Modelling Acreage, Production and Yield Supply Response to Domestic Price Volatility

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This paper deals with the impact of domestic price volatility on acreage, yield and production of wheat, rice and maize for a set of 66 developing countries. We exploit a dataset ranging from 2005 to 2012 of domestic prices collected from FAO-GIEWS, WFP and FEWS.NET. The resulting system is estimated with a one-step System Generalized Method of Moments (GMM-sys). We show that farmers respond negatively to price instability reducing production, acreage allocation and yield. According to our estimates high expected prices determine an increase of the quantity produced and a raise in maize acreage and rice yields. Non-price factors have also a significant role on supply response. Among all, we show that climate shocks, agricultural inputs and macroeconomic variables such as the financial deepening, influence the ability of farmers to cope with price risks. Financial deepening in part mitigates the negative effect of price instability on the producers' welfare, suggesting that policy reforms aimed at favouring implementation of developing countries' financial sector can help farmers to respond more efficiently to prices changes.

Keywords: *Domestic food prices; Agricultural Supply response; GMM-sys*

JEL Classification codes: Q11, Q12, Q18

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1. INTRODUCTION

The food price spikes of 2007-2008 have marked the beginning of a strong international and domestic commodity price dynamics. In 2008, many commodities prices increased by more than 50%1. Two further price spikes occurred, in late 2010/early 2011 and mid 2012 leading to unprecedented price movements in the recent history. These shocking boom and bust cycles stimulated an increasing concern by policy makers towards causes and consequences of their formation, especially in terms of national and global food security. Indeed, people with limited coping mechanisms that spend a large share of their income in staple foods were greatly affected by the inflation generated by the international market to domestic market price pass-through (Banerjee and Duflo, 2007; Dorosh et al., 2009). Predictably, the soaring food prices, their nature and their implications led many researchers to pay increasing attention at their recent dynamics. Authors such as Abbot et al. (2009), Piesse and Thirtle (2009), Timmer (2010), Headey and Fan (2010), Gilbert and Morgan (2010), Abbott and De Battisti (2011), gave an important contribution to this literature. In particular, Trostle (2010) highlighted that price fluctuations were driven by many drivers. In this regard authors such as Gilbert and Morgan (2010), Abbott and De Battisti (2011) and OECD-FAO (2011) provided a consolidated discussion of a set of elements that have driven food prices dynamics, identifying among others supply and demand factors, weather climate change, market speculation and stock management, trade restrictions, exchange rates and energy prices (Von Braun and Tadesse, 2012). The relative importance and the impact of these causes have been broadly assessed in the literature. Some of the most questioned drivers affecting food price surges are represented by supply side factors. Many articles and policy briefs referred to climatic factors, high fuel prices and increased land demand for biofuel as responsible of declining production and stocks which in turn are the more immediate causes of the supply-demand imbalance. The FAO report ”Price Volatility in Food and Agricultural markets: Policy Responses” (FAO-IMF-UNCTAD, 2011) highlights climatic factors as one of the main drivers contributing to 2007/2008, 2010 and 2011 soaring food prices and supply shocks. Extreme events like the 2008 drought occurred in Australia - which is one of the main world suppliers of wheat-in Canada and in the Black Sea region induced massive shortages in world wheat supply.

Again, between 2010 and 2011, several events such as Australian and Russian federation droughts as well as downward revisions of crops forecasts by US government, caused strong market reactions followed by price

[1] The international prices of maize and wheat roughly doubled, while rice prices became three times higher in few months (Headey and Fan, 2010a)

bursts. In 2011/2012 an unusually strong La Nina created problems in many markets while in 2013 severe weather disruptions worsened staple crops yields in several countries. Price increased also as a result of the increased land competition due to biofuel production subsidies.

However, according to a recent FAO Outlook (OECD-FAO, 2013), food commodity markets are becoming increasingly balanced and less affected by price volatility with respect to recent years thanks to improved supplies and a recovery in global inventories of cereals. Indeed, the prices of most basic crops have decreased in the second half of 2013. This has been due to higher supply capacity, in particular to production increases, higher stocks and more export availabilities. OECD-FAO (2013) forecast that the expansion of agricultural production is likely to slow down in the next few years with slower area and productivity growth. This along with increasing demand will likely reduce the speed of stocks renewal making commodity markets more vulnerable to high price fluctuations. Furthermore, as Schiff and Montenegro (1997) stressed out, it is crucial to consider also the importance of non-price factors or constraints to supply response. Non-price factors, such as environmental conditions or limited access to credit, are among the most binding constraints for agricultural development (Thiele, 2000) and must be considered in any serious policy mix trying to stabilise prices and manage volatility. Therefore, analysing how supply response reacts to expected prices and their volatility is a key research question, as they seriously threat on the food security of millions of individuals and constitute a fundamental issue for policy formulation

While a growing number of studies have examined the impact of prices on agricultural supply response at household and national level (see section 2.2), very limited empirical research has been undertaken to assess the impact of price volatility on production, yield and acreage at global level. To the best of our knowledge only Subervie (2008), Haile and Kalkuhl (2013), Haile et al. (2014) have tried to address this question in a global perspective framework. Since collecting data on prices in developing countries is difficult, these authors employed international prices as a proxy for domestic prices. However, we believe that this prevents to capture political, social and environmental determinants which contributed to price surging as well as to farmers production decisions in local communities. Therefore, this paper explores how domestic food commodity prices and their volatility influenced supply response of wheat, rice and maize over the last decade. We employ a panel econometric estimation based on a standard version of the Nerlove model (see Nerlove, 1971; Askary and Cummings, 1977) to test (i) how price risk, expressed as domestic price volatility, affects supply response in terms of yield, acreage and production of major food commodities; (ii) whether domestic expected prices and non-price factors, in particular financial deepening and yield shocks, play a role in explaining the agricultural supply response. The rest of the paper is organized as follows. Section 2 presents an overview of the Nerlovian models literature as well as the most recent applications of agricultural supply response models, section 3 introduces the empirical model discussing the Difference Generalize Method of Moments (DIFF-GMM) and System Generalized Methods of Moments (SYS-GMM) estimators in conjunction with the problem of endogenous regressors and weak instruments. This section also provides a description of the variables employed in the analyses and source of data. Empirical results are discussed in section 4. Section 5 summarizes the most important findings and discusses policy implications.

2. LITERATURE REVIEW

2.1 Models of Agricultural Supply Response

Agricultural supply response has been a fundamental issue in the past and still continues to attract much attention due to the recent food crisis and uncertainty in future food supply. Agricultural economics has a long tradition in estimating Agricultural Supply Response (ASR) models. This literature has gone through many important empirical and theoretical frameworks (see Rao (1989) for a survey).

There are basically two frameworks developed in the literature to conduct supply response analysis, both developed in the 50s. The first is the supply function approach developed by Griliches (1959) for the aggregate supply response. The second is the Nerlovian partial adjustment model which was developed by Nerlove (1956) to assess the supply response of single commodities.

Griliches (1959) developed a model to estimate the aggregate supply elasticity of farm products and it is based on the aggregation of the demand elasticities estimates for all the inputs and estimates of their distributive shares. This approach is less frequently applied since it requires both detailed input prices - which are difficult to get - at which the inputs are supplied to the farmers and simultaneous estimations of input demand and output supply functions.

According to McKay et al. (1999), Nerlovian models (Nerlove 1958, 1971) allow to explain dynamic optimization behaviour of farmers, their decisions and their reactions to moving targets. The Nerlove partial adjustment model is based on a one-stage procedure and models the dynamics of agricultural supply by incorporating price expectations and/or adjustment costs, giving at the same time the flexibility to introduce non-price shifters in the model. For instance, the desired quantity to be produced for a given agricultural commodity (Q_t^d) in period t is a function of the expected output prices P_t^e (i.e. the price, at planting time, the farmer expect to get after the harvest), and a vector of other exogenous regressors Z_t.

$$lnQ_t^d = b_0 + b_1 lnP_t^e + b_2 lnZ_t + \epsilon_t \tag{1}$$

with b representing the parameters to be estimated and ϵ_t the error capturing unobserved random factors affecting the quantity produced. The major issue in equation (3.1) is that the desired quantity is related to P_t^e and, since the effective price may not be equal to the expected price the desired output adjustment is only partial:

$$lnQ_t - lnQ_{t-1} = \lambda\left(lnQ_t^d - lnQ_{t-1}\right) + \mu_t \tag{2}$$

where λ is the partial adjustment coefficient and Q_t is the actual output. When λ is close to one the adjustment is almost immediate, whilst a low λ implies a very slow adjustment to variation in exogenous variables (Griliches, 1959). The actual change in output is a fraction of the change required to achieve the optimal output level Q_t^d .

