change over time and which factors determine such a variation.
The results of the equation 10 for balanced and unbalanced panels are reported in table 13. The only two variables, which are significant at 5%, are the dummies for literacy and attendance of the primary school of the household head.
By comparing the results from the tables 10 and 13, it is possible to analyse the impact of household features on the psychological risk preferences. The difference in magnitude and significance of the coefficients of literacy dummies in the two tables suggests that the ability to read and write increases the psychological risk aversion of the household heads, because it makes them aware of the existing risks and at the same time induces them to be involved in more complex market transactions. In particular, the participation in more complex market transactions seems more significant that the psychological risk component.
Instead, the attendance of the primary school provides the household heads confidence and skills to face some of these risk and leads to a reduction of the risk aversion parameter. Since the difference in magnitude and significance between the coefficients of the dummies for attendance of the primary school in the tables 10 and 13 is negligible, it is possible to stress that such variable affects the psychological component of the household risk attitudes and not how households employ risk-bearing institutions.
The coefficients for household size and age of the household head are significant in the table 10 and not significant in the table 13: this difference implies that these factors do not change the psychological attitudes of the households, but the strategy how households employ risk-bearing institutions.
In particular, the larger the household size, the higher the probability that each individual can be insured by other household members against the risk not to be able to make a living in a given period of the year: in this regard, the household size represents a risk-sharing mechanism. At the same time, the age of the household head is an insurance mechanism, because the older the household head is, the higher his or her experience and the more likely he or she will able to manage in an efficient way the household and to make sure its livelihood. From the analysis of this paper it is possible to draw some important conclusions. Risk aversion parameter and income have a large and positive effect on food security.
The results of the econometric exercise confirm that farm household sell the crops with large market potential and consume the ones with limited selling opportunities.

This is the case of rice, which faces an increasing demand by urban households: since the market price for rice is high, its sale increases the food purchasing power of farm households and allow them to make sure their food security in the medium term.
Furthemore, risk aversion is negatively determined by the attendance of the primary school, which provides to the household head the skill needed to face some of the risks, and negatively driven by the prices of some crops like cassava, which induce the expectation of higher farm gate prices and then higher profit in the next period in the mind of the household heads.
Finally, the attendance of primary school by the household head reduces the psychological risk aversion, while all other household features have just an impact on the strategy how households employ the risk-bearing institutions. In particular, attendance of primary school provides confidence and skills to the household heads to face some of the challenges, which there are in a risky environment.
The above explained study investigates the farm household behaviour in the sample, without distinguishing between the actions of the net-seller and net-buyer households. These results are valid for the entire population of farm households, since the Uganda LSMS sampling design makes sure representativeness of the analysis at national and sub-national level (Himelein, 2012).
In order to disentangle the difference of behaviour between net seller and net buyer farm households, the empirical model was extended through a market position variable, which is equal to 1 if the household is a net seller, 0 otherwise.
Such an approach - entailed in the equation 11 - is able to focus on the behaviour of the sub-sample of the net sellers: the estimation results are reported in the tables 11 and .
While the coefficients of farm gate prices are negative in the second stage estimation of the full sample model as reported in the table 9, the same coefficients are positive in the net seller sub-sample model as shown in the table 11. In the latter estimation the significance and magnitude of the coefficients of farm gate prices are larger than in the former one.
In both models the coefficients for income and price risk aversion are positive: for the net sellers sub-sample the coefficient for income is smaller in magnitude, but more significant than in the full sample model. Instead, the coefficient for price risk aversion is smaller in magnitude and less significant in the net seller than in the full sample.
In the first step estimation there are only few differences between the full and net seller sample models: the coefficient for maize market price is not significant in the full sample model, while it becomes significant and negatively correlated with the price risk aversion for the net seller sub-sample. The other coefficients of consumer market prices have the same sign and similar magnitude in the net seller sub-group as in the full sample model.
The market participation dummy is not significant, while the survey wave 2011-2012 dummy is highly significant in both models and larger in magnitude for the net sellers sub-group than for the full sample. All other coefficients reported in the first-step estimation of the net seller sub-sample model keep the same significance and magnitude of the full sample estimation.
The results are as expected: indeed, the higher are the farm gate prices, the larger is the dietary energy consumption of the farm household. In addition, income is less relevant for net sellers than for the entire sample, because the former group harvest directly the crops on its land and therefore it needs less income for satisfying its dietary needs.
In the same fashion, price risk aversion is less important for the net seller dietary energy consumption, because they do not need to buy food on the market, if an adverse price shock occurs.

The household price risk aversion grew in 2011-2012 - with the respect to the average of the former waves 2009-2010 and 2010-2011 - both for the net seller sub-group and for the full sample. Such an increase is therefore indifferent to the fact that a farm household is a net seller or a net buyer, as the insignificance of the market participation dummy points out.
The result of the net seller subsample model provides evidence, that the net seller farm households become more risk averse, if they face adverse market conditions in the previous periods, although they need less income to purchase crops on the market than net buyer families.

