



Zentrum für Entwicklungsforschung
Center for Development Research
University of Bonn

ZEF-Discussion Papers on Development Policy No. 175

Mekbib G. Haile, Matthias Kalkuhl and Joachim von Braun

Short-term global crop acreage response to international food prices and implications of volatility

Bonn, February 2013

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Mekbib G. Haile, Matthias Kalkuhl and Joachim von Braun, Short-term global crop acreage response to international food prices and implications of volatility, ZEF- Discussion Papers on Development Policy No. 175, Center for Development Research, Bonn, February 2013, pp. 33.

ISSN: 1436-9931

Published by:

Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Walter-Flex-Straße 3
D – 53113 Bonn
Germany
Phone: +49-228-73-1861
Fax: +49-228-73-1869
E-Mail: zef@uni-bonn.de
www.zef.de

The authors:

Mekbib G. Haile, Center for Development Research (ZEF), University of Bonn. Contact: mekhaile@uni-bonn.de

Matthias Kalkuhl, Center for Development Research (ZEF), University of Bonn. Contact: mkalkuhl@uni-bonn.de

Joachim von Braun, Center for Development Research (ZEF), University of Bonn. Contact: jvonbraun@uni-bonn.de

Acknowledgement

Authors are grateful to Lukas Kornher (ZEF) and two external reviewers, Ulrich Koester (University of Kiel) and Getaw Tadesse (IFPRI), for their reviews and comments on an earlier version of this paper. Mikko Bayer provided valuable data and research assistance. We acknowledge Bayer CropScience AG and the Federal Ministry of Economic Cooperation and Development of Germany for their financial support of the related research project at ZEF.

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 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. Such aggregate estimates are also valuable to verify whether involved country-specific estimations add up to patterns that are apparent in the aggregate international data. 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 0.25; price volatility tends to reduce acreage response of some crops; 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 northern hemisphere spring than in winter and the response varies across months.

JEL classifications: O11, O13, Q11, Q13, Q18, Q24

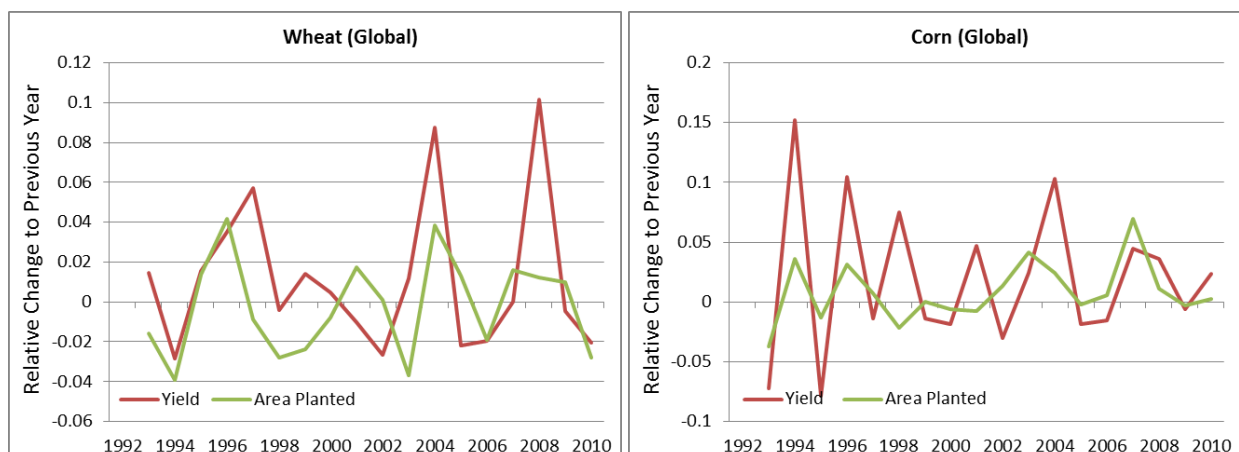
Keywords: food price volatility, acreage response, price expectation, land use, food supply