Moreover, quantities are assumed to be driven by price expectations which in Nerlove's model are assumed to be adaptive. It is assumed that farmers adjust their expectations as a fraction γ of the difference between realized and expected price:

$$lnP_t^e - lnP_{t-1}^e = \gamma(lnP_{t-1} - lnP_{t-1}^e) \quad (3)$$

that after some manipulation leads to:

$$P_t^e = \gamma lnP_{t-1} + (1-\gamma)lnP_{t-1}^e + \epsilon_t \quad (4)$$

Substituting (1) in (2) and (4) in the resulting relation yields

$$lnQ_t = \pi_0 + \pi_1 lnP_{t-1} + \pi_2 lnQ_{t-1} + \pi_3 Z_t + \mu_t \quad (5)$$

with $\pi_1 = \lambda\gamma b_1$ and b_1 representing respectively the short-run and long-run price elasticities of Q_t with respect to P_t. Over the time, several additional drivers have also been included. These variables consist of output price relative to a variable input price index (Lee and Helmberger, 1985; Tweeten and Quance, 1969), expected net returns per acre (Davison and Crowder, 1991) and acreage value (Bridges and Tenkorang, 2009). Although many variants of the Nerlove formulation have been proposed for the ASR estimation, this model (as well as Griliches model) has always shown some limits on both empirical and theoretical grounds. Firstly, problems associated with the econometric estimation (i.e. the OLS may produce spurious results as series are often $I(1)$, cf. Binswanger, 1989) and secondly the absence of a glaring difference between short-run and long-run elasticities when both adaptive expectations and partial adjustment are present (Schiff and Montenegro, 1997; McKay et al., 1999; Thiele, 2000). Based on the results obtained by authors such as Reca (1980), Bapna (1981), Chhibber (1982) and Bond (1983), which reported downward biased estimates of the short-run and long-run elasticities (approximately around 0.2 and 0.4), Thiele (2003: 6) stated that the ”Nerlove method specifies the dynamics of supply in a very restrictive way”.

The 60s witnessed an increasing interest towards developing countries. For this reason, several modifications have been introduced to the Nerlovian model to take into consideration self-consumption of food crops. For example, income elasticity of consumption within the households replaced the output in the model (Khrisna, 1962; Behrman, 1966). Later Askari and Cummings (1977) made a comprehensive literature review on supply response to understand the factors lying behind the large differences in supply response elasticities. They found that variables like farm size, access to irrigation, yield risk, literacy level (i.e. non-price variables) had a positive impact on the magnitude of the direct supply price elasticity. Finally, in the last decades the application of dynamic econometric approaches such as cointegration, Error Correction Models (ECM) and the panel data econometrics in the shape of fixed, random effects models and Generalised Method of Moments (GMM) largely contributed to a better estimation of the short run and long run dynamics (Nerlove, 1971; Arellano and Bond, 1991). Cointegration analysis serves to avoid spurious regression when handling non-stationary series, in particular, if combined with ECM it offers reliable long run and short run elasticity estimates. Panel data econometrics has a distinct advantage of providing country and temporal variations for dynamic models. This approach is the most suitable for our analysis and will be discussed in detail in section 3.

2.2. Country and cross-country level contributions on supply response

This article builds on a broad literature on crops supply response (output, yield or acreage) to prices. A number of earlier studies apply the Nerlovian models to study the crop supply response (Askari and Cummings, 1977; Rao, 1989) whilst others consider both producer and consumer economic behaviors in a more theoretically consistent framework (Lee and Helmberger, 1985; Chavas and Holt, 1990; Lin and Dismukes, 2007).

In this section we will provide a brief summary of the most recent works on the supply response at country and cross-country/cross-region levels. There is a vast literature on food grain responses to prices. Farooq et al. (2001) using a translog profit function approach, finds that basmati paddy rice supply response to own price was inelastic (0.27), and other factors such as the area under paddy and age of basmati varieties are particularly relevant to explain it. Danielson (2002) studied the responsiveness of crop output to farm gate prices in Tanzania, analyzing whether economic reforms have had the expected impact on crop output by controlling for some supply determinants, finding that the structural adjustment of Tanzanian agricultural sector was quite weak in improving the individual crops supply response.

However in the last two decades, most of the existing studies were likely to use either Cointegration/Error Correction Models' approach (when addressing country level supply response) or Generalized Method of Moments models (when dealing with cross-country analyses). Mushtaq et al. (2002) with an impulse response and cointegration analysis found that wheat and rice acreage response to prices was not significant, while in the long run, for other crops the results were in line with the downward biased estimates found in the literature.

Direct and indirect pricing policies, macroeconomic distortions and non-price factors can have - in the long run - an impact on agricultural production. In this regard, Thiele (2003) applied a cointegration analysis on time series data from 1965 to 1999 for a set of Sub-Saharan African countries finding that supply elasticities are less than 1 and suggesting new macroeconomic and agricultural reforms. Supply response to price incentives is also a broadly assessed topic. The Vector Error Correction Model (VECM) was used by Olubode-Awosola (2006) to show that agriculture (at aggregate level) is less responsive to price incentives and that, interestingly, capital and credit have an insignificant effect on supply shifts. By contrast, Mose's et al. (2007) analysis on maize production in Kenya finds a strong response of farmers to price incentive elasticities: lower than -1 for fertilizers prices and 0.53 and 0.76 for short and long run supply response to maize.

The paper of Vitale et al. (2009) represents an example of supply response studies conducted at micro-level. Within a Nerlovian partial equilibrium framework they estimated unconventional determinants for supply response, namely the household subsistence requirements, their fixed endowment of resources and crop rotation. The model, fitted to the choices of a sample of 82 Malian farmers between 2004 and 2007, shows acreage responses lower than those found by the other studies. By focusing on a sample of 10 Asian countries, Imai et al. (2011) find that there is a significant yield response to higher farm-gate or wholesale prices, as well as a significant effect of oil prices (-) and other non-price factors such as transportation costs (-) on yield. The most common non-price factors used in supply response empirical analysis include irrigation, investment in research and development (R&D), extension services, access to capital and credit, agro-climatic conditions and rural infrastructure (Yu and Fan, 2011).

Agbola and Evans (2012) employed a Fully Modified Ordinary Least Squares (FMOLS) to analyse the supply response of rice and cotton under water trading in the Murray Darling Basin in Australia. They found inelastic responsiveness to price of water both in the long and the short run, implying that water price impact on the two commodities was basically too low to trigger any significant shift in the production towards a water intensive colture. Gosalamang et al. (2012) assess the reaction of beef producers to price incentives for Botwsana between 1993-2005 and found that prices are effective in obtaining the desired output level for beef (1.511 and 1.057 the short and long run elasticities). Panel analysis have been employed for cross-country comparisons but also for cross-region analyses, as for example Ogundari and Nanseki (2013) did for Nigeria. They employed FMOLS, dynamic panel ordinary least squares (DOLS) and one-step Blundell-Bond GMM models to study Nigerian regional acreage and yield supply responses. In a recent study, Boansi (2014) underlines that increasing yield levels and ensuring stability requires an interplay of different forces that range from biophysical factors to socio-economical and structural drivers.