Conclusions

This study was able to answer the research question whether the occurrence of exogenous shocks induces a change of price risk aversion over time and then how the time-varying risk aversion parameter affects production and consumption pattern by the farm households.
This research employs the risk aversion parameter introduced by (Bellemare et al., 2013b), which takes into account not just the household psychological risk attitudes, but also the market imperfections and availability of institutions which facilitate risk-bearing (Mendola, 2007) (Janvry et al., 1991). Nevertheless, unlike (Bellemare et al., 2013b) the paper develops a micro-founded empirical model, where the risk aversion parameter is allowed to change over time and not just across households. This empirical model is estimated within a two-stage structural approach, which controls for the endogeneity between dietary energy consumption and risk aversion.
The study assesses the behaviour of the farm households, which consume and produce crops at the same time. They are different from standard consumers, because their production and consumption decisions are interlinked. In particular, they can obtain profit by selling their agricultural output on the market or they can consume their own production (Taylor and Adelman, 2003). Unlike for standard consumers, budget for farm household is not fixed, but endogenously determined by positive farm profit component which is to be added to negative elasticity between price and consumer's demand (Mendola, 2007).
The results of the empirical analysis suggest that the risk aversion parameter is not constant over time and that households can become more risk averse, if they face adverse market conditions in the previous periods.
Given the endogeneity of the risk aversion parameter, a set of instruments were selected, which were proven to be exogenous and relevant.
Moreover, risk aversion parameter and income have a large and positive effect on food security. In particular, farm households make sure their food security in the medium term, since they sell the crops, which have market potential and provide to them additional income, and they consume the harvested crops without selling opportunities.
Indeed, the reduction of dietary energy consumption derived from the giving up the harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained. Indeed, the elasticity of DEC with the respect to income is much higher in absolute value than the one of DEC with respect to the rice farm gate price.
Instead, the determination of the risk aversion parameter is due to the building up of the expectations of the farm households. High market prices of crops like cassava, which have high marketing potential, at time t-1 induce the expectation that their market prices and then their farm gate prices will be high at time t as well. This expectation leads to the reduction of the risk

aversion parameter. On the contrary, high market prices of crops like sweet potatoes or beans with little commercialization has no strong impact on the risk aversion parameter.

Finally, the attendance of primary school by the household head reduces the psychological risk aversion, while all other household features have just an impact on the strategy how households employ the risk-bearing institutions. In particular, attendance of primary school reduces the pscyhological risk aversion of the households, because it provides confidence and skills to the household heads to face some of the challenges, which there are in a risky environment.

The conclusions of the analysis are valid for the entire sample of net seller and net buyer farm households. The risk aversion parameter changes over time both in the net seller sub-group and in full sample, but price risk aversion is less relevant for food security in the former than in the latter. Indeed, net sellers can more easily satisfy their dietary energy consumption, since they harvest directly the crops.

Knowledge of the importance of the exogenous shocks for the determination of the time-varying risk aversion parameter is useful for design of development policies. Finally, awareness of the key contribution of the harvest sale on the market to the farm household food security could stress the relevance of measures for the development of agricultural markets in developing countries

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Annex I

Mathematical derivation of the price risk aversion matrix

The following derivation is based on (Bellemare et al., 2013b) and (Bellemare et al., 2013a). Consider a farm household, which can at the same time consume and produce each commodity j and sell its marketable surplus MS_j, i.e. the difference between the harvested and the consumed amount of the crop j.
In each period the farm household maximizes its indirect utility function $V(p, y)$ subject to the budget constraint y, the level of which depends on the production and consumption decisions taken under uncertainty by the household in the previous period. Indeed, at any time the household optimizes its behaviour, by choosing the alternatives on the basis of a set of beliefs about the probability that the commodity prices p_j will reach a given level.
The price risk aversion matrix A_{ijt} is defined as the variation of the utility function $V(p, y)$ due to changes in the commodity prices p_j and p_i, net of the variation of the utility function $V(p, y)$ due to changes of the income y.

$$A_{hj} = \frac{V_{p_i pj}}{V_y} \tag{12}$$

where $V_{p_i pj}$ is the second derivative of the indirect utility function $V(p, y)$ with respect to the commodity prices p_j and p_i as well as V_y is the first derivative of the indirect utility function $V(p, y)$ with respect to the income y.
The equation 12 can be expressed in matrix form as well:

$$\mathbf{A} = \left(\frac{-1}{V_y}\right) \begin{bmatrix} V_{p_1 p1} & V_{p_1 p2} & \dots & \dots & V_{p_1 pk} \\ V_{p_2 p1} & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ V_{p_k p1} & \dots & \dots & \dots & V_{p_k pk} \end{bmatrix} \tag{13}$$