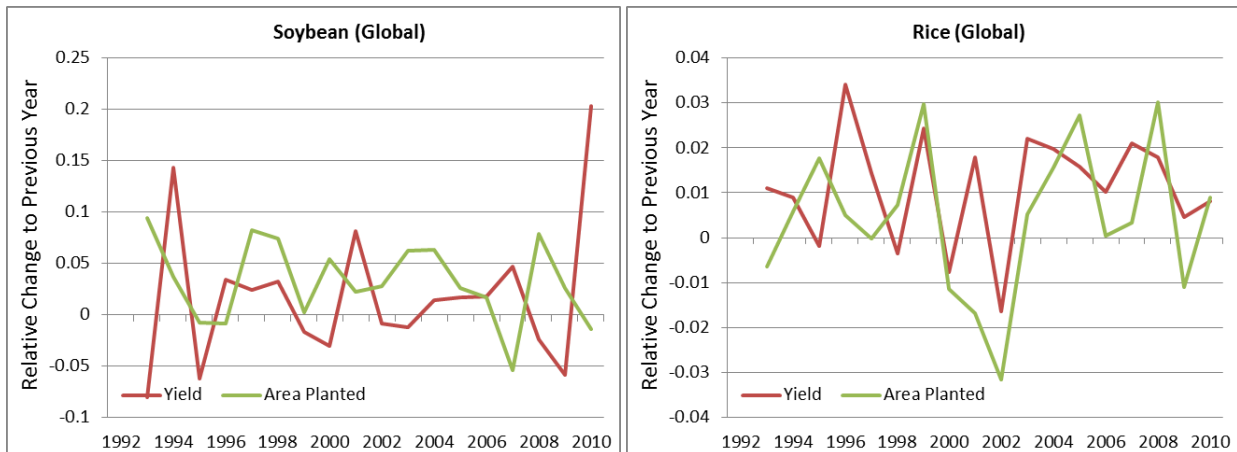
1. Introduction

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).

Figure 1 Annual fluctuations of global area planted and yield per area planted.





Source: Authors' calculations based on data from FAO (2012) and national sources

As the total global harvest quantity equals the product of area planted and yield per area planted, it is possible to decompose harvest fluctuations into an area and a yield component.¹ Figure 1 shows the annual fluctuations of these two variables. It becomes apparent that yield fluctuations are of slightly higher magnitude than area fluctuations for most crops except for rice, although for the latter they are of similar order of magnitude. Regarding corn, yield fluctuations seem to have decreased within the last two decades while area fluctuations have increased. 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 price expectation formation models as expected prices are not directly observable. We further consider the impact of uncertainty (or risk) in the price

¹ As opposed to the typical definition of yield as the ratio of harvest and area harvested, we use area planted instead, which is the proper decision variable of the farmer. Due to weather and pest events, farmers may harvest substantially less area than what was planted. Hence, harvested area contains more stochastic influences.

expectation process – expressed by different price volatility measures – that might influence the farmers’ acreage decisions. Finding a robust answer to our research questions requires testing for different price expectation formation models as expected prices are not directly observable. We further consider the impact of uncertainty (or risk) in the price expectation process – expressed by different price volatility measures – that might influence the farmers’ acreage decisions. While upward output price trends are an incentive for agricultural producers to make agricultural investments such as expanding acreage, output price volatility introduces risks that affect a risk-averse agricultural producer (von Braun & Tadesse, 2012). Price volatility is typically measured as the standard deviations of price returns (Gilbert & Morgan 2011).

There is an extensive literature on the estimation of land allocation decisions in agricultural economics. The acreage response literature has actually gone through several important empirical and theoretical modifications. These include acreage response studies in line with the Nerlovian general supply response function (Askari & Cummings, 1977; Nerlove, 1956) and recently in a theoretically more consistent mode that integrate both producer and consumer economic behavior (Chavas & Holt, 1990, 1996; Lin & Dismukes, 2007). 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. Given that previous analyses at the micro level show the acreage effect of price volatility at micro and national level, it is rational to ask whether this effect ensues at the global scale. The analysis at global scale appears to be even more important as the impacts are likely to affect national and household level land allocations. Such global analysis involves data aggregation that could result in potential estimation bias. Nevertheless, since each producer faces the same international price in our global level

analysis, the potential aggregation bias will be less problematic. 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 which in turn may affect land use dynamics.

