4thICAAAE 2013 SEPTEMBER 22-25, Hammamet Tunisia
4th International Conference of the African Association of Agricultural Economists
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Invited paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia

249- How does food supply respond to high and volatile international food prices? An empirical evaluation of inter- and intra- seasonal global crop acreage response

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Abstract

Understanding how producers make decisions to allot acreage among crops and how decisions about land use are affected by changes in prices and their volatility is fundamental for predicting the supply of staple crops and, hence, assessing the global food supply situation. The innovations of the present paper are estimates of monthly (i.e. seasonal) versus annual global acreage response models for four staple crops: wheat, soybeans, corn and rice. We focus on the impact of (expected) crop prices, oil and fertilizer prices and market risks (price volatility and spikes) as main determinants for farmers' decisions on how to allocate their land. Primary emphasis is given to the magnitude and speed of the allocation process. Estimation of intra-annual acreage elasticity is crucial for expected supply and for input demand, especially in the light of the recent short-term volatility in food prices. The econometric results indicate that global crop acreage responds to crop prices and price risks, input costs as well as a time trend. Depending on respective crop, short-run elasticities are about 0.05 to 0.15; price volatility tends to reduce acreage response as do price spikes on top of that. Comparison of the annual and the monthly acreage response elasticities suggests that acreage adjusts seasonally around the globe to new information and expectations. Given the seasonality of agriculture, time is of the essence for acreage response: the analysis indicates that acreage allocation is more sensitive to prices in spring than in winter and the response varies across months.

JEL classifications: O11, O13, Q11, Q13, Q18, Q24
Key words: food price volatility, acreage response, price expectation, land use, food supply

[1] Authors thank Mikko Bayer for his excellent data assistance. We acknowledge Bayer CropScience AG and the Federal Ministry of Economic Cooperation and Development of Germany for the financial support.

1. Introduction

Prices of agricultural commodities are inherently unstable. The variability of prices is mainly caused by the stochasticity of weather and pest events that influence harvest and that are exacerbated by the inelastic nature of demand and supply. Besides these traditional causes for price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potential destabilizing impacts on prices (von Braun & Tadesse, 2012).

The aim of this paper is to better understand the global short-term supply dynamics of the four basic staple crops, namely wheat, corn, soybeans and rice. These commodities are partly substitutable at the margin in production and demand, and constitute a substantial share of the caloric substance of world food production (Roberts & Schlenker, 2009). Abstracting from the 'external' weather and pest shocks that are hardly predictable some months in advance, we focus on the acreage allocation decision as one important determinant of short-term supply. For these and other unpredictable conditions that usually occur after planting, the agricultural economics literature favored acreage over output response in order to estimate crop production decision (Coyle, 1993).

As the total global harvest quantity equals the product of area planted and yield, it is possible to decompose harvest fluctuations into an area and a yield component. Having a good prediction of acreage decisions therefore reduces the uncertainties regarding future harvests. This, in turn, allows a rough forecast on the next period's food supply situation which may already indicate possible shortages. Since an increase in productivity through technological progress and intensification is a rather long-term process, area expansion and re-allocation is the most important short-term decision variable for the farmer (Roberts & Schlenker, 2009; Searchinger et al, 2008). Hence, our research centers on two crucial questions regarding the global short-term supply of staple crops: (i) How *strongly* do farmers react to (expected) prices and price changes and (ii) how *fast* do farmers react to price changes in terms of acreage adjustments?

The econometric model of the short-term acreage response focuses on an annual specification as well as an (innovative) monthly specification which is obtained by applying the details of the crop calendar for major producing countries in order to derive monthly acreage allocation at the global level. Finding a robust answer to our research questions requires testing for different models of price expectation formation since expected prices are not directly observable. We will further consider the impact of uncertainty (or risk) in the price expectation process – expressed by different price volatility and price spike measures – that might influence the farmers' acreage decisions. We make a distinction between price volatility and price spikes and alternatively use them to capture the impact of price uncertainty on planted acreage. While the former refers to the dispersion of a price series from the long term trend- and hence is directionless the latter measures the changes in price levels over two periods (von Braun & Tadesse, 2012). Price spikes are given by the logarithmic ratio of two subsequent prices whereas price volatility is typically measured in terms of standard deviations of logarithmic prices. Alternative price volatility measures are discussed in subsequent sections.

There is an extensive literature on the estimation of land allocation decisions in agricultural economics. Nevertheless, there are various reasons to reconsider the research on acreage allocation and price relationships. The majority of the previous empirical literature investigating acreage response focuses largely on particular crops for specific regions. These studies are also concentrated in few countries such as the United States (Arnade & Kelch, 2007; Liang et al, 2011), Canada (Coyle, 1992; Weersink et al, 2010) and few others (Lansink, 1999; Letort & Carpentier, 2009). To our knowledge, there are few studies that estimate acreage elasticity at the country level (e.g. Barr et al, 2009; Hausman, 2012), and none at the global level. The effect of price volatility is usually considered as a microeconomic problem for producers. However, there are several factors (such as foreign direct investment in agriculture) that render the global and country level agricultural production to be equally affected by price volatility as the farm level production. Another reason for the renewed research interest in the topic is the growing demand for biofuels and the financialization of agricultural commodities, which are suspected to have contributed to the high and volatile food prices that in turn may affect land use dynamics.

The paper is structured as follows: the next two sections give a brief overview of temporal and spatial global acreage dynamics where we explain the functioning of the crop calendar. Next, we introduce the empirical framework by some theoretical considerations about acreage response and explain our data sources. After discussing the econometric results for different model specifications, we conclude with some further suggestions regarding global food supply and food price volatility.