To derive an analytical form of A_{hj}, (Bellemare et al., 2013a) start from the indirect utility function $V(p, y)$.
The diagonal elements of the matrix in the equation 13 measure the direct impact of the variance of the prices on the household utility function, holding everything constant, while the off-diagonal elements represent the indirect effect of the covariance between a given price and the other prices on the household utility function, holding everything constant.
By applying the Roy's identity to the indirect utility function $V(p, y)$, it is possible to obtain the demand function MS_j:

$$MS_j = \frac{V_{p_j}}{V_y} \tag{14}$$

where V_{p_j} is $\frac{\partial V}{\partial p_j}$ the first derivative of the indirect utility function $V(p, y)$ with respect to the commodity price p_j. Similarly,

$$MS_i = \frac{V_{p_i}}{V_y} \longleftrightarrow V_{p_i} = MS_i V_y \tag{15}$$

By taking the second derivative of the equation 15 with respect to p_j and applying the product rule it is possible to obtain:

$$V_{p_i pj} = MS_i V_{yp_j} + V_y \left(\frac{\partial MS_i}{\partial p_j} \right) \tag{16}$$

Similarly, by taking the second derivative of the equation 15 with respect to y and applying the product rule it is possible to obtain:

$$V_{p_i y} = MS_i V_{yy} + V_y \left(\frac{\partial MS_i}{\partial y} \right) = V_{yp_i} \tag{17}$$

The last equality is the result of the Young's theorem on the symmetry of second derivatives, which can be applied because the following two requirements hold:

1. $V(p, y)$ is a differentiable function over (p, y)

2. Cross-partial derivatives of $V(p, y)$ exist and are continuous at all points on some open set

Replacing 17 in 16 the following equation is obtained:

$$V_{p_i pj} = MS_i \left[MS_j V_{yy} + V_y \left(\frac{\partial MS_j}{\partial y} \right) \right] + V_y \left(\frac{\partial MS_i}{\partial p_j} \right) \tag{18}$$

Then,

$$V_{p_i pj} = MS_i MS_j V_{yy} + MS_i V_y \left(\frac{\partial MS_j}{\partial y} \right) + V_y \left(\frac{\partial MS_i}{\partial p_j} \right) \tag{19}$$

After the first term in the right hand side of the equation 19 is multiplied by $\left(\frac{V_y y}{V_y y}\right)$, the second term by $\left(\frac{M_j y}{M_j y}\right)$ and the third term by $\left(\frac{M_j p_j}{M_j p_j}\right)$, it is possible to obtain:

$$V_{p_i pj} = MS_i MS_j V_{yy} \left(\frac{V_y y}{V_y y} \right) + MS_i V_y \left(\frac{\partial MS_j}{\partial y} \right) \left(\frac{M_j y}{M_j y} \right) + V_y \left(\frac{\partial MS_i}{\partial p_j} \right) \left(\frac{MS_j p_j}{MS_j p_j} \right) \tag{20}$$

Since the Arrow-Pratt risk aversion coefficient $R = -\left[V_{yy} \left(\frac{y}{V_y} \right) \right]$, the income elasticity of marketable surplus of commodity j, $\eta_j = \left[\left(\frac{\partial MS_j}{\partial y} \right) \left(\frac{y}{M_j} \right) \right]$, and the cross-price elasticity between the marketable surplus of the crops i and j, $\epsilon_{ij} = \left[\left(\frac{\partial MS_i}{\partial p_j} \right) \left(\frac{p_j}{MS_i} \right) \right]$, the equation 20 becomes:

$$V_{p_i pj} = -\left(\frac{MS_i MS_j R V_y}{y} \right) + \left(\frac{MS_i V_y \eta_j MS_j}{y} \right) + \left(\frac{MS_i V_y \epsilon_{ij}}{p_j} \right) \tag{21}$$

Then, MS_iV_y is multiplied out from the equation 21:

$$V_{p_ipj} = MS_iV_y \left[\left(\frac{-MS_jR}{y} \right) + \left(\frac{\eta_j MS_j}{y} \right) + \left(\frac{\epsilon_{ij}}{p_j} \right) \right] \tag{22}$$

After the first and the second term of the right hand side is multiplied by $\left(\frac{p_j}{p_j}\right)$ and by multiplying out $\left(\frac{1}{p_j}\right)$ it is possible to obtain:

$$V_{p_ipj} = \frac{MS_iV_y}{p_j} \left[-R\beta_j + \eta_j\beta_j + \epsilon_{ij} \right] \tag{23}$$

Then,

$$V_{p_ipj} = \frac{MS_iV_y}{p_j} \left[\beta_j \left(\eta_j - R \right) + \epsilon_{ij} \right] \tag{24}$$

By introducing the equation 24 in the equation 12, which defines the price risk aversion matrix A_{hj}, the following result is obtained:

$$A_{hj} = \frac{V_{p_ipj}}{V_y} = \frac{MS_i}{p_j} \left[\beta_j \left(\eta_j - R \right) + \epsilon_{ij} \right] \tag{25}$$