This study, therefore, investigates the responsiveness of global agricultural cropland to changes in output prices and the uncertainty therein. The study provides a global short- and medium-term acreage elasticity which hints at how major agricultural commodity producers respond to the recent high food prices and volatility. Estimation of intra-annual acreage elasticity is crucial especially in the light of the current short-term volatile food prices for policy makers, agricultural investors, and for the agribusiness sector including input supply industries.

The article is structured as follows: the following 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

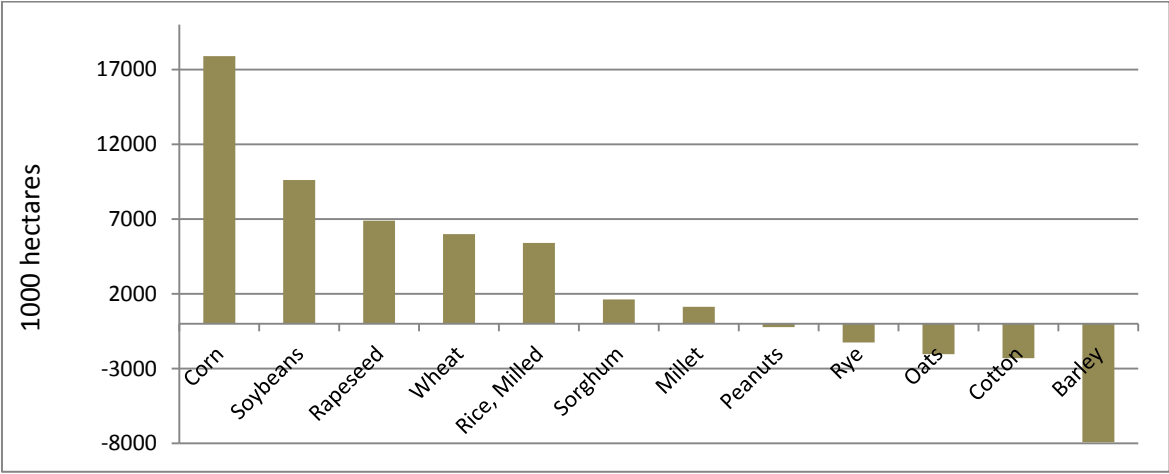
Currently, the factors behind high agricultural commodity prices are conversely debated. Demand shocks that have persisted in the past decade played a significant role: the rapid worldwide shift towards corn use for fuel, aggressive Chinese soybean import, and higher demand for food (especially meat) 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. While new acres are still important sources of changes in acreage for the developing and emerging countries, shifting land from low- to high- demand crops is also a key source in the developed countries

where total arable land has become more binding. As a result, 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).

It is not without reason that we primarily focus on these basic agricultural commodities. They play a crucial global importance 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. It is likely that total cropland supply will be even more inelastic in the future due to population pressure, desertification and other climatic factors. This implies that the acreage response of countries towards high and volatile agricultural commodity prices will be predominantly via land reallocations.

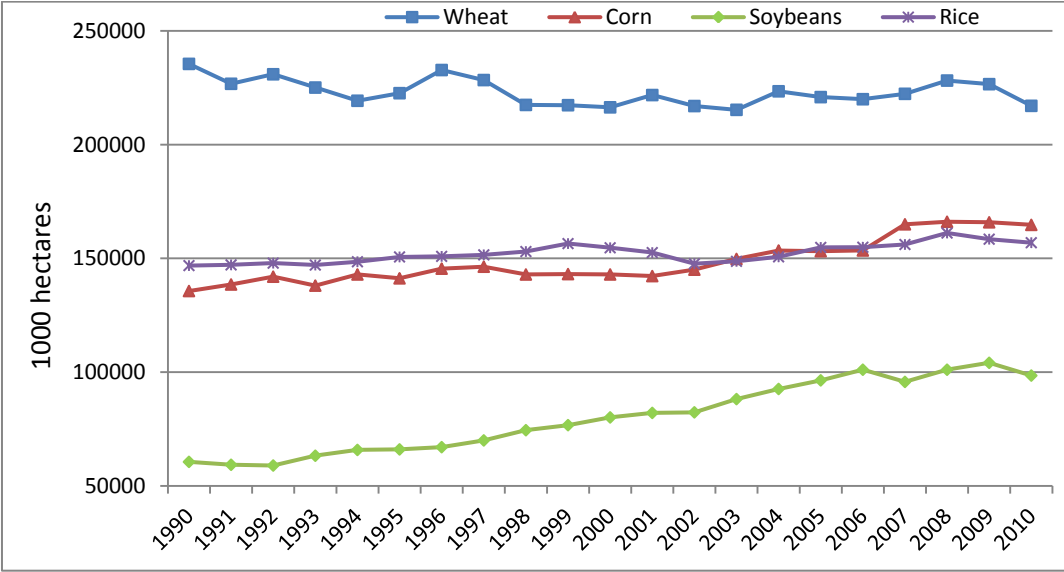
Figure 2. Total harvested area change for major crops in the world between 2004/05 and 2010/11