2. Global acreage change and price dynamics

Currently, the factors behind high agricultural commodity prices are conversely debated. Demand shocks that have persisted in the past decade played a significant role: the rapid worldwide shift towards corn use for fuel, aggressive Chinese soybean import, and higher demand for food (especially meat) due to higher income levels in several emerging economies are some of these demand-side causes (Abbott et al 2011; Gilbert, 2010; Mitchell, 2008). These surges in demand, accompanied by the growing world population, have a remarkable bearing on the global land allocation. For instance, the additional Chinese soybean demand was to a large extent met by soybean acreage expansion in Latin America (Abbott et al, 2011). There have also been several other acreage allocation and reallocation changes all over the world following the recent output price variations. There have recently been remarkable foreign agricultural investments in many developing countries, primarily focusing on growing high-demand crops including corn, soybeans, wheat, rice and many other biofuel crops (von Braun & Meinzen-Dick, 2009).

These crops play a crucial global role both from the demand and the supply side perspective. They are principal sources of food in several parts of the world with differential preferences across countries. To this end, Roberts & Schlenker (2009) reported that these crops comprise a three-quarter of the global calories content. The use of corn, soybeans and wheat as a feed for livestock and dairy purposes has also grown due to higher demand for meat following rapid economic growth in the emerging economies. Corn production has also another source of demand from the emerging market for biofuel. These crops also constitute a sizable share of global area and production. Corn, wheat and rice, respectively, are the three largest cereal crops cultivated around the world. According to data from FAO (2012), they constitute above 75% and 85% of global cereal area and production in 2010, respectively. About a third of both the global area and production of total oil crops is also attributed to soybeans.

Figure 2 depicts the area changes of selected crops in the past 6 years. Agricultural producers have so far mainly responded to the increase in food prices by bringing in more land into production. However, close to 30% of the increase in area of the high-demand crops in the past 6 years was composed of displaced low-demand crops. Figure 2 shows that the five major crops that have shown expansion in area cultivation added about 45 million hectares of land within the previous 6 years. Corn and soybeans alone contribute close to 60% of the area increase during this period.

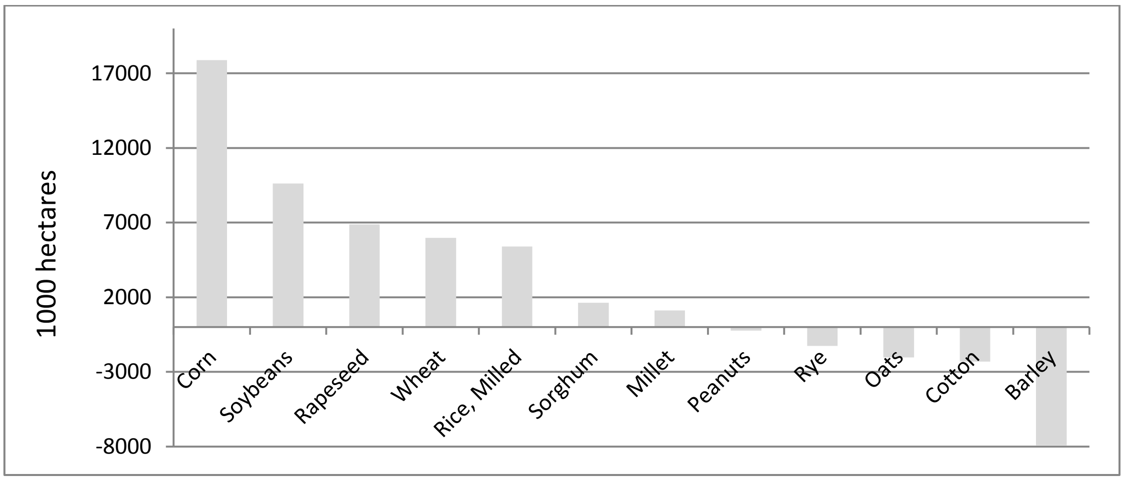

Figure 1. Total harvested area change for major crops in the world between 2004/05 and 2010/11
Source: FAS 2012, United States Department of Agriculture (USDA).

3. Monthly patterns of global cropped acreage

Global crop acreages, both sown and harvested, are neither uniformly distributed among all months within a year nor across geographical regions in the world. The global cropped acreage is rather concentrated to a few months depending on agro-ecological zones of the key producer countries. In fact, as can be seen in Figure 4, most of the global planted acreage of these crops is cultivated in two major crop seasons, winter and spring.[2] While most of the global wheat is sown in northern hemisphere winter, with a peak in October, the majority of the global corn is planted in spring, mainly in April and May. Nevertheless, global soybean is cultivated both in the spring and winter seasons, with major peaks in May and November respectively. Rice planting is relatively more spread throughout the year with a peak in the early summer. There are several regions in diversified agro-ecological zones where rice can be planted all year round. The data section below describes how we obtain monthly acreage and production data used in this study.

[2] In this study "winter" and "spring" refer to the respective seasons in the northern hemisphere.