Annex II

Mathematical derivation of the model

For simplicity's sake, the optimization problem described in the equation 1 is solved for just two crops, Maize and Cassava, and the final result is later extended to the case of N crops[6]. Let's now assume that consumption can be described by a Cobb-Douglas function as follows:

$$U(MS_{MA,t}, MS_{CA,t}) = MS_{MA,t}^{\alpha} MS_{CA,t}^{1-\alpha} \tag{26}$$

where $MS_{MA,t}$ is the marketable surplus of maize, $MS_{CA,t}$ is the marketable surplus of cassava and α is the standard Cobb-Douglas parameter. Efficiency is reached when the following condition is satisfied:

$$\frac{P_{MA}^{P}}{P_{CA}^{P}} = MRS_{MS_{CA,t},MS_{MA,t}} \tag{27}$$

$$\frac{\partial U/\partial MS_{MA,t}}{\partial U/\partial MS_{CA,t}} = \frac{\alpha MS_{MA,t}^{\alpha-1} MS_{CA,t}^{1-\alpha}}{MS_{MA,t}^{\alpha}(1-\alpha) MS_{CA,t}^{1-\alpha-1}} \tag{28}$$

$$\frac{P_{MA}^{P}}{P_{CA}^{P}} = \frac{\alpha}{(1-\alpha)} \frac{MS_{CA,t}}{MS_{MA,t}} \tag{29}$$

$$MS_{CA,t} = \frac{(1-\alpha)}{\alpha} \frac{P_{MA}^{P}}{P_{CA}^{P}} MS_{MA,t} \tag{30}$$

Given the usual budget constraint:

$$P_{MA}^{P} MS_{MA,t} + P_{CA}^{P} MS_{CA,t} = Y_t \tag{31}$$

By plugging the equation 30 into equation 31, it is possible to obtain the following result:

$$P_{MA}^{P} MS_{MA,t} + P_{CA}^{P} \frac{(1-\alpha)}{\alpha} \frac{P_{MA}^{P}}{P_{CA}^{P}} MS_{MA,t} = Y_t \tag{32}$$

$$\left[1 + \left(\frac{(1-\alpha)}{\alpha}\right)\right] P_{MA}^{P} MS_{MA,t} = Y_t \tag{33}$$

$$\frac{1}{\alpha} P_{MA^P} MS_{MA,t} = Y_t \tag{34}$$

$$MS_{MA,t} = \frac{\alpha Y_t}{P_{MA}^{P}} \tag{35}$$

A similar exercise can be performed with respect to cassava in order to obtain indirect utility function:

$$MS_{CA,t} = \frac{(1-\alpha) Y_t}{P_{CA}^{P}} \tag{36}$$

It is possible to derive indirect utility function $V(P_{MA}^{C}, P_{CA}^{C}, Y_t, A_{hj})$ by introducing optimal

[6] For readers' convenience, the index h is omitted, but it should be taken into account that an observation for each household h is provided

marketable surplus, equations 35 and 36, into direct utility function, equation 26 (Mas-Colell et al., 1995, 50-60):

$$V(P^P_{MA}, P^P_{CA}, Y_t, A_{ijt}) = A_{ijt}\left[\frac{\alpha Y_t}{P^P_{MA}}\right]^{\alpha}\left[\frac{(1-\alpha)Y_t}{P^P_{CA}}\right]^{1-\alpha} \tag{37}$$

$$V(P^P_{MA}, P^P_{CA}, Y_t, A_{ijt}) = A_{ijt}Y\left(\frac{\alpha}{P^P_{MA}}\right)^{\alpha}\left(\frac{(1-\alpha)}{P^P_{CA}}\right)^{1-\alpha} \tag{38}$$

Then taking the logarithm the following equation yields:

$$\ln V(P^P_{MA}, P^C_{CA}, Y, A_{ijt}) = \ln\left[A_{ijt}Y\left(\frac{\alpha}{P^P_{MA}}\right)^{\alpha}\left(\frac{(1-\alpha)}{P^P_{CA}}\right)^{1-\alpha}\right] \tag{39}$$

$$\ln V(P^P_{MA}, P^P_{CA}, Y, A_{ijt}) = c - \alpha\ln P^P_{MA} - (1-\alpha)\ln P^P_{CA} + \ln Y + \ln A_{ijt} \tag{40}$$

where $c = \alpha\ln\alpha + (1-\alpha)\ln(1-\alpha)$

Finally, the equation 40 can be generalized to a farm household optimization problem over N crops, as shown in the equation 6.