Source: FAS 2012, United States Department of Agriculture (USDA).

Figure 3 depicts the annual global planted acreage of the four crops since 1990. Although the annual planted corn and soybean acreages seem to show an upward trend, visual inspection shows that there exist year-to-year acreage variations for all crops. In fact, Figure 1 above shows that annual acreage changes for soybeans, corn and wheat have become more variable since about 2002 relative to the preceding 5 years. Moreover, the growth of planted wheat and rice acreages has been relatively more stable compared to that of soybeans and corn in the past two decades. The global soybean acreage has been steadily growing since about the mid-1990s except for a decline of about 5% in 2007. Planted corn area has also shown a consistent upward trend in the past decade except a slight decline in 2009. Periods of major acreage increase in global corn has usually been at a cost of soybean acreage, or vice versa. For instance, a close to 5% decline in global planted acreage for soybeans in 2007 was accompanied by an increase of about 7% in the global acreage for corn (Figure 1). This is due to the fact that the two crops are typically planted in similar seasons, have similar land requirements and are good substitutes for animal feed. Including data starting from the 1960s into figures 1 and 3 indicates that the annual growth of global planted areas for these crops was relatively stable in the middle two decades compared to the 1970s and the recent decade. Given that several previous literature indicated that volatility of agricultural commodity prices have shown similar trend during the same period, it is rational to empirically investigate whether price volatilities are one of the key factors behind these acreage variations.

Figure 3. Global planted acreage trend based on the crop calendar database



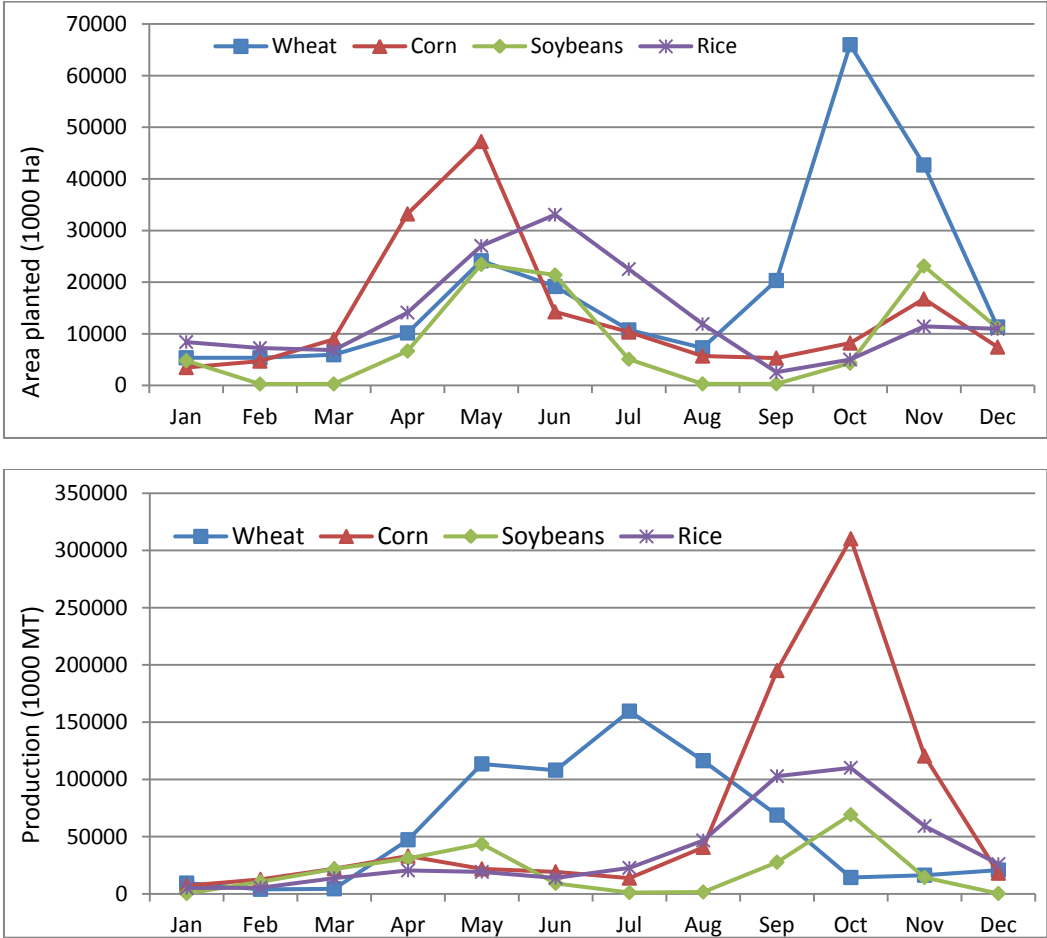
Source: FAO (2012) and national data sources.