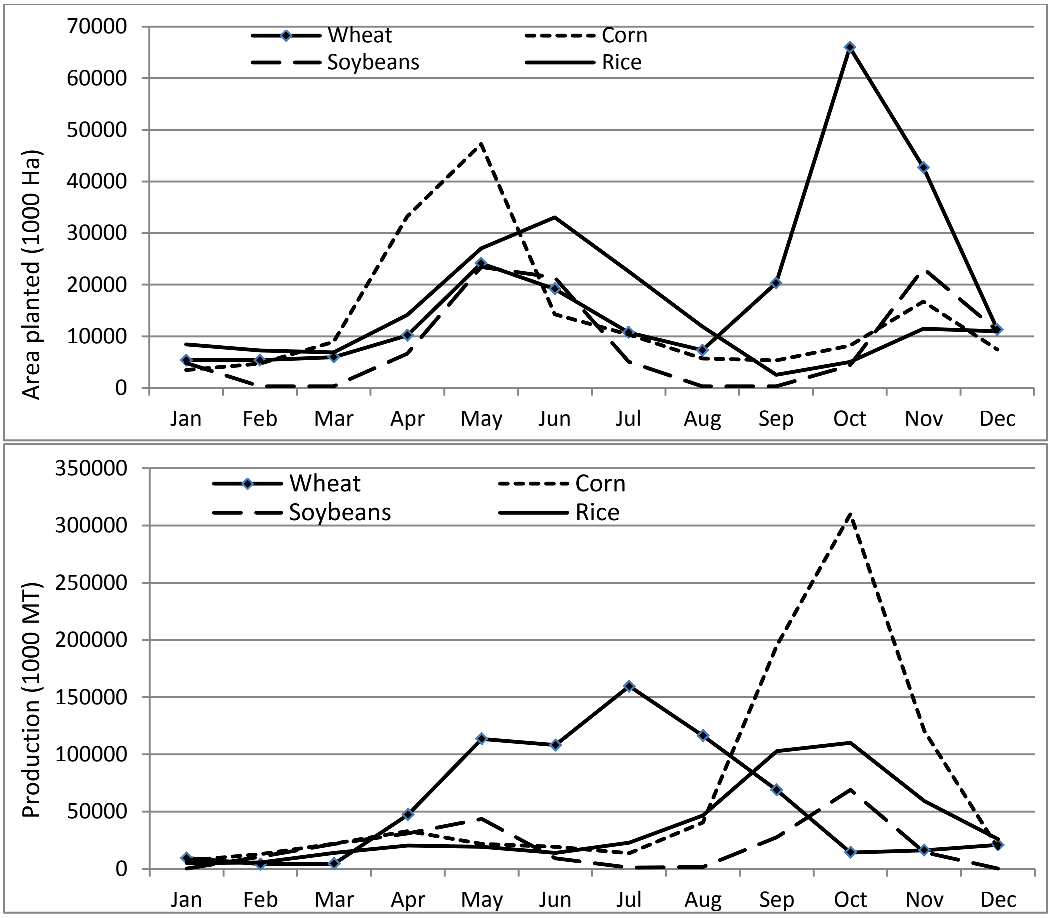

Figure 2. Global monthly planted acreage (top) and production (bottom) of selected crops
Source: Authors' calculations based on global crop calendar information and data from FAO (2012) and national data sources.

Figure 4 shows monthly global acreage and production using data in 2008. The figure clearly shows how the growing periods vary across crops. Considering the peak planting and harvesting months, the growing periods range from as short as 3-4 months for rice, soybeans and spring wheat to as long as 8-9 months in the case of winter wheat. Unlike spring wheat and the other crops which continuously grow from sowing to harvesting, winter wheat is sown in fall and stays dormant during the winter and resumes growing in spring of the following year. What is also clear from the above figure is that there is no major planting and harvesting in the world for about a third of the year, December to March.

Mapping where and when planting and harvesting takes place in the globe is crucial for many reasons. It helps to predict how farmers respond to changes in price expectations and weather events (yield expectations). It has also implications for food production, storage and trade relationships between countries. In developing countries where storage capacity of households is limited and where markets are thin or nonexistent, concentration of production of global staple crops in a few countries and a few months has adverse ramifications for global food and nutrition security. It limits the options that poor countries could import food in case of any supply and/or demand shocks in these specific countries and/or seasons. Such agricultural seasonality in planting and hence in production is well documented in the agricultural economics literature as an essential factor for variations in international food prices (Chambers et al, 1981; Deaton & Laroque, 1992; Moschini & Hennessy, 2001). However, the literature concerning intra-annual acreage and production adjustments is scanty.

4. Empirical Framework

4.1. Theoretical base

Modeling crop production in terms of acreage response is preferred to output supply since, unlike observed output, planted area is not influenced by the conditions after planting (e.g. weather, pest) (Coyle, 1993). Agricultural producers do also respond to output price primarily in terms of changes in acreage (Roberts & Schlenker, 2009; Searchinger et al, 2008), especially in the short-term. Several agricultural economists adopted Nerlove's partial adjustment and adaptive expectations model (Nerlove, 1956) to estimate acreage response equations, with various theoretical and empirical modifications (Chavas & Holt, 1990, 1996; Lin & Dismukes, 2007). This section describes the theoretical framework for a profit maximizing farmer who chooses the optimal allocation of land to a certain crop under price certainty and, in the second part, extends the model for price uncertainty.

4.1.1. Output price certainty

Consider a multi-output profit Π maximizing agricultural producer with a fixed total cropland $\bar{l}$ that can be allocated for N crops where l_i denotes the acreage allocated for the i-th crop (Arnade & Kelch, 2007; Chambers & Just, 1989). The decision problem for the producer is given by

$$\text{Max}_{x,l}\,\Pi(\boldsymbol{p},\boldsymbol{w},\boldsymbol{l},\boldsymbol{z}) = \boldsymbol{p}'\boldsymbol{y}(\boldsymbol{x},\boldsymbol{l},\boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x}$$

$$s.t. \sum_{i=1}^{N} l_i \leq \bar{l}$$

where **p, y** are vectors of output price and quantity respectively; **w** and **x** are vectors of input price and quantity respectively; $\boldsymbol{l}$ denotes the vector of land which in its sum is fixed by $\bar{l}$ but allocatable and **z** is a vector of other fixed inputs (machinery and equipment). The Lagrangian of this land constrained restricted profit function is given as

$$L = \boldsymbol{p}'\boldsymbol{y}(\boldsymbol{x},\boldsymbol{l},\boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x} - \phi\left(\bar{l} - \sum_{i=1}^{N} l_i\right)$$

where ϕ is the shadow price of the land constraint.