Annex III

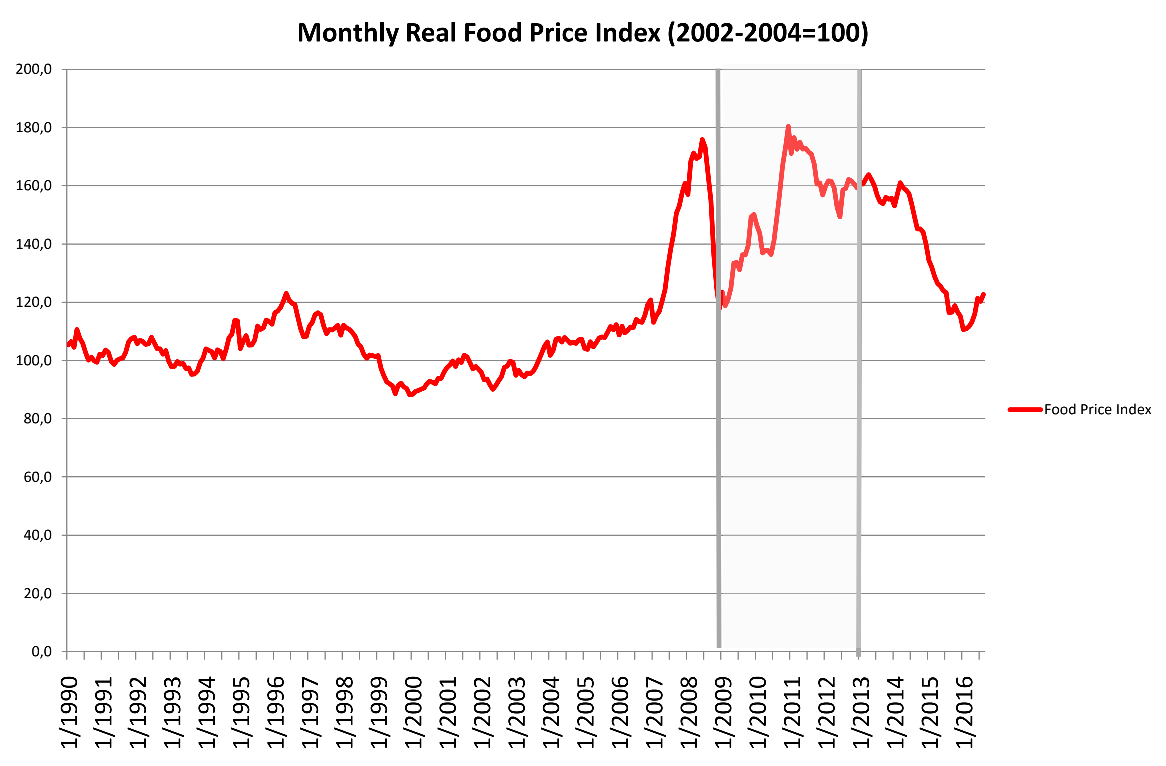

Figure 1: Monthly Real Food Price Index [2002-2004=100] (FAO, 2016)

Table 1: **Acronyms and Abbreviations**

Symbol	Meaning
UGX	Ugandan Shilling
MAFAP-FAO	Monitoring and Analysing Food and Agricultural Policies - Food and Agriculture Organization
IFAD	International Fund for Agricultural Development
WFP	World Food Programme
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
DEC	Dietary Energy Consumption
OLS	Ordinary Least Squares
FGLS	Feasible Generalized Least Square
IV	Instrumental Variable
U(.)	Direct utility function
V(.)	Indirect utility function
MS_{jt}	Marketable Surplus of the crop j
P_{jt}^{P}	Farm gate price of the crop j
P_{j}^{C}	Market price of the crop j
A_{ijt}	Price risk aversion parameter (Bellemare et al., 2013b)
$\beta_{jt} = \left(\frac{P_{jt}^{P} MS_{jt}}{Y_t}\right)$	Budget share of marketable surplus of commodity j
η_j	Income elasticity of marketable surplus of commodity j
R	Arrow-Pratt coefficient of relative risk aversion
ϵ_{ij}	Cross-price elasticity between the marketable surplus of the crops i and j
α_j	Cobb-Douglas parameter
Y_t	Full income (Becker, 1965)

Table 2: **Dummy variables**

Dummy variable	Meaning: Dummy= 1	Meaning: Dummy= 0
Literacy	Household head is literate	Household head **is not** literate
Attendance of the primary school	Household head attended primary school	Household head **did not** attend primary school
Attendance of secondary school	Household head attended secondary school	Household head **did not** attend secondary school
Gender	Male	Female
Survey Wave	2011-2012	2009-2010 or 2010-2011

Table 3: **Lagrange Multiplier test - two-ways effects**[a]

H_0 **individual and time effects are not significant**				
Test type	Breusch, Pagan	Honda	King and Wu	Gourieroux, Holly, and Monfort
Asymptotic distribution	Chi square	Normal	Normal	Chi square
Test statistics	722.63***	18.304***	-0.45717	721.67***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

[a] Plantains Market price was not included as instruments in the IV regression

Table 4: **Wu-Hausman test: Instrumental variable estimator vs. OLS**[a]