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 4. Global monthly planted acreage (top) and production (bottom) of selected crops in 2008.



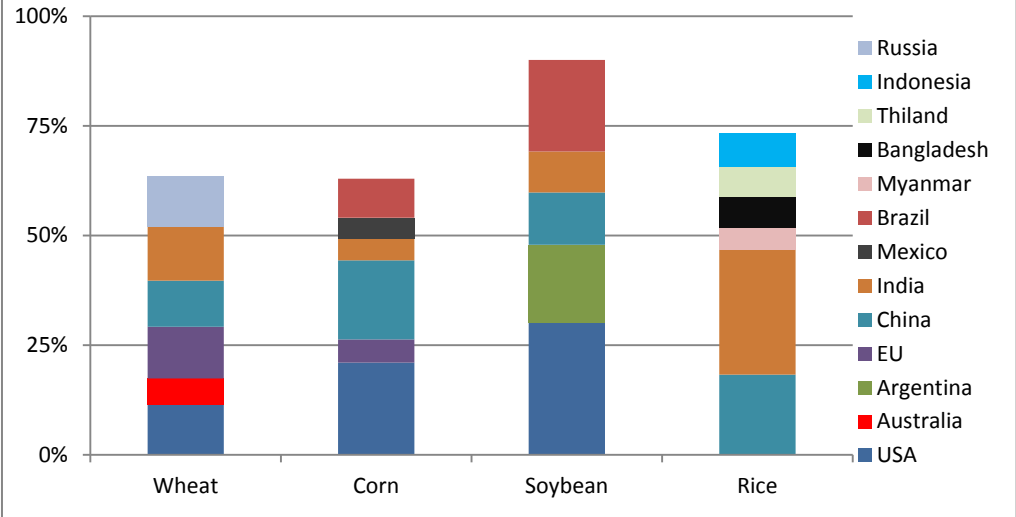
Source: Authors' calculations based on global crop calendar information and data from FAO (2012) and national data sources.

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.

With regard to the geographical distribution, Figure 5 illustrates that the global acreage of these crops is dominated by few countries. It can be seen that the top 5 soybean growing countries cultivated close to 90% of the global soybean acreage planted in 2008. Above 60% of the global cultivated land for both corn and wheat is also found in the top 5 growing

countries and the European Union (EU-27). Similarly, close to half of the global rice acreage is planted in China and India.