This allows us to obtain the crop-specific profit functions from which we can solve the choice variable functions including the acreage allocation function:

$$l_i^* = l_i^*(\boldsymbol{p},\boldsymbol{w},\bar{l},\boldsymbol{z})$$

This general acreage demand formulation implies that each acreage response equation is a function of all output and variable input prices, the total fixed cropland and other fixed inputs.

4.1.2. Output uncertainty prices

We now assume a risk-averse agricultural producer whose land allocation decisions are subject to price uncertainty. Uncertainty is a typical feature of agricultural production for several underlying reasons (Moschini & Hennessy, 2001). The profitability of a land allocated to a certain crop is affected by the uncertainty of the crop's price that in turn affects the acreage allocation decision of the producer. This section elaborates the mean-variance utility function (Coyle, 1992, 1999; Lansink, 1999). This approach incorporates risk-aversion and price uncertainty and generalizes the standard price certainty models described in the above section.

In the mean-variance approach, the risk preferences of the farmer are specified in terms of a utility function where the certainty equivalent of the expected utility maximization is expressed in term of the first two moments of profit (mean, $\overline{\Pi}$ and variance, σ_{Π}^2)

$$E\ U(\Pi) = E\ \Pi(\boldsymbol{p}, \boldsymbol{w}, l, \boldsymbol{z}) - \tfrac{1}{2}\ \alpha\ \sigma_{\Pi}^2 = \Pi(E[\boldsymbol{p}], \boldsymbol{w}, l, \boldsymbol{z}) - \tfrac{1}{2}\ \alpha\ \sigma_{\Pi}^2$$

where α is a measure of risk aversion which represents risk averse ($\alpha > 0$), risk neutral ($\alpha = 0$), and risk loving ($\alpha < 0$) producers respectively. Assuming that crop prices **p** remain the only random variables in the model (input prices **w** are deterministic), randomness of the producer's profit comes from the revenue rather than the cost component. Conditional on the acreage allocations to each crop, the expected mean and variance of profit are:

$$E\Pi = E[\boldsymbol{p}]'\boldsymbol{y}(\boldsymbol{x}, \boldsymbol{l}, \boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x}$$

$$\sigma_{\Pi}^2 = \boldsymbol{y}'\boldsymbol{\Omega_p}\boldsymbol{y}$$

where Ω_p denotes the covariance matrix of crop prices where Ω_{pij}refers the (co)variances of crops i and j. Using these mean and variance of the profit function results in the following certainty equivalent indirect expected utility function

$$E\ U^*(\mathbf{p}, \mathbf{w}, \boldsymbol{\Omega_p}, \boldsymbol{l}) = Max_{x,l}\left\{E\ U(\Pi) \equiv \left[E[\boldsymbol{p}]'\boldsymbol{y}(\boldsymbol{x}, \boldsymbol{l}, \boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x} - \frac{1}{2}\alpha\boldsymbol{y}'\boldsymbol{\Omega_p}\boldsymbol{y}\right]\right\}$$

Given a total cropland constraint, $\sum_{i=1}^{N} l_i \leq \bar{l}$, the Lagrangian for the above indirect expected utility function results in the following land constrained utility maximization problem:

$$L = \sum_{i}^{n} E[p_i]y_i(\boldsymbol{x}, l, \boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x} - \frac{1}{2}\alpha\boldsymbol{y}'\boldsymbol{\Omega_p}\boldsymbol{y} - \phi(\bar{l} - \sum_{\boldsymbol{i}}^{\boldsymbol{n}} l_i)$$

Therefore, the optimal allocation of land to crop *i* at a specific period *t* can be derived as

$$l_i^* = l_i^*(E[\boldsymbol{p}], \boldsymbol{w}, \Omega_p, \bar{l}, \boldsymbol{z})$$

Unlike the land allocation functions resulting from the traditional price-certainty models, above model allows the acreage allocation effects of output price uncertainty. However, the results of the price-certainty model can be obtained if either the risk aversion measure α is zero or if the covariance of crop prices $\boldsymbol{\Omega_p}$ is a null matrix. Risk aversion implies that marginal costs are lower than output prices, implying that optimal acreage and hence output with price certainty is greater than with price uncertainty (Lansink, 1999).

4.2. *Model Specification*

4.2.1. *Price expectations*

The farmer has to make his optimal crop acreage choices subject to output prices which are not known at the time when planting decisions are made. Thus, expected rather than observed output prices are used for decision making. Neither is there an *a priori* technique to identify the superior price expectation model nor does the empirical literature provides unambiguous evidence on which expectation model to use for empirical agricultural supply response estimation (Nerlove & Bessler, 2001; Shideed & White, 1989). Thus, we employ several alternative expectation assumptions in our empirical global acreage response model. First, we use the price of the harvesting period prior to the planting period as proxy for expected harvest crop prices (Coyle et al, 2008; Hausman, 2012). This corresponds to a naïve expectation model where farmers base their future price expectation on the most recent harvest price. Second and in a somewhat different fashion, we consider crop prices during the pre-planting month(s). These prices contain more recent price information for farmers and they are also closer to the previous harvest period, conveying possibly new information about the future supply situation. Third, when applicable, the new-crop harvest time future prices traded in the months prior to planting are used to represent farmers' prices expectations (Gardner, 1976).