H_0 **Both instrumental variable and OLS estimators are consistent, but OLS is more efficient** H_a **OLS estimator is inconsistent, while instrumental variable estimator is consistent**		
Panel type	Unbalanced Panel	Balanced Panel
Test statistics	286.755***	244.92***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] Plantains Market price was not included as instruments in the IV regression

Table 5: **Hausman test: Fixed Effect vs. Random Effect**

H_0 **Both Random and Fixed Effect estimators are consistent, but Random Effect is more efficient** H_a **Random Effect estimators is inconsistent, while Fixed Effect is consistent**				
Panel type	Unbalanced Panel		Balanced Panel	
Estimation Methodology	IV Standard Panel	IV Panel GLS	IV Standard Panel	IV Panel GLS
Test statistics	21.874***	52.257***	4.4771	46.947***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: **Sargan-Hansen test: Overidentifying restrictions**[a]

	H_0 **Joint exogeneity of all instruments (joint validity of all overidentifying restrictions)** H_a **At least one istrument is endogenous**			
Panel type	Unbalanced Panel		Balanced Panel	
Instruments specification	with Plantains Market Price_{t-1}	without Plantains Market Price_{t-1}	without Plantains Market Price_{t-1}	without Plantains Market Price_{t-1}
Test statistics	275.53***	6.228	175.92***	7.236

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

[a] The instruments chosen are Beans Market price, Cassava Market price, Maize Market price, Rice Market price, Sweet potatoes Market price, Household size, Number Children, Number Sons, Number Daughters, Literacy (dummy), Attendance Any school (dummy), Attendance Secondary School (dummy), Head male, Head Age and Wave 2011-2012 (dummy). Plantains Market price was included in the first, but not in the second test.

Table 7: **Test for weak instruments**[a,b] **(Stock and Yogo, 2005)**

H_0: **Instruments are weak**		
Endogenous variables	Test statistics	
	Unbalanced Panel	Balanced Panel
Plantains Farm Gate Price	22.179***	16.514***
Beans Farm Gate Price	99.623***	85.747***
Cassava Farm Gate Price	421.557***	380.901***
Maize Farm Gate Price	124.821***	115.233***
Rice Farm Gate Price	33.535***	32.715***
Sweet potatoes Farm Gate Price	597.631***	554.695***
Income	189.561***	185.243***
Price Risk Aversion	57.707***	51.854***
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

[a] all variables are in natural logarithm and the farm gate price are expressed in Ugandan Shilling (UGX) per Kilogram

[b] Plantains Market price was not included as instruments in the IV regression

Table 8: **FGLS Regression**[a]

Independent variables	Dependent Variable: Dietary Energy Consumption	
	Unbalanced Panel	Balanced Panel
Plantains Farm Gate Price[b]	-0.051^{***}	-0.051^{***}
	(0.0125)	(0.0128)
Beans Farm Gate Price[b]	-0.047^{***}	-0.047^{***}
	(0.0078)	(0.008)
Cassava Farm Gate Price[b]	-0.073^{***}	-0.073^{***}
	(0.0078)	(0.008)
Maize Farm Gate Price[b]	-0.03^{***}	-0.03^{***}
	(0.009)	(0.009)
Rice Farm Gate Price[b]	-0.008	-0.008
	(0.021)	(0.022)
Sweet potatoes Farm Gate Price[b]	-0.072^{***}	-0.072^{***}
	(0.0083)	(0.0085)
Income	0.44^{***}	0.44^{***}
	(0.015)	(0.015)
Price Risk Aversion	0.18^{***}	0.18^{***}
	(0.015)	(0.015)
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a]: all variables are in natural logarithm and the farm gate price are expressed in Ugandan Shilling (UGX) per Kilogram

[b]: the coefficients of the farm gate prices are multiplied by (-1), following the derivation of the theoretical model in equation 6

Table 9: **Second Stage Instrumental Variable Regression**[a]
(Full sample: net sellers & net buyers)

Independent variables	Dependent Variable: Dietary Energy Consumption		
	Unbalanced Panel Fixed Effect	Balanced Panel Fixed Effect	Balanced Panel Random Effect
Plantains Farm Gate Price	-0.43	-0.43	0.051
	(0.42)	(0.42)	(0.28)
Beans Farm Gate Price	$-0.17^{\diamond}$	$-0.17^{\diamond}$	-0.44^{***}
	(0.09)	(0.09)	(0.12)
Cassava Farm Gate Price	-0.015	-0.015	0.13
	(0.049)	(0.049)	(0.12)
Maize Farm Gate Price	-0.123	-0.123	-0.052
	(0.127)	(0.127)	(0.123)
Rice Farm Gate Price	-0.50^{*}	-0.50^{*}	-0.122
	(0.195)	(0.195)	(0.52)
Sweet potatoes Farm Gate Price	-0.0477	-0.0477	-0.084
	(0.048)	(0.048)	(0.06)
Income	0.642^{*}	0.642^{*}	0.56^{*}
	(0.27)	(0.27)	(0.25)
Price Risk Aversion	0.45^{***}	0.45^{***}	0.51^{*}
	(0.133)	(0.133)	(0.21)
Intercept	Not included	Not included	-3.45
			3.195
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\diamond}p < 0.1$