To the best of our knowledge, only few works have been published on supply response to prices at global level (Subervie, 2008; Haile and Kalkuhl, 2013, Haile et al., 2014) and quite surprisingly none of them make use of domestic prices. Moreover, when agricultural supply response analysis to price instability was performed for a specific set of crops (maize, rice, soybean and wheat) in terms of acreage, yield or production level (as in Haile and Kalkuhl, 2013; and Haile et al., 2014), usually the conditions under which price behaves are not specified. Vice-versa, when macroeconomic variables (financial deepening, infrastructure) are included in the model (Subervie, 2008), the analysis of supply response to price instability is performed only on the country production index. Our goal is to fill this gap in the literature, estimating the wheat, maize and rice supply response to price instability using a panel model that includes also non-price variables.

3. EMPIRICAL FRAMEWORK

3.1. The Model

Preliminary data investigation, data availability, and the meaningfulness of some variables largely determined our selection of variables. Assuming that there are i countries and j commodities analysed in period t, we substitute our set of variables in the model given in equation (3.5) and estimate the impact of domestic price instability on acreage, yield and production, reported respectively in equation (3.6), (3.7) and (3.8). The general forms of agricultural supply response functions can be written as follows:

$$ln\,Yld_{ij,t} = \gamma_i\, lnYld_{ij,t-1} + \delta_i\, VOL_{ij,t} + \beta_1 lnE\left(P_{ij,t-p}\right) + \boldsymbol{Z}'_{A,t} + \eta_i + u_{ij,t} \tag{6}$$

$$lnArea_{ij,t} = \gamma_i\, lnArea_{ij,t-1} + \delta_i\, VOL_{ij,t} + \beta_1 lnE\left(P_{ij,t-p}\right) + \beta_2\, \omega_{ij,t-1} + \boldsymbol{Z}'_{B,t} + \eta_i + u_{ij,t} \tag{7}$$

$$ln\,Prod_{ij,t} = \gamma_i\, lnProd_{ij,t-1} + \delta_i\, VOL_{ij,t} + \beta_1 lnE\left(P_{ij,t-p}\right) + \beta_2\, \omega_{ij,t-1} + \boldsymbol{Z}'_{C,t} + \eta_i + u_{ij,t} \tag{8}$$

with

$$\boldsymbol{Z}'_{A,t} = \boldsymbol{Z}'_{\boldsymbol{B},t} = \boldsymbol{Z}'_{C,t} = \beta_3 FTC_{i,t} + \beta_4 FTP_t + \beta_5 FiDe_{i,t}\,,$$

where $Yld_{ij,t}$, $Area_{ij,t}$ and $Prod_{ij,t}$ reflect respectively the country i's - commodity j's yield (Kg/Ha), area harvested (Ha) (which is used as proxy of planted area), and production (tonnes) in period t to the j -th crop. The log-lagged acreage, yield and production are part of the relevant information set that the farmer considers in his planting decisions. $VOL_{ij,t}$ represents the price risk variable, which is computed using the annual volatility (SDLOG) of own monthly prices, ln $E\left(P_{ij,t-p}\right)$ is the expected price registered in the month before planting, ωij,t − 1 is the lagged country-crop yield shock occurred in the previous year, which we assume being connected to weather instability; fertilizers consumption $FTC_{i,t}$, and nominal international fertilizers prices FTP_t, are used as proxies for inputs; the financial deepening variable ($FiDe_{i,t}$) is proxied with the domestic credit to private sector by banks as percentage of GDP; η_i represents the country-specific unobserved fixed effects and $u_{ij,t}$ is the error term.

Further, we fine tune the basic model with two further specifications. First, we include an interaction term between the price volatility and the financial deepening in order to investigate whether producers risk management capacity with respect to domestic price volatility may be buffered through the improvement of the financial system. Second, we add among controls the relative importance of agriculture in the country's economy ($AGDP_t$) since we are expecting that supply response will differ across countries with a higher share of gross domestic product coming from agriculture: the higher the agricultural share of GDP, the higher the output in terms of production and area but the lower the crop yields. As it is usual in developing countries, higher shares of agriculture over GDP are associated with low yields. This is due to several factors that make the agricultural productive structure less efficient (i.e. lower mechanization, low input adoption, higher incidence of extreme weather events). It is worth noting that since the data on domestic prices were not available for all three commodities in each country, adding the expected prices of the substitute/complementary commodity to the model would have led to a large reduction of the number of observations. For this reason we do not control for the cross-price effect on yield, area and production.

3.2. Data and the Econometric Method

The empirical model in this study utilizes country level yearly data to estimate supply responses for three agricultural commodities (wheat, maize and rice) for 66 countries, 25 of which belonging to Africa, 14 to Asia, 11 to Eastern Europe, 16 for Latin and Central America2. Farmers acreage, production and yield are estimated by pooling time series with cross section data (individual countries). All data were transformed to natural logarithms prior to undertaking the analysis. The period studied spanned from 2005 to 20123. The data employed for the dependent variable (acreage, yield and production at country-commodity level) is obtained from FAOSTAT - the FAO's online agricultural database (FAO, 2014). Monthly domestic price data at country-commodity level for wheat, maize and rice from WFP-VAM, FAO GIEWS and FEWS.NET complement the dataset. Since data on domestic prices at production level are poor, we used wholesale and retail prices as proxies for prices at production level by assuming that prices at wholesale/retail level reflect prices at farm-gate. Following Boansi (2014) we include nitrogen fertilizers consumption (expressed as tons of nutrients) as a proxy for inputs for all the countries in our sample. Phosphate fertilizers consumption is employed for Ethiopia. Cabo Verde, Chad, Central African Republic data on fertilizers are not available. Data on fertilizers consumption was obtained from the Fertilizers Archive Domain of FAOSTAT. International prices of fertilizers were obtained from the World Bank Commodities Price Data (The Pink Sheet). We use as a proxy of financial deepening the ”Domestic credit to private sector by banks as percentage of GDP”, which is drawn from the World Development Indicators provided by the World Bank.

By taking advantage of domestic monthly data, we decided to consider the seasonality of he different country-crops by picking for each country the prices registered in the month(s) before planting. Indeed pre-planting months contain a good approximation of the information that farmers have when they make their crop investment decisions. For countries harvesting twice per year, we approximate price expectations with the average of prices collected in each pre-planting month. Moreover, similarly to Haile et al. (2014) in order to trace the annual planting season we construct a monthly crop calendar using the information on agricultural seasonality for main staple food crops provided by GIEWS Country Briefs (see Figures 1-3)4. As mentioned above, this work captures price risk with a measure of domestic price volatility. Following Balcombe (2011) we use the standard deviation of changes in the logarithm of prices (SDLOG). This approach is widely used in agricultural economics as this is a unit free measure. Similarly to Haile et al. (2014), yield shocks are captured following the procedure developed by Roberts and Schlenker (2009: 1237), which consists in ”taking jack-knifed residuals from fitting separate yield trends for each crop in each country5”. To estimate the short run

[2] The countries for which data are available are reported in Figures 1-3.
[3] See Table 5 for further information about time length and source of each variable.
[4] cf. http://www.fao.org/giews/countrybrief/.
[5] As noted by Roberts and Schlenker, ”OLS residuals give biased estimates of the errors while jackknifed residuals, derived by excluding the current observation when determining the current residual, give unbiased estimates of the error”(p. 1237)

dynamic supply responses we employ a panel data regression technique, which is a relevant method of longitudinal data analysis because it allows for a number of regression analyses in both units and time dimensions. It also gives room for data analysis especially when the data come from various sources and the time series are quite short for separate time series analysis (Baum, 2006).

In our context, employing the classic OLS estimators is likely to give a biased result as they do not take into account for possible correlation between the lagged term of dependent variable y_{it-1} and the country fixed effects error component (Baltagi, 2008). In particular OLS overstates the value of the coefficient of the lagged dependent attributing to it the power that belongs to fixed effects. This effect would be particularly emphasized in contexts like ours, with a panel characterized by ”small T , and large n”.