4.2.2. *Price risks*

As mentioned above, this study captures price risk in two alternative ways: using price volatility and price spikes. We calculated the standard deviations of the monthly logarithmic prices during the preceding 12 months as one way of measuring price volatility. We also calculated the variances of the log returns of output prices over the preceding 12 months as an alternative volatility measure. Price spikes are measured as monthly or annual price changes- calculated as the logarithmic return of prices as

$$Spike = dlnP_t = \ln(\frac{P_t}{P_{t-1}}) \quad t = \text{month or year}$$

They reflect relative changes in log returns during the planting period as compared to the period before. Furthermore, in the monthly specification, price spikes measure sudden price changes in a specific period that may or may not last in the long run.

4.2.3. *Global acreage estimation*

The quadratic specification, which is commonly applied to describe profit or revenue functions (Coyle, 1992; Guyomard et al, 1996), allows linear equations for the choice variables. The acreage demand equations can be specified most generally as:

$$l_i = \alpha_i + \sum_{j=1}^{4} \beta_{ij} p_j + \sum_{j=1}^{4} \sum_{k \geq j}^{4} \sigma_{ijk} \Omega(p)_{jk} + \theta_i Z_i + \varepsilon_i \qquad (1)$$

where l_i denotes the acreage planted to the i-th, p_j is the expected price for the j-th crop, $\Omega(p)_j$ is the (co)variance (i≠j) of crop prices, Z_i denotes other explanatory variables (e.g. a period lag of acreage as proxy for soil conditions or land constraints, l_{t-1}, time trend t, dummy variables d, production costs w, and the error term ε. If all the (co)variances of expected output prices, σ_{ij} are zero, the above acreage response equations are consistent to the price-certainty or risk neutrality model:

$$l_i = \alpha_i + \sum_{j=1}^{4} \beta_{ij} p_j + \theta_i Z_i + \varepsilon_i$$

We have used price spikes as alternative measures of own price uncertainty. Given the above definition of price spikes, we specify the general empirical acreage model as

$$l_i = \alpha_i + \sum_j^4 \beta_{ij} p_j + \sigma_i d \ln P_i + \theta_i Z_i + \varepsilon_i \qquad (2)$$

The time trend captures technological change over time and the effect of the increase in output demand resulting from increases in demand for biofuel, income and population on all acreage changes. We also included lagged own crop acreages in our analysis to control for land and soil requirements as well as adjustment costs of crop rotation.

4.3. Data

The econometric model relies on a comprehensive and elaborate database covering the period 1961-2010. The empirical model utilizes global and country-level data to estimate global acreage responses for the key world crops. While data on planted acreage were obtained from several relevant national statistical sources, harvested area for all countries was obtained from the Food and Agricultural Organization of the United Nations (FAO). The international spot market output and input prices were obtained from the World Bank's commodity price database. All commodity futures prices were obtained from the Bloomberg database. Finally, the US Consumer Price Index (CPI) used in this study was obtained from the US bureau of Labor statistics. All price used in our estimation all are in real terms - deflated by the US CPI.

Since world harvested and planted acreage data are published annually, we use country-level data to construct the global monthly database. The monthly database is innovative in using country-specific crop calendar to trace the annual harvest and acreage data back to the respective harvesting and planting months for each crop. While the crop-calendar for emerging and developing countries is obtained from the General Information and Early Warning System of the FAO, the Office of the Chief Economist of the USDA is the source of the crop-calendar for the advanced economies. Area harvested is used as a proxy for planted area if data for the latter is not available from the relevant national agricultural statistics. A symmetric triangular probability distribution is used to apportion values to each month in case of multiple planting and harvesting months. The acreage and harvest data for the rest of the world is evenly distributed across all months.

5. Results and Discussion

In the following section, we discuss several regression results to highlight the relationship between acreage, prices and price uncertainty. We have conducted the standard statistical unit root tests, augmented Dickey-Fuller and Phillips-Perron tests (Dickey & Fuller, 1979; Phillips & Perron, 1988), for each of the time series in the acreage response models for all four crops. The unit-root test results indicate that all the level price variables are non-stationary. However, the price volatility and price spike as well as the acreage variables for all crops were found to be stationary series. The typical solution to avoid spurious regression resulting from a non-stationary time series, but not cointegrated, is differencing the series until we get a non-stationary series, I(0). However, if either the dependent or the independent variable or both is stationary, which is the case in the present study, differencing the series results in model misspefication. In such circumstances, including lagged values of the dependent and independent variables as regressors helps avoid the problem of spurious regression. Our regression results have both the lagged dependent and independent variables as explanatory variables and thus the estimated coefficients are asymptotically consistent.

All acreage and price variables (except for price volatilities, which are rates; and price spikes, which are negative as well as positive) are specified as logarithms in the econometric models of proceeding discussion. Hence, the estimated coefficients can be interpreted as short-run price elasticity of acreage. Since autocorrelation is a problem in most of the econometric estimations, we used the Newey-West autocorrelation adjusted standard errors.[3]

5.1. Annual acreage response

The annual regression gives a conventional estimate of supply elasticities that indicate how annual global acreage changes in response to annual price changes. To our knowledge, this is a first study to estimate acreage elasticities at a global scale. Additionally, short term price movement indicators are considered to assess the impact of price risk or rapidly changing prices. The first and second columns of each crop's regression results reported in Table 1 use price volatility and price spike variables as a proxy for price risk, respectively.