[a]: all variables are in natural logarithm and the farm gate price are expressed in Ugandan Shilling (UGX) per Kilogram

Table 10: **First Stage Fixed Effect Instrumental Variable Regression**[a]
(Full sample: net sellers & net buyers)

Independent variables	Dependent Variable: Price Risk Aversion	
	Unbalanced Panel	Balanced Panel
Beans Market Price (t-1)	0.014 (0.021)	0.014 (0.021)
Cassava Market Price (t-1)	-0.13^{***} (0.024)	-0.13^{***} (0.024)
Maize Market Price (t-1)	-0.033 (0.021)	-0.033 (0.021)
Rice Market Price (t-1)	0.0125 (0.024)	0.0125 (0.024)
Sweet Potatoes Market Price (t-1)	0.048^{*} (0.024)	0.048^{*} (0.024)
Household Size	-0.076^{*} (0.036)	-0.076^{*} (0.036)
Number Children	0.023 (0.029)	0.023 (0.029)
Number Daughters	-0.041 (0.044)	-0.041 (0.044)
Literacy (dummy)	0.37^{**} (0.13)	0.37^{**} (0.13)
Attendance Primary School (dummy)	-0.32^{*} (0.14)	-0.32^{*} (0.14)
Attendance Secondary School (dummy)	-0.006 (0.11)	-0.006 (0.11)
Head Gender (Male=1)	0.133 (0.21)	0.133 (0.21)
Head Age	-0.0022^{*} (0.001)	-0.0022^{*} (0.001)
Wave 2011-2012 (dummy)	0.87^{***} (0.11)	0.87^{***} (0.11)
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $' p < 0.1$

[a]: all variables are in natural logarithm and the market prices are expressed in Ugandan Shilling (UGX) per Kilogram

Table 11: **Second Stage Fixed Effect Variable Regression**[a]

(Net seller sub-sample)

Independent variables	Dependent Variable: Dietary Energy Consumption	
	Unbalanced panel Fixed effect	Balanced panel Fixed effect
Plantains Farm Gate Price	0.044 (0.085)	0.043 (0.085)
Beans Farm Gate Price	0.32*** (0.084)	0.32*** (0.084)
Cassava Farm Gate Price	0.057 (0.047)	0.057 (0.047)
Maize Farm Gate Price	0.22* (0.087)	0.22* (0.087)
Rice Farm Gate Price	0.59** (0.19)	0.59** (0.19)
Sweet potatoes Farm Gate Price	0.088* (0.043)	0.088* (0.043)
Income	0.56*** (0.16)	0.56*** (0.16)
Price Risk aversion	0.30* (0.12)	0.30* (0.12)
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\diamond}p < 0.1$

[a]: all variables are in natural logarithm and the farm gate price are expressed in Ugandan Shilling (UGX) per Kilogram

Table 12: **First Stage Fixed Effect Variable Regression**[a]
(Net seller sub-sample)

Independent variables	Dependent Variable: Price Risk Aversion	
	Unbalanced Panel	Balanced Panel
Beans Market price (t-1)	0.012	0.012
	(0.021)	(0.021)
Cassava Market price (t-1)	−0.132***	-0.132***
	(0.024)	(0.024)
Maize Market price (t-1)	−0.043*	−0.043*
	(0.022)	(0.022)
Rice Market price (t-1)	0.015	0.015
	(0.024)	(0.024)
Sweet potatoes Market price (t-1)	0.049*	0.049*
	(0.024)	(0.024)
Household size	−0.085*	−0.085*
	(0.036)	(0.036)
Number Children	0.025	0.025
	(0.029)	(0.029)
Number Daughters	−0.039	−0.039
	(0.044)	(0.044)
Literacy (dummy)	0.360**	0.360**
	(0.128)	(0.128)
Attendance Primary School (dummy)	−0.366*	−0.366*
	(0.144)	(0.144)
Attendance Secondary School (dummy)	0.005	0.005
	(0.108)	(0.108)
Head Gender (Male=1)	0.177	0.177
	(0.211)	(0.211)
Head Age	−0.002*	−0.002*
	(0.001)	(0.001)
Wave 2011-2012 (dummy)	0.959***	0.959***
	(0.111)	(0.111)
Market Participation (Net Seller=1)	0.095	0.095
	(0.085)	(0.085)
Number observations	N=3284 households T= 1 - 3 time periods	N=2491 households T= 3 time periods

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{'}p < 0.1$

[a]: all variables are in natural logarithm and the market prices are expressed in Ugandan Shilling (UGX) per Kilogram