Figure 5. Global sown area share of major producer countries (2008)

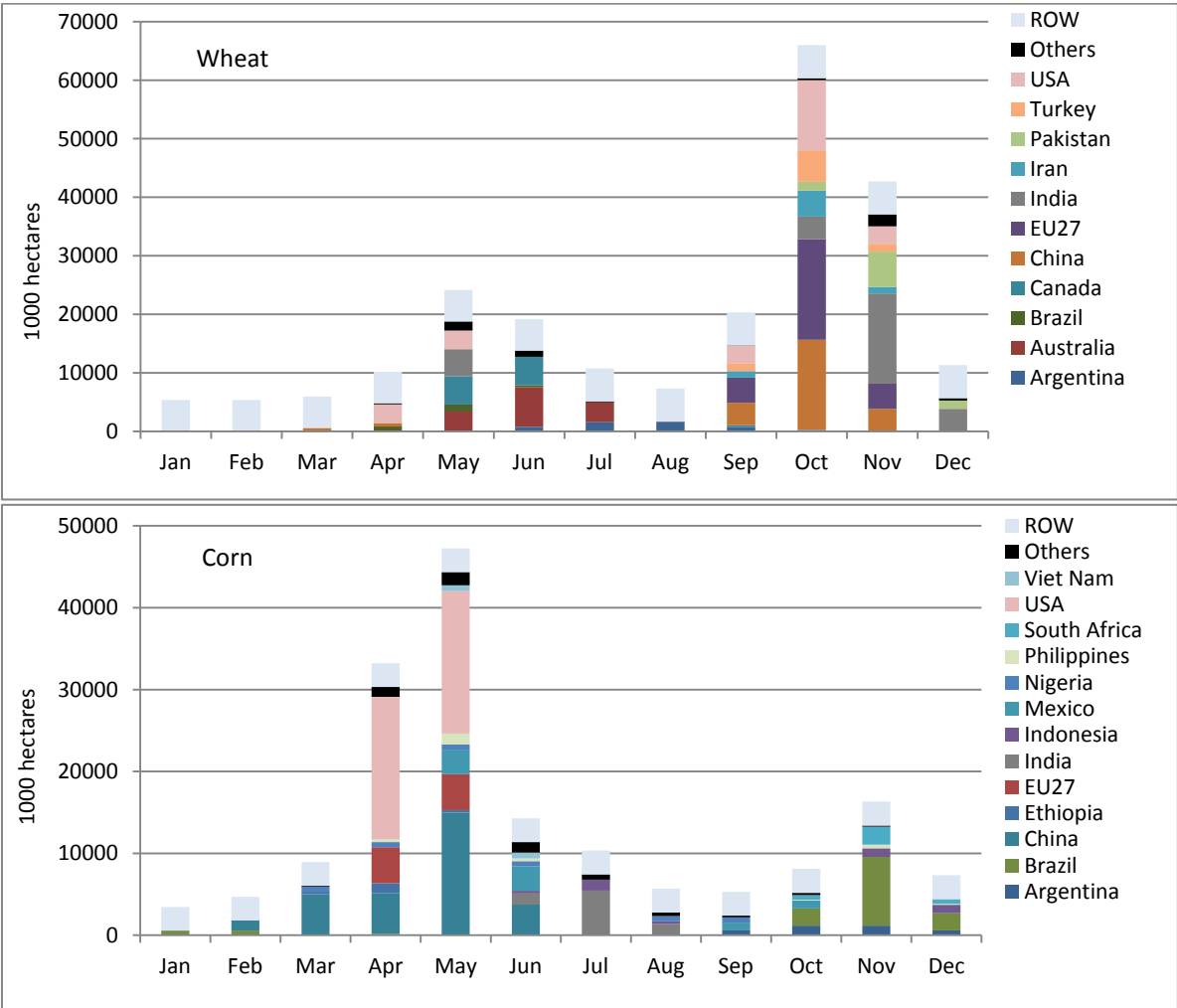


Source: Data from FAO (2012) and national sources

Therefore, it is sufficient to use data from key producer countries in order to get a good representation of global cultivations for these crops. The countries for which we compiled crop calendar data comprise greater than 70% and 85% of both the world production and sown acreage for wheat and for the other three crops, respectively. The monthly cropped acreages of selected growing countries for which we have observations are given in Figures 6 (wheat and corn) and 7 (soybeans and rice). These figures add a spatial dimension to the temporal dynamics depicted in Figure 4 above. The countries reported under the category ‘Others’ are those for which we have crop calendar data but with a global acreage share of less than unity.³ The annual data for the rest of the world (ROW) are uniformly distributed across all months in each year. While countries in the North produce the larger share of winter wheat and rice, those in the South do have an equivalent share of the global soybean and corn production.

³ The countries for which we compiled crop calendar data along with respective national data sources are reported in Table A1 in the Appendix.