Table 1. Annual acreage response estimates

	Wheat		**Corn**		**Soybeans**		**Rice**[+]	
Variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Lagged own acreage	0.611***	0.702***	0.211	0.221	0.715***	0.795***	0.701***	0.643***
	(0.077)	(0.088)	(0.134)	(0.132)	(0.100)	(0.094)	(0.055)	(0.065)
Own futures price	-0.009	-0.011	0.038*	0.037	0.135**	0.129**	0	0.002
	(0.016)	(0.013)	(0.024)	(0.025)	(0.050)	(0.051)	(0.009)	(0.010)
Lagged own spot price	0.062***	0.043**	0.067**	0.057**	-0.007	0.011	0.027***	0.029**
	(0.020)	(0.020)	(0.033)	(0.030)	(0.062)	(0.049)	(0.009)	(0.011)
Lagged own price volatility	-0.173**		-0.064		0.202		-0.076**	
	(0.085)		(0.070)		(0.161)		(0.037)	
Lagged own price spike		0.023		0.007		0.087**		-0.016*
		(0.022)		(0.021)		(0.039)		(0.008)
Fertilizer price	0.005	0	-0.017*	-0.016*	-0.059**	-0.072***	-0.005	-0.005
	(0.015)	(0.016)	(0.009)	(0.009)	(0.023)	(0.024)	(0.007)	(0.007)
year of planting crops	0.001*	0.001	0.009***	0.008***	0.011***	0.009**	0.002***	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)	(0.000)	(0.001)
Intercept	2.064*	2.469**	-8.116***	-7.248***	-19.525***	-15.940***	-0.702	-0.785
	(1.163)	(1.070)	(1.896)	(1.477)	(6.053)	(5.789)	(0.523)	(0.655)
R-squared	0.75		0.97		0.99		0.96	
N					49			

*p<0.10, ** p<0.05, *** p<0.01

Notes: Autocorrelation adjusted standard errors in parentheses. [+]We used pre-planting month spot prices instead of futures prices in case of rice.

Table 1 shows the global annual acreage response results. Instead of relying solely on an adaptive expectation scheme built from lagged farm prices, the empirical model in this study is also forward-

[3] Thus, the reported R-squared values are from a usual OLS regression

looking in the sense that farmers base their expectations on futures prices as well. For wheat, corn and soybeans, cash prices of the planting months in the year before harvesting are considered as the expected harvest period prices. Since most of the sowing for the harvest of a specific year for these crops occurs during the spring of the same year or during the winter of the previous year, we lagged both spot prices and volatility. As rice is planted in most of the months throughout the year, we use the same-year values. The futures prices refer to the new-crop, harvest time futures prices, observed in the months when planting decisions are made. As these periods differ from country to country, we use the planting and harvesting periods of the US as a reference since it accounts for a large share of global production of the interest crops. We also considered futures contracts traded in the US. While, in the case of wheat, the expected prices are derived from the average July wheat futures traded from October to December, the futures prices for corn and soybeans are the average December corn futures prices observed from March to May and the average November soybeans futures prices observed from April to June, respectively.

The regression estimates for the own-spot short-run price elasticities range from 0.03 (rice) to 0.07 (corn), which is low but fairly consistent with other estimates: for instance, Roberts and Schlenker (2009) estimated supply elasticities for the caloric aggregate of the four staple crops between 0.06 and 0.11. The result shows that soybean and corn producers are forward looking in terms of making their harvest time price expectations based on the new crop future prices. Doubling new-crop harvest time own futures prices increases global acreage by 13% for soybeans and 4% for corn, although corn would also respond by additional 6-7% if lagged annual spot prices also increased. However, the global acreage for wheat seems to respond to spot prices rather than to futures prices. Own price volatility reduces global wheat and rice acreage significantly, the respective estimated coefficients are -0.17 for wheat and -0.07 for rice. Price spikes affect soybean production positively and rice production negatively while it has no clear impact on wheat and corn acreages. Fertilizer prices seem to negatively affect the global soybean and corn acreages in the annual model. The time trend which mainly captures the increase in output demand resulting from increases in demand for biofuel, income and population is relevant for all acreage changes. Global acreages of corn and soybeans show relatively stronger time trends implying annual growth rates of about 1%.

5.2. Monthly acreage response

The annual regression is able to predict global annual acreage changes based on averaged annual prices. One important feature of the crop calendar and the disaggregation method is that it allows calculating short-term supply elasticities on a monthly basis using price (and other information) that exhibit more intra-annual fluctuation. This will help to identify the magnitude and the speed of the farmers' response to prices. We will present two different estimations: the first gives monthly price elasticities of crop acreage which are the same for all months (representing intra-annual supply elasticity); the second estimates month-specific elasticities that differ from month to month. While the latter turns out to fit the data better, the former allows a more direct comparison with the annual regression and is easier to represent.

5.2.1. *Intra-annual supply elasticities*

The advantage of estimating month-independent supply elasticities is to have a rough estimation of acreage change given the price information of one month. To account for the effect of seasonality that may arise due to climatic and geographic conditions that constrain the planting months, month dummies are applied.[4] As our disaggregation of (mainly wheat) planting months changes in 1992 due to the breakdown of the Soviet Union, we further employ additional month dummies for the years after 1991.

Tab. 2: Intra-annual supply response estimates

Variables	**Wheat**	**Corn**	**Soybeans**	**Rice** +
Lagged own acreage	0.83***	0.83***	0.96***	0.65***
	(0.031)	(0.038)	(0.010)	(0.025)
Own spot price (t-1)	0.070*	-0.076	-0.041	0.013*
	(0.039)	(0.057)	(0.065)	(0.007)
Own spot price (t-2)	-0.021	0.089**	0.105*	
	(0.040)	(0.051)	(0.062)	
Lagged Own price volatility	-0.538*	0.336	0.605	0.037
	(0.369)	(0.327)	(0.384)	(0.086)
Lagged fertilizer price	0	-0.007	-0.032**	-0.004
	(0.016)	(0.008)	(0.016)	(0.005)
Year	0.001	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Intercept	0.435	-1.454	-4.793**	-0.797
	(1.216)	(1.151)	(1.862)	(0.534)
R-squared	0.99	0.99	0.99	0.99
N			588	

* p<0.10, ** p<0.05, *** p<0.01

Notes: Autocorrelation adjusted standard errors in parentheses. +The price for rice is the average price of the previous 12 months.