A suitable solution to this issue could be represented by purging the panel from the fixed effects via the Within Groups estimator (WG). However, as stated by Nickell (1981) and Bond (2002) employing the WG does not resolve this problem, as the dependent variable keeps moving together with the random component6. Thus, the use of OLS and WG estimators gives rise to an endogeneity problem, commonly found in the literature under the name of ”dynamic panel bias”. This leads to coefficients which are biased in opposite

directions. Many studies have discussed and proposed a solution to this problem. Kiviet (1995) and Bruno (2005) proposed respectively to estimate balanced and unbalanced panels with Least Square Dummy Variable (LSDV) and then correct for the bias. These two approaches have been criticized as performing badly when endogenous regressors are present in the sample. In cases where T is small and the LSDV estimator is biased and inconsistent, a number of estimators have been proposed. Anderson and Hsiao (1982) suggested to first-differencing the equation, thus eliminating the individual effect μ and using either $\Delta y_{i,t-2}$ or $y_{i,t-2}$ as instruments for $\Delta y_{i,t-1}$. Despite the consistency of the estimates, the model lacked the use of all the moment conditions. Thus Holtz-Eakin et al. (1988) and Arellano and Bond (1991) developed the so called difference Generalized Method of Moments (GMM-diff) estimator, which treated the model as a system of equations, one for each period, making use of a set of additional instruments/moment condition sets. The predetermined and endogenous variables in first differences are basically instrumented with suitable lags, while strictly exogenous regressors enter the matrix of instruments as first differences. Moreover, the GMM estimator does not require any particular distribution of the error term, therefore even in presence of heteroskedasticity it produces consistent estimates of the unknown parameters. Even if fixed effects are expunged and the endogeneity problem is solved by differencing the data, this approach is however believed to suffer of a weakness of internal instruments. (Blundell and Bond, 1998), because if the dependent variable is persistent (random walk or random walk with drift) or is a near unit-root process then the lagged levels convey little information about future changes and the estimator performs poorly. Binder et al. (2005)

using a Monte Carlo experiment show that the conventional GMM estimators based on standard orthogonality conditions break down if the underlying time series contains unit roots. Therefore, it is mandatory to perform unit root tests in our series. These issues have led to the introduction of the system Generalized Method of Moments (GMM-sys) by Blundell and Bond (1998), who show that the biases generated by near unit

[6] For larger T the dynamic panel bias becomes insignificant and the panel FE returns a better specification of the model;

root processes can be strongly limited by exploiting initial stationary restrictions on the initial condition processes. This method assumes that any correlation between endogenous variables and unobserved or fixed effects are constant over time and allows to add the original equations in level to the system, so that additional moment conditions could both reduce the downward bias and at the same time increase efficiency. For instance, it considers two different sets of equations. The first one is the GMM-diff, which uses lagged levels as instruments for first difference equations, whilst the second equation takes the first difference of the variables to make them exogenous with respect to the fixed effect and use them as instruments in the first equation (Roodman, 2009). Prior to start with the analysis we check whether the series are stationary or not by employing two different panel unit root tests: the Levin et al. (LLC) panel unit root test, which tests the null hypothesis of non-stationarity and the Hadri (2000) test which tests the null hypothesis of stationarity. If the series are integrated of order 1 we proceed further with the GMM-sys estimation.

The adoption of GMM-sys is supposed to cope with the unit-root problem leading to more asymptotically efficient estimates than the GMM-diff. This is because it explores a higher number of moment conditions. Based on Blundell and Bond (1998) we use the levels and the differences of the explanatory variables as instrumental variables. In order to avoid inconsistent estimates, we check for the correlation of the unit specific effects (that if present may lead to biased GMM-sys estimates) by employing standard Sargan tests, which test the ”null hypothesis of instruments validity”. Moreover, to evaluate the performance of both the GMMs, we validate our estimates checking for the autocorrelation of residuals by using the AR(1) and AR(2) Arellano-Bond tests.

4. RESULTS AND DISCUSSION

This section presents and discusses the empirical results of the supply response analysis using GMM-sys approach. We first test for the presence of unit-root processes by means of panel unit root tests. Then we report the system GMM results combined with tests for serial autocorrelation of the residuals and for the validity of the system GMM instruments employed in the model.

4.1. Dynamic panel unit root tests results

This section reports the panel tests for the presence of a random walk in the series. It is important to test for the presence of a unit root as it will generate downward biased estimates in the standard GMM estimator. We employ LLC and Hadri panel unit root tests which test respectively for stationarity and non-stationarity of the time series. LLC is commonly used to test for stationarity but since it suffers of the classical type II error (Greene, 2003), it is recommended to test also for the null hypothesis of no unit root. We therefore employ the Hadri's test. The combination of both tests is crucial to confirm or deny conclusions about the presence of unit-root. The results of the two tests are presented in Table 1. Under the LLC the null hypothesis of non-stationarity could not be rejected for almost all the series under examination (whether or not a trend is included generates different results), but the null of non-stationarity for the series in differences is rejected. The results for the Hadri test lead us to reject the null hypothesis of no unit root in levels and fail to reject the hypothesis of stationarity under the first-difference. The combination of results obtained from both tests suggests that all the series are *I* (1) processes.

Table 1. Conventional panel unit root tests.

	Level				First Difference			
	Levin-Lin-Chu		Hadri		Levin-Lin-Chu		Hadri	
	No Trend	Trend	No Trend	Trend	No Trend	Trend	No Trend	Trend
A_{wheat}	0.2[2]	-2.17[2]	5.92[2]***	8.96[2]***	-4.15[2]***	-5.95[2]***	0.51[0]	-1.284[0]
	(0.528)	(0.02)	(0.000)	(0.000)	(0.000)	(0.000)	(0.305)	(0.905)
A_{maize}	-1.66[2]*	-1.02[2]	6.69[1]***	12.42[1]***	-6.97[2]***	-9.74[2]***	-2[0]	-3.59[0]
	(0.051)	(0.15)	(0.000)	(0.000)	(0.000)	(0.000)	(0.971)	(0.999)
A_{rice}	-1.38[2]	-0.17[2]	10.62[1]***	14.33[1]***	-4.37[2]***	-5.16[2]***	-1.25[0]	-1.08[0]
	(0.08)	(0.43)	(0.000)	(0.000)	(0.000)	(0.000)	(0.899)	(0.869)
Y_{wheat}	1.5[2]	-2.26[2]**	6.3[1]***	6.76[1]***	-4.27[2]***	-6.66[2]***	0.42[0]	-1.66[0]
	(0.938)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.333)	(0.959)
Y_{maize}	0.632[2]	-2.84[2]**	7.52[1]***	13.07[1]***	-5.94[2]***	-10.02[2]***	-2.83[0]	-3.8[0]
	(0.732)	(0.02)	(0.000)	(0.000)	(0.000)	(0.000)	(0.999)	(0.999)
Y_{rice}	4.92[2]	1.58[2]***	7.11[1]***	12.15[1]***	-0.31[2]	-4.29[2]***	0.13[0]	-2.25[0]
	(0.999)	(0.943)	(0.000)	(0.000)	(0.37)	(0.000)	(0.451)	(0.988)
$Prod_{wheat}$	2.35[2]	-0.66[2]	5.13[1]***	13.51[1]***	-4.47[2]***	-7.4[2]***	-0.23[0]	-2.42[0]
	(0.999)	(0.252)	(0.000)	(0.000)	(0.000)	(0.000)	(0.591)	(0.999)
$Prod_{maize}$	-0.93[2]	-3.62[2]***	6.7[1]***	14.87[1]***	-6.3[2]***	-10.31[2]***	-2.3[0]	-3.79[0]
	(0.171)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.988)	(0.999)
$Prod_{rice}$	-1.15[2]	-0.63[2]	11.19[1]***	15.65[1]***	-4.78[3]***	-6.81[2]***	0.01[0]	0.13[0]
	(0.124)	(0.263)	(0.000)	(0.000)	(0.000)	(0.000)	(0.499)	(0.445)
ω_{wheat}	2.42[2]	-1.62[2]*	5.89[1]***	5.66[1]***	-3.34[2]***	-5.95[2]***	-1.89[0]	-2.76[0]
	(0.999)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.97)	(0.99)
ω_{maize}	2.78[2]	-1.18[2]	6.12[1]***	6.97[1]***	-3.54[2]***	-5.88[2]***	-1.22[0]	-2.55[0]
	(0.991)	(0.881)	(0.000)	(0.000)	(0.005)	(0.000)	(0.85)	(0.999)
ω_{rice}	4.01[2]	2.23[2]	8.83[1]***	10.05[1]***	-3.29[2]***	-5.34[2]***	-1.04[0]	-2.46[0]
	(1.000)	(0.988)	(0.000)	(0.000)	(0.005)	(0.000)	(0.85)	(0.999)
$E(P_{wheat})$	-14.04[2]***	-9.16[2]***	4.56[1]***	5.05[1]***	-8.67[2]***	-12.32[2]***	-0.351[0]	-1.43[0]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.363)	(0.924)
$E(P_{maize})$	-14.22[2]***	-10.13[2]***	5.21[1]***	8.44[1]***	-32.81[2]***	-19.86[2]***	-0.24[0]	-3.48[0]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.59)	(0.998)
$E(P_{rice})$	-7.38[2]***	-11.83[2]***	6.86[1]***	9.21[1]***	-17.73[2]***	-7.59[2]***	0.95[0]	-1.439[0]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.169)	(0.925)
$FiDe$	11.85[2]***	19.04[2]***	11.85[1]***	19.03[1]***	-1.44[2]***	-3.21[2]***	7.38[0]	4.08[0]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FTC	-4.72[2]***	-2.67[2]***	11.515[1]***	5.725[1]***	-7.39[2]***	-8.95[2]***	0.199[0]	0.914[0]
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.421)	(0.180)
FTP	1.93[2]	-9.19[2]***	12.55[1]***	23.23[1]***	-1.74[2]**	-2.2[2]***	-2.67[0]	-3.75[0]
	(0.973)	(0.000)	(0.000)	(0.000)	(0.041)	(0.013)	(0.996)	(0.999)

Panel unit-root tests are based on Levin et al. (2002) and Hadri (2000). Asterisks indicates the level of significance: 1% ***, 5% **, 10%*. The null hypothesis of LLC is the presence of unit root, conversely Hadri's test has under the null hypothesis the stationarity. Figures in parentheses ( ) indicate the p-values. Figures in [ ] indicate the lag length for LLC test (we employ Bartlett kernel) and bandwidth for Hadri test (we use Quadratic Spectral kernel).

4.2. GMM-sys estimation

Following the procedure reported in the previous section we estimate our model using the generalized method of moments estimator. Since our series are non stationary in levels, the GMM-diff estimator will not be efficient. For instance, the lagged levels would have been used as instruments for the first differences equations, but since all our series are non stationary, these instruments are not suitable in this context. The level instruments for the first differenced equations will tend to be weak because the lagged levels are weakly correlated to subsequent first differences, the consequence of which is finite-sample biases (Blundell and Bond, 1998). In light of this we will employ in this study the GMM-sys estimator. In addition to using lagged levels in the equations for first differences, the lagged differences of variables are also used as instruments in equation for levels.

Table 2 describes the GMM-sys estimates for wheat, maize and rice yield response functions. At the bottom of the tables we report tests for the null hypothesis that errors are not correlated at the second order (i.e. dynamics are correctly specified). Of course, the The results indicate that as the price of maize increases also the area allocated to the production of corn increases. The own price elasticity of maize acreage response reported in this study is slightly higher than the average of the elasticities reported at state level by the Food and Agricultural Policy Research Institute. Though, these measures are particularly sensitive to the estimator used. Abrar et al. (2004) reported for the Southern region of Ethiopia an elasticity of acreage to price of maize of about 0.57. Table 4 reports the results for the production response. Price coefficients are positive and statistically significant in all the three specifications for both wheat and maize, with short run elasticities ranging between 0.261 and 0.379 for wheat and between 0.396 and 0.542 for maize. Hence, price increments have a positive impact also on the quantity produced, which yields the highest price coefficients.

AR(1) hypothesis, i.e. errors not correlated at the first order, is always rejected because in the first difference equations errors are distributed like MA(1). The most relevant test for the validity of the instruments in GMM-sys is the Sargan test, which is $\chi 2$ distributed and tests the validity of the instruments under the null hypothesis.

We are interested in evaluating the response of expected prices, domestic price instability and a set of non-price variables on wheat, maize and rice yield, acreage and production. For each crop we estimate three model specifications which we report in three different columns.

In the first column we show the basic specification of the model, in the second column we report the estimates of the model with the interaction term between volatility and credit, while in the third column we include among controls the agricultural GDP expressed as a share of total GDP. All variables have the expected sign, but estimates are not always statistically significant.

Yield responses to own price expectations are positive and statistically significant at 1% for rice showing short-run elasticity values of approximately 0.25. Yield responses to expected prices for wheat and maize are not significant. However, concerning rice the results indicate that as the price of rice increases, yields do so: e.g., farmers are most likely to improve capital investments for example by purchasing new farm equipment or improved seeds. The values obtained are consistent with the range of short run elasticities

(0.19 - 0.27) reported by Goodwin et al. (2012). According to Berry (2011), the existing research on price-yield response - which relied uniquely on OLS estimates - produced ”bad

price-yield estimates”, with values ranging between 0 (Roberts and Schlenker, 2009) and 0.15 (Huang and Khanna, 2010). As regards acreage response (Table 3), only the own price elasticity of maize acreage is found to be always significant. The short run maize acreage response with respect to price of maize is estimated to range between 0.397 – when accounting for the relative importance of agriculture in the country’s economy - and 0.566.

The results indicate that as the price of maize increases also the area allocated to the production of corn increases. The own price elasticity of maize acreage response reported in this study is slightly higher than the average of the elasticities reported at state level by the Food and Agricultural Policy Research Institute7. Though, these measures are particularly sensitive to the estimator used. Abrar et al. (2004) reported for the Southern

[7] http://www.fapri.iastate.edu/tools/elasticity.aspx.

region of Ethiopia an elasticity of acreage to price of maize of about 0.57. Table 4 reports the results for the production response. Price coefficients are positive and statistically significant in all the three specifications for both wheat and maize, with short run elasticities ranging between 0.261 and 0.379 for wheat and between 0.396 and 0.542 for maize. Hence, price increments have a positive impact also on the quantity produced, which yields the highest price coefficients.

Table 2. GMM-sys estimates of world yield response for wheat, rice and maize.

	Wheat (W1)	Wheat (W2)	Wheat (W3)	Maize (M1)	Maize (M2)	Maize (M3)	Rice (R1)	Rice (R2)	Rice (R3)
$\ln Y_{j,t-1}$	-0.091	-0.078	0.134***	-0.079	0.458***	0.440***	0.015	0.005	0.212***
	(0.106)	(0.102)	(0.034)	(0.158)	(0.057)	(0.041)	(0.051)	(0.058)	(0.047)
VOL_j	0.603	1.047	-0.685***	-0.511**	1.316	-0.830**	-0.582***	-0.532	0.067
	(1.104)	(1.487)	(0.170)	(0.191)	(0.702)	(0.280)	(0.139)	(1.959)	(0.594)
$\ln E(P_{t-p})$	-0.210	-0.177	-0.034	0.241	0.023	0.039	0.248***	0.245***	0.243***
	(0.126)	(0.110)	(0.018)	(0.160)	(0.052)	(0.072)	(0.019)	(0.022)	(0.027)
$\ln(FTC)$	0.055***	0.058***	0.056**	0.144***	0.060**	0.028	0.053***	0.059***	0.016***
	(0.012)	(0.010)	(0.016)	(0.031)	(0.020)	(0.020)	(0.004)	(0.005)	(0.005)
$\ln(FTP_t)$	0.046	0.051	-0.059**	-0.228*	-0.082*	0.046	-0.128***	-0.160***	-0.031
	(0.097)	(0.094)	(0.018)	(0.116)	(0.038)	(0.076)	(0.019)	(0.026)	(0.033)
$\ln(FiDe_{it})$	0.351*	0.325*	-0.045	0.390***	0.229***	0.135***	0.191***	0.132	0.019
	(0.136)	(0.138)	(0.044)	(0.054)	(0.059)	(0.037)	(0.016)	(0.122)	(0.056)
$\ln(FiDe_{it})*VOL_j$		-0.021	0.022***		-0.020	0.032**		0.041	-0.006
		(0.032)	(0.006)		(0.016)	(0.011)		(0.076)	(0.016)
$\ln(AGDP_{it})$			-0.208**			-0.261**			-0.286***
			(0.057)			(0.083)			(0.021)
_cons	8.549***	8.518***	8.274***	9.653***	4.464***	6.170***	9.864***	10.206***	8.927***
	(0.587)	(0.562)	(0.469)	(1.577)	(0.509)	(0.491)	(0.516)	(0.815)	(0.572)
N	195	195	180	276	276	261	239	239	232
AR(1):p-val	0.004	0.002	0.003	0.005	0.006	0.000	0.000	0.001	0.000
AR(2):p-val	0.249	0.534	0.669	0.301	0.318	0.689	0.943	0.675	0.665
Sargan test: p-val	0.374	0.443	0.104	0.694	0.124	0.077	0.162	0.080	0.101
F test: p.val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: standard errors in parentheses; asterisks *,**,*** indicate 10%, 5%, 1% significance levels. We report the p-values of the AR(1) and AR(2) Arellano-Bond tests, the p-values of the Sargan test for the null hypothesis of instruments validity, and the F-test of the joint validity of the model.