Table 13: **Psychological Risk Aversion Regression (Fixed Effect)**

Independent variables	**Dependent Variable: Psychological risk aversion**	
	Unbalanced Panel	Balanced Panel
Household children number: 1-5	0.02	0.01
	(0.12)	(0.13)
Household children number: 5-10	0.05	0.05
	(0.12)	(0.12)
Household children number: 10-15	-0.01	-0.01
	(0.22)	(0.22)
Household size: 1-10 members[a]	0.04	0.04
	(0.06)	(0.06)
Household size: 20-33 members[a]	-0.15	-0.15
	(0.21)	(0.21)
Household daughters number: 1-3[a]	0.00	0.00
	(0.06)	(0.07)
Household daughters number: 6-9[a]	0.14	0.14
	(0.18)	(0.19)
Head Gender (Male=1)	0.06	0.07
	(0.05)	(0.05)
Household head: age < 18[a]	-0.05	-0.04
	(0.09)	(0.09)
Household head: age 18-45[a]	-0.11	-0.12
	(0.09)	(0.10)
Household head: age 45-75[a]	-0.11	-0.12
	(0.10)	(0.11)
Wave 2011-2012 (dummy)	0.11	0.11
	(0.14)	(0.14)
Literacy (dummy)	0.26^{*}	0.26^{*}
	(0.12)	(0.12)
Attendance Primary school (dummy)	-0.34^{*}	-0.35^{*}
	(0.15)	(0.15)
Attendance Secondary School (dummy)	-0.06	-0.06
	(0.09)	(0.10)
Number observations	2057	1988

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a]: these variables are categorical: therefore, the coefficient should be interpreted as differential with respect to the reference category. The reference category was omitted to avoid perfect multicollinearity. In particular, the reference cateogry for household size is a number of members between 10 and 20; for the number of daughters is a number between 3 and 6; for the age of the head, when he or she is over 75 years

Epilogue

In this Ph.D. thesis the topic of vertical and spatial price transmission was dealt with from the three different points of view:

1. In the first essay the impact of geographical dispersion on vertical price transmission along the Uganda coffee value chain was assessed. By building upon (Sexton, 1990), the essay brings an original contribution to the literature, since (Sexton, 1990) employs a single spatial price gap equation instead of a system of well-founded behavioural equations in agricultural markets, which is indeed a major improvement delivered by this essay. Moreover, in this analysis the Seemingly Unrelated Regression technique is employed for empirical analysis, while (Sexton, 1990) develops just a theoretical model and it is not interested to do any econometric exercise. In particular, evidence was provided, that there is room for local oligopsony, because traders exploit their market power and overcharge transport and transaction costs to farmers. Indeed, farmers are not able to skip traders in the value chain, because a significant information asymmetry is prevailing in the market.

2. In the second essay the short-term impact of price insulating policies on spatial price transmission of maize, rice and wheat in Cameroon, Kenya and Tanzania in the period 2005-2015 is assessed. This empirical analysis provides different results than previous literature like, inter alia, (Anderson and Nelgen, 2012b) and (Anderson and Nelgen, 2012c) because it estimates the impact of tariff and non-tariff trade policies on spatial price transmission in the agricultural markets not on yearly, but on monthly data. Employment of monthly data allows assessing more precisely short-lived movements of the analysed series, which could disappear because of aggregation bias at lower yearly frequency. The main results of the analysis is that trade policies were able to insulate the country from the price shocks on the international markets during the food price spike crisis, when this protection was mostly needed.

3. In the third essay it is assessed whether the occurrence of exogenous shocks induces a change of price risk aversion over time and then how the time-varying risk aversion parameter affects production and consumption pattern by the farm households. The results of the empirical analysis suggest that the risk aversion parameter is not constant over time and that households can become more risk averse, if they face adverse market conditions in the previous periods. Furthermore, this paper provides evidence that peasants do not aim just at need satisfaction, but they behave in an optimal way and make sure their food security in the medium term. Indeed, they prefer to increase their income instead of directly consuming the harvested crop,

because the reduction of dietary energy consumption derived from the giving up the harvest for sale is more than offset by the rise of food purchasing power due to the larger profits obtained.

All these research questions are very relevant from a scientific and policy-related perspective. The three essays extend and improve previous literature as well as they provide important and innovative contribution to the understanding of the mechanisms of spatial and vertical price transmission.

Although a significant effort was made to deal in a rigorous and comprehensive way with the main analytical issues, this Ph.D. thesis was not able to address all research questions, which the complexity of spatial and vertical price transmission within the agricultural markets suggested.

For instance, an interesting question could concern how the availability of credit affects the production, consumption and investment decisions taken by the economic actors, who operate within the agricultural value chain. The impact analysis of price insulating policies on spatial price transmission within a general equilibrium model could also provide innovative evidence. Finally, the identification of the psychological factors of farmer price risk aversion as well as the connection between risk, credit and saving could lead to major results.

Such research questions are left to further work, given the limited availability of space and time for the achievement of this Ph.D. thesis.