Table 2 summarizes the monthly regression results. In this case, we assume farmers base their expectations on the spot prices during the two pre-planting months except for rice where we take annual average price. Based on the way we measure price spikes, the pre-planting period own price variables capture their effects on acreage changes and hence we do not run separate regressions. The dependent own acreage variables are the values corresponding to same month of the previous year.

It is interesting to see that monthly acreage adjustments in response to prices are in the same order of magnitude as the annual acreage response estimates. This shows that the prices preceding the planting period of these crops contain relevant information that the producers base – on global average – their harvest time price expectations on. We also observe that the acreage allocation decision of corn and soybean producers is affected by spot prices prevailing two months prior to planting month whereas for wheat farmers the spot price in the month immediately before the planting month is more important. Hence, doubling of these respective own spot prices may lead to global acreage increase of between 7% and 11% for each of these crops in the short-run. The global

[4] The coefficients of monthly dummies are not reported for the sake of brevity

monthly rice acreage is the least responsive to own prices (elasticity: 0.013). Own price volatility seems not to affect monthly global acreages except in the case of wheat acreage, where volatility has negative effect. Consistent to the annual econometric results, fertilizer prices negatively affect monthly soybean acreages. Although at a lower rate relative to the annual model, global acreages of corn, soybeans and rice have increasing trend implying, annual average growth rates of about 0.2%.

5.2.2. *Month-specific supply elasticities*

For the second short-term regression we estimate the acreage response in one specific month depending on prices in the preceding month as well as individual crop area allocated in the same month of the previous year. Table 3 shows the results for the most important planting months.

In general, the regression results with price volatility (1) and of price spikes (2) lead to fairly consistent estimates of all coefficients. The coefficients of the price spike variables have the *a priori* expected negative sign in almost all crop acreage equations. One slight difference is that the own price soybean acreage elasticities were smaller in magnitude when volatilities were used. Price spikes have a negative effect on global corn acreage during the spring season and on September wheat acreage. In the proceeding discussion, we rely on the results obtained from the specifications with price volatility.

The month specific acreage response estimations show several interesting results. In General, compared to both the annual and the previous intra-annual supply response estimates, the month-specific own price short-run acreage elasticities of all crops are significantly higher (particularly during the spring planting period). Moreover, area planted during spring is generally more sensitive to own prices than area planted in winter. In other words, the results show that acreage responsiveness to prices is not invariant across months: it differs from month to month as dominant planting decisions are taken in different countries. The short run own-price acreage elasticity for wheat ranges from 0.206 in May to 0.041 in October. Similarly, short-run own-price acreage elasticities range from 0.125 (corn in April), 0.158 (Soybeans in June), and 0.022 (rice in June) to fairly price insensitive acreages in winter (November). This variation may partly be explained by the lower availability of land during spring but also by the market integration and agricultural market structure of the specific countries where most of the planting within a specific month takes place.

It is also consistent across all acreage response estimations in this study that fertilizer price index has a significant negative effect on soybean acreage- with higher elasticities in the latter estimation. It has also negative acreage effects on corn (Tab.1) and wheat planted in May (Tab.3). One explanation for the negative relationship could be that when fertilizer prices are high, acreage expansion is more profitable than increasing intensification. Regarding the time trend, the global acreage of all crops planted in spring has been consistently growing at a rate of about 0.6% (wheat), 0.7% (corn), 0.8% (soybeans), and 0.2% (rice) every year.