Volatility of domestic prices with respect to yield is found to be statistically significant for wheat and maize (when controlling for the agricultural share of GDP) and rice but only in the basic specification. The negative sign and its magnitude indicates that farmers are on average risk averse agents who react to price instability by reducing investments in technology and diversifying the production (Von Braun and Tadesse, 2012). Concerning the responsiveness of the planted area to price volatility, the estimated coefficients are all statistically insignificant with the exception of wheat area, which responds negatively to price instability. The magnitude of the coefficient is -0.65. We did not find any significant

relationship between volatility and production for both wheat and maize. A negative and statistically significant coefficient is registered for rice. Evidence from the past literature suggested that the use of fertilizers during the early part of the growing season can represent an important mechanism by which realized yields may be influenced by price variation. Good proxies of fertilizers usage can be both consumption of nitrogen micro-nutrient, which is the most representative active principle in their composition, and the urea real price of fertilizer. The price of fertilizers is a production cost to farmers, and its variation may lead farmers to reduce either the amount of fertilizer used - which eventually impacts yields - or the area under cultivation. In the latter case farmers apply fertilisers to less area under cultivation, maintaining however constant the total amount of fertilizer per hectare. Positive and significant relationships between fertilizers consumption and yield are registered for all the crops, while negative coefficients of prices of fertilizers indicate that an increase in the fertilizers prices will have a negative impact on yields. This finding is consistent among all the cases analyzed. In each table, columns W3, M3 and R3 show the results of including agricultural share of GDP as an additional control variable. The influence of the relative importance of agriculture in the country's economy, returns opposite results with respect to yield and production. The yield response to larger agricultural share of GDP is negative and statistically significant, suggesting that countries with higher agricultural added values are characterized by less improved production technologies or limited input usage, which may for instance result in lower protection against pest diseases and weather disruptions with subsequent impacts on yields. Regarding production, which is expressed in tonnes of crop per year, we find for rice a positive correlation with AGDPt: the higher the agricultural share over GDP, the higher the production in absolute value. We fail to find any significant relationship with acreage.

Table 3. GMM-sys estimates of world acreage response for wheat, rice and maize.

	Wheat (W1)	Wheat (W2)	Wheat (W3)	Maize (M1)	Maize (M2)	Maize (M3)	Rice (R1)	Rice (R2)	Rice (R3)
$\ln Y_{j,t-1}$	0.992***	0.992***	1.000***	1.040***	0.956***	0.946***	0.689***	0.694***	0.670***
	(0.014)	(0.011)	(0.012)	(0.052)	(0.018)	(0.022)	(0.087)	(0.083)	(0.083)
VOL_j	-0.143	-0.610*	-0.654*	-1.157	-0.469	-0.362	1.682	2.554	-0.316
	(0.392)	(0.289)	(0.259)	(1.440)	(1.825)	(1.753)	(1.064)	(2.440)	(2.088)
$\ln E(P_{t-p})$	-0.018	-0.026	0.013	0.566*	0.463*	0.397*	0.088	0.086	0.176*
	(0.079)	(0.058)	(0.052)	(0.247)	(0.218)	(0.199)	(0.108)	(0.109)	(0.084)
$\omega_{j,t-1}$	0.035*	0.032*	0.033*	-0.015	0.027	-0.016	0.123*	0.125*	0.044
	(0.014)	(0.012)	(0.012)	(0.085)	(0.076)	(0.079)	(0.059)	(0.059)	(0.041)
$\ln(FTC_{it})$	0.001	0.002	-0.000	-0.011	0.074*	0.088**	0.137***	0.137***	0.152***
	(0.011)	(0.009)	(0.010)	(0.063)	(0.034)	(0.032)	(0.038)	(0.038)	(0.041)
$\ln(FTP_t)$	0.009	0.024	-0.012	-0.675*	-0.334	-0.270	-0.141*	-0.149*	-0.172**
	(0.077)	(0.058)	(0.038)	(0.284)	(0.185)	(0.172)	(0.065)	(0.066)	(0.054)
$\ln(FiDe_{it})$	0.008	-0.021	0.003	0.507	-0.235	-0.189	0.235**	0.265*	0.179
	(0.027)	(0.024)	(0.019)	(0.351)	(0.161)	(0.165)	(0.071)	(0.122)	(0.112)
$\ln(FiDe_{it})$*VOL_j		0.011*	0.014*		0.050	0.048		-0.019	0.056
		(0.004)	(0.006)		(0.052)	(0.051)		(0.058)	(0.055)
$\ln(AGDP_{it})$			0.010			0.065			0.013
			(0.019)			(0.052)			(0.159)
_cons	-0.003	-0.006	0.051	2.596	2.891*	2.108	2.319***	2.185**	2.787*
	(0.401)	(0.297)	(0.263)	(1.336)	(1.251)	(1.211)	(0.627)	(0.697)	(1.203)
N	195	195	180	276	276	261	204	204	232
AR(1):p-val	0.005	0.005	0.007	0.000	0.000	0.000	0.000	0.000	0.000
AR(2):p-val	0.049	0.038	0.047	0.329	0.930	0.867	0.035	0.047	0.077
Sargan test: p-val	0.159	0.123	0.088	0.104	0.041	0.036	0.213	0.259	0.044
F test: p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: standard errors in parentheses; asterisks *,**,*** indicate 10%, 5%, 1% significance levels. We report the p-values of the AR(1) and AR(2) Arellano-Bond tests, the p-values of the Sargan test for the null hypothesis of instruments validity, and the F-test of the joint validity of the model.

Financial deepening has also a strong influence on yield response for wheat and maize crops. The results reveal that credit to private sector by banks may assist farmers to cope with price instability. In particular, including the interaction term which simulates the effect of having access to credit in a context with price instability, we obtain positive figures and statistically significant coefficients. This finding is relevant, particularly in the case of wheat producers (in terms of yield, acreage and production), suggesting that financial deepening can assist in buffering the supply effects of instability. However, these results must be interpreted carefully. Positive values do not necessarily mean that there is a direct causal relationship between expanding financial institutions and food insecurity alleviation. Rural financial institutions expansion in areas with inadequate markets and susceptible to weather risks, may have a non-positive effect, unless it is developed a good strategy of asset diversification coupled with adequate loan loss provisions (Diagne and Zeller, 2001). Therefore at policy level it has to be considered that although financial deepening improves the farmers productivity it is not a panacea for poverty alleviation. The full potential of credit access in increasing the welfare of the poor can only be realized together with adequate investments in hard and soft infrastructure as well as investments in human capital. Access to credit is also dependent on a range of agro-ecological factors like extreme weather events such as floods, droughts and so on. We hypothesize that the yield deviations from a trend are likely to be attributed to random weather fluctuations. The resulting coefficients are slightly higher than the ones employed by Haile and Kalkuhl (2013) for wheat acreage, whereas regarding production response, our results show a positive and statistically significant relationship for all the three crops under analysis.

Table 4. GMM-sys estimates of world production response for wheat, rice and maize.

	Wheat (W1)	Wheat (W2)	Wheat (W3)	Maize (M1)	Maize (M2)	Maize (M3)	Rice (R1)	Rice (R2)	Rice (R3)
$\ln Y_{j,t-1}$	1.031***	1.006***	1.035***	0.690**	0.129	0.562***	0.283***	0.546***	0.676***
	(0.027)	(0.017)	(0.035)	(0.234)	(0.172)	(0.080)	(0.048)	(0.147)	(0.090)
VOL_j	0.283	0.215	0.628	-0.114	-1.005	-0.006	-0.902*	1.121	-0.350
	(0.529)	(0.789)	(0.969)	(1.485)	(2.426)	(1.222)	(0.413)	(0.680)	(2.658)
$\ln E(P_{j-p})$	0.363*	0.261**	0.379*	0.542*	0.477*	0.396*	0.303***	-0.050	-0.075
	(0.161)	(0.091)	(0.192)	(0.255)	(0.223)	(0.176)	(0.085)	(0.090)	(0.055)
$\omega_{j,t-1}$	0.157***	0.174***	0.180***	-0.130	0.095***	0.102***	0.175***	0.143***	0.104***
	(0.013)	(0.014)	(0.018)	(0.118)	(0.018)	(0.024)	(0.012)	(0.017)	(0.015)
$\ln(FTC_{it})$	0.000	0.019	0.002	0.261*	0.540***	0.365***	0.106**	0.220**	0.197***
	(0.015)	(0.012)	(0.020)	(0.121)	(0.102)	(0.058)	(0.032)	(0.071)	(0.053)
$\ln(FTP_t)$	-0.183	-0.367**	-0.570*	-0.060	0.046	-0.208	-0.164**	-0.092	-0.110**
	(0.127)	(0.134)	(0.263)	(0.197)	(0.177)	(0.225)	(0.050)	(0.063)	(0.037)
$\ln(FiDe_{it})$	0.112*	0.031	0.030	-0.211	-0.480	-0.011	0.420*	0.378**	0.116
	(0.045)	(0.042)	(0.047)	(0.152)	(0.330)	(0.212)	(0.182)	(0.119)	(0.227)
$\ln(FiDe_{it})$*VOL_j		0.029*	0.029		-0.027	0.044		0.000	0.127
		(0.014)	(0.016)		(0.111)	(0.038)		(0.020)	(0.109)
$\ln(AGDP_{it})$			-0.054			0.478			0.305**
			(0.056)			(0.244)			(0.087)
_cons	0.628	1.896**	3.064*	3.181	8.175***	2.423	8.362***	2.948**	1.438*
	(0.560)	(0.691)	(1.487)	(2.177)	(2.253)	(1.493)	(0.623)	(1.047)	(0.675)
N	195	195	180	276	276	261	239	239	232
AR(1):p-val	0.000	0.000	0.003	0.007	0.002	0.000	0.001	0.000	0.013
AR(2):p-val	0.505	0.283	0.015	0.090	0.772	0.750	0.087	0.330	0.762
Sargan test: p-val	0.128	0.432	0.223	0.411	0.033	0.155	0.312	0.216	0.645
F test: p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: standard errors in parentheses; asterisks *,**,*** indicate 10%, 5%, 1% significance levels. We report the p-values of the AR(1) and AR(2) Arellano-Bond tests, the p-values of the Sargan test for the null hypothesis of instruments validity, and the F-test of the joint validity of the model.

5. CONCLUSIONS

In the last decade domestic staple food prices experienced several boom and bust cycles. The upward spikes registered in 2008, late 2010/early 2011 and mid 2012 posed serious threats to farmers, particularly in developing countries. This paper investigates the influence of domestic price volatility and expected prices on the area cultivated, yield and production at global scale by using Generalized Methods of Moments dynamic estimation that, compared to other estimators, is found to deal better with ”weak instruments” issues and endogenous regressors. Following this approach a supply response model is derived for wheat, rice and maize for the period 2005-2012.

Several conclusions can be drawn from our findings. First of all world farmers respond strongly to high domestic prices and to domestic price volatility. High prices result in an increase of the quantity produced, and often to an increase in acreage allocation (for maize) and yields (for rice). Price instability leaves the farmers uncertain about whether they are going to be paid a high price or not: this has implications in particular on investment decisions about production with relevant impacts on yields. This risk averse behaviour is evident among wheat, maize and rice producers. Lack of access to risk managements opportunities as well as lack of access to credit tend to exacerbate the effect of price movements on welfare of producers. This frequently leads to poverty traps. The results support our hypothesis about the positive relationship of financial deepening with supply responses, suggesting policy makers to improve local financial systems with well targeted policy reforms of the financial sector in order to facilitate lending and borrowing between financial institutions and poor households. Furthermore, besides prices and financial deepening, other factors must be considered for supply response to be realised: fertilizers consumption and fertilizers prices have respectively a positive and negative relationship in particular with crop yields in almost all models, while yield shocks are positively related with both production and acreage.

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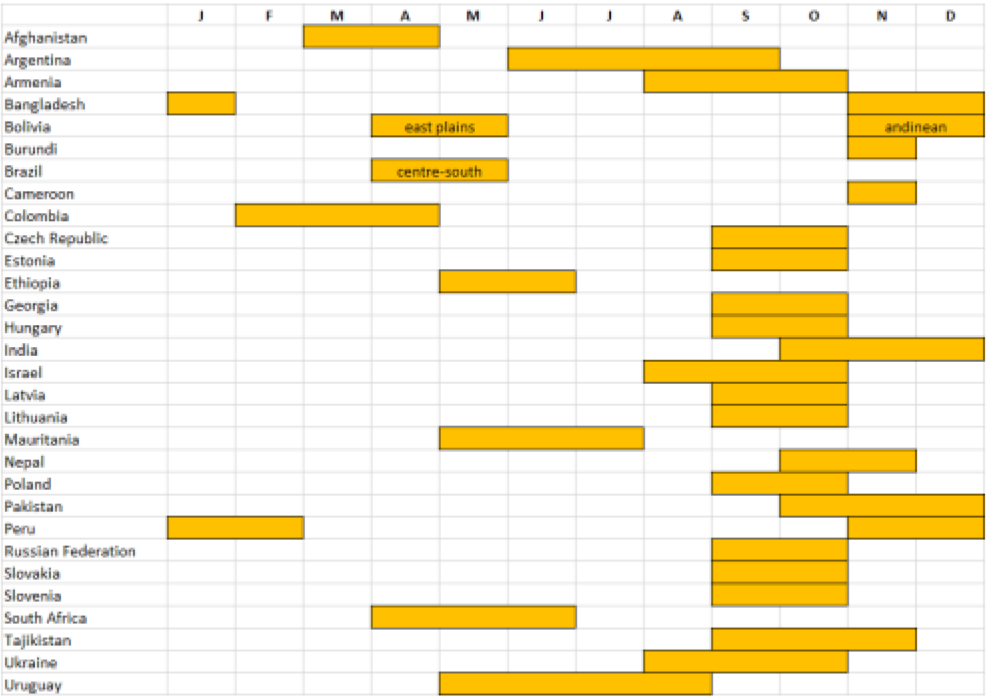
7. APPENDIX

Table 1. List of variables used in our study.

Variable name	label	Unit	Range	Source	Level
$lnArea_{ij}$	Area Harvested	Ha/Year	1961-2012	FAO-STAT	CC
$lnYld_{ij}$	Yield	Hg/Ha/Year	1961-2012	FAO-STAT	CC
$lnProd_{ij}$	Production	Tonnes/Year	1961-2012	FAO-STAT	CC
$VOL_{ij,t}$	SDLOG Annual Volatility	Unit Free Measure	2005-2013	FAO-GIEWS WFP-VAM FEWS.NET	CC
$E(P_{ij,t})$	Expected Price	USD/Kg	2005-2012	FAO-GIEWS WFP-VAM FEWS.NET	CC
$\omega_{ij,t-1}$	Yield Risk	Jackknifed residuals of deviation from trend	1961-2012	FAO-STAT	CC
$FTC_{i,t}$	Fertilizers consumption	Ion Metric Tonnes of N nutrients per year	2000-2012	FAO-STAT	C
FTP_t	Intl. Prices of Fertilizers	USD/Kg	2000-2012	World Bank Pinksheet	C
$FiDe_{i,t}$	Domestic credit to private sector by banks (% of GDP)	Unit Free Measure	1961-2012	WDI	C
$AGDP_{i,t}$	Agriculture, value added (% of GDP)	Unit Free Measure	2000-2012	WDI	C

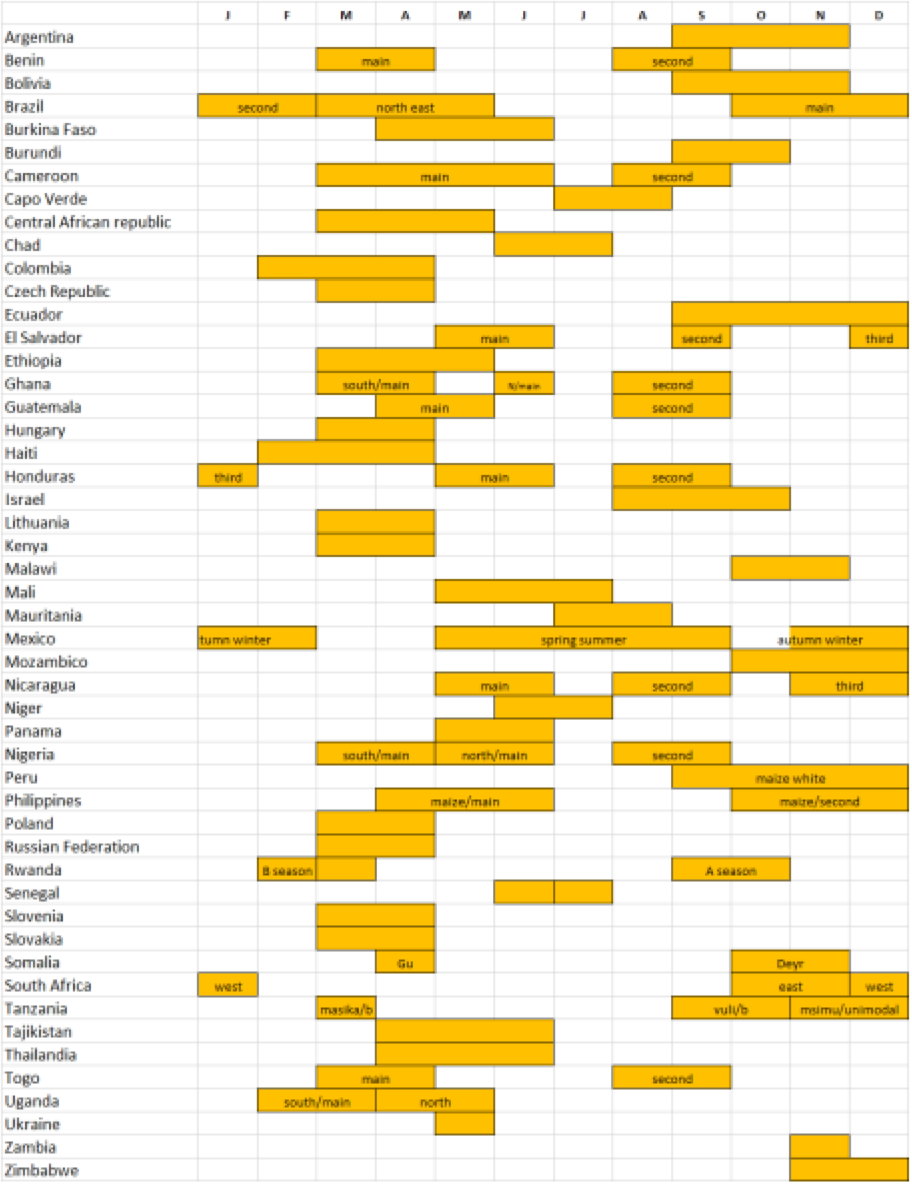
C = Country
CC = Country-Commodity

Figure 1. Wheat Crop Calendar, planting seasons.



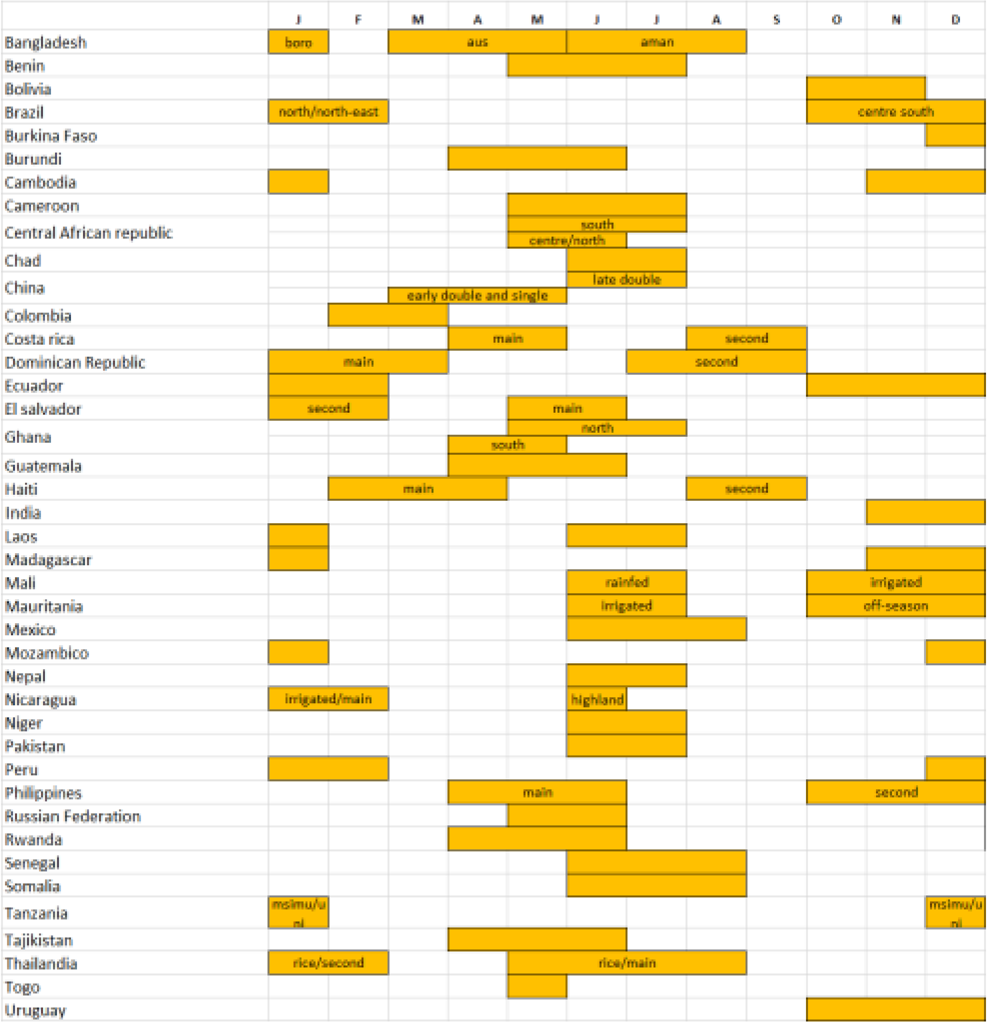
Source: Own Elaboration on FAOSTAT GIEWS data

Figure 2. Maize Crop Calendar, planting seasons.



Source: Own Elaboration on FAOSTAT GIEWS data

Figure 3. Rice Crop Calendar, planting seasons.



Source: Own Elaboration on FAOSTAT GIEWS data