Tab. 3: Month-specific elasticities for typical planting months of all crops

Variables	**Wheat**						**Corn**					
	May		Sept.		Oct.		Apr.		May		Nov.	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Lagged own area	0.492***	0.54***	0.576***	0.569***	0.862***	0.867***	0.346***	0.298**	0.365***	0.44***	0.646***	0.68***
	(0.094)	(0.076)	(0.112)	(0.106)	(0.068)	(0.067)	(0.122)	(0.139)	(0.116)	(0.107)	(0.102)	(0.107)
Own price	0.206***	0.206***	0.048**	0.047*	0.041**	0.037**	0.122***	0.125***	0.099***	0.112***	-0.049*	-0.029
	(0.056)	(0.069)	(0.023)	(0.024)	(0.017)	(0.015)	(0.043)	(0.031)	(0.030)	(0.024)	(0.029)	(0.037)
Own price volatility	-1.627		-0.602*		-0.265		-0.544		0.002		1.224	
	(1.024)		(0.328)		(0.240)		(0.757)		(0.400)		(0.795)	
Own price spike		-0.492		-0.157		-0.039		-1.062**		-0.744***		-0.292
		(0.517)		(0.098)		(0.115)		(0.457)		(0.251)		(0.201)
Fertilizer price index	-0.079**	-0.109*	-0.006	-0.01	-0.01	-0.011	-0.016	-0.023	-0.009	-0.02	0.030*	0.022
	(0.034)	(0.062)	(0.013)	(0.015)	(0.012)	(0.011)	(0.025)	(0.019)	(0.019)	(0.016)	(0.016)	(0.019)
year	0.006***	0.006***	0.001	0.001	0.001	0.001	0.007***	0.008***	0.007***	0.007***	0	0
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	-8.121***	-7.142***	2.484	2.912	-0.735	-0.493	-8.606***	-9.102***	-8.394***	-8.489***	4.115**	2.218
	(2.036)	(1.955)	(1.914)	(1.872)	(1.264)	(1.186)	(2.840)	(1.879)	(1.611)	(1.350)	(1.699)	(2.051)
R-squared	0.61	0.57	0.70	0.70	0.82	0.82	0.87	0.89	0.94	0.95	0.74	0.74
N			49						49			
	Corn						**Rice**					
	May		June		Nov.		May		June		Nov.	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Lagged own area	0.793***	0.789***	0.789***	0.779***	0.925***	0.931***	0.662***	0.663***	0.680***	0.685***	0.556***	0.567***
	(0.114)	(0.110)	(0.060)	(0.060)	(0.039)	(0.038)	(0.063)	(0.067)	(0.063)	(0.066)	(0.110)	(0.107)
Own price	0.104**	0.126***	0.158***	0.194***	0.052	0.032	0.019*	0.019*	0.022**	0.021*	-0.01	-0.015
	(0.045)	(0.024)	(0.042)	(0.028)	(0.097)	(0.105)	(0.010)	(0.010)	(0.010)	(0.010)	(0.020)	(0.021)
Own price volatility	0.567		0.197		0.886		0.113		0.131		-0.213	
	(0.759)		(0.735)		(0.713)		(0.179)		(0.165)		(0.292)	
Own price spike		0.007		-0.439*		0.706		0.011		0.053		-0.199
		(0.221)		(0.244)		(0.607)		(0.07)		(0.123)		(0.24)
Fertilizer price index	-0.052**	-0.056***	-0.057***	-0.070***	0.012	0.037	0	-0.001	-0.006	-0.005	0	0.001
	(0.020)	(0.019)	(0.021)	(0.021)	(0.072)	(0.077)	(0.010)	(0.011)	(0.011)	(0.010)	(0.015)	(0.014)
Year	0.004*	0.005**	0.008***	0.009***	0.004	0.003	0.001***	0.001***	0.002***	0.002***	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Intercept	-6.587*	-7.739***	-13.88***	-15.832***	-6.643	-5.263	0.431	0.375	-0.51	-0.511	0.464	0.853
	(3.580)	(2.718)	(3.858)	(3.239)	(6.929)	(7.192)	(0.576)	(0.569)	(0.663)	(0.651)	(2.035)	(2.042)
R-squared	0.95	0.94	0.98	0.98	0.99	0.99	0.93	0.93	0.95	0.95	0.82	0.82
N			49						49			

Notes: * p<0.10, ** p<0.05, *** p<0.01

Note: Robust standard errors are in parentheses. All price, volatility, and spike variables are lagged once and hence refer to the pre-planting month values.

6. Conclusions

In recent years global crop production has faced a series of emerging issues and showed noticeable variations in acreage. Factors such as ongoing developments in bio-technology, fluctuations in corn and soybean prices due to the rising demand for ethanol, and changes in production costs affect producers' acreage allocation decisions. These changes have huge implications for the global food supply as well as for the agribusiness sector such as input supply industries. To this end, a recent study showed that land use changes as a result of expansion of biofuel significantly decreases global food supply mainly in developing countries (Timilsina et al, 2012).

This study is the first of its kind in estimating annual and intra-annual acreage responses at a global scale. We have used a country-specific crop calendar in order to apportion annual acreage values into respective planting months and also in order to choose the most likely output prices that shape producers' price expectations. This enables us to investigate how crop acreages in one part of the world are affected by harvest changes in the other part of the world. Although the estimated short-run global acreage responses to price changes are generally small, they differ across crops and from month to month. Acreage responds to monthly as well as to annual price changes, the latter being slightly stronger. Soybean and corn area furthermore responds to futures prices while wheat and rice area can best be explained by spot price changes. Generally, soybeans and corn acreages are more responsive to prices (with annual short-run own-price elasticities between 0.1 and 0.14) than wheat (0.07) and rice with elasticities close to zero. The low acreage supply elasticities may be indicative of the need for productivity improvements to meet (growing) demand as area expansion is economically and environmentally limited.

Our disaggregation from annual to monthly acreage data allows us to further study the intra-annual acreage responses to prices and other factors. The monthly acreage response model resulted in month-independent price elasticities that are of comparable magnitude to the annual price elasticities. However, the month-specific price elasticities reveal that global acreages respond stronger to price changes in some specific months than in others. More specifically, the area planted during spring is more price sensitive than area planted in winter- since more area is available in the winter as more crops compete for land during spring. This may also reflect other country-specific reasons including national policies, which limit the flexibility of crop acreage adjustments. Furthermore, the short-term price dynamics are decisive for all crop acreages. For instance, a strong price increase that comes immediately before planting will not materialize in an equal acreage increase than if price change would have stayed for a longer period. Farmers might perceive such unexpected price jumps as outliers signaling risks rather than as price incentive.

Results from this study suggest that the effects on aggregate supply response of price uncertainty, measured by own price volatility and price spikes, for the major global field crops are not strong and vary across commodities. Own price volatility and price spikes have negative effects on monthly global corn acreages. Furthermore, both the annual and monthly regression results revealed that price volatility reduces global wheat acreage. The annualized wheat price volatility in the years

2008 and 2010 was 0.153 and 0.166 – roughly three times the value 0.06 which could be regarded as a value for 'normal' times. With the estimated coefficients, a 10% higher wheat price volatility reduces wheat acreage by close to 2% in the annual and even higher in the monthly acreage response (5.4%).

The intra-annual acreage analysis provides a stepping stone for establishing a global short-term supply model that predicts area planted, and therefore expected harvest, according to current world market prices. In addition to indicating potential food supply shortages, such supply model helps to analyze whether current prices are consistent with 'fundamentals' or whether they are driven by speculation or trade disruption. Future research that focuses on panel regressions for comparable country groups may help to integrate elasticities and current price series into a global monthly forecast model with regional resolution. A major challenge will be to integrate expectations regarding yield response to price change, in particular yield fluctuations in a context of weather events such as El Niño and La Niña.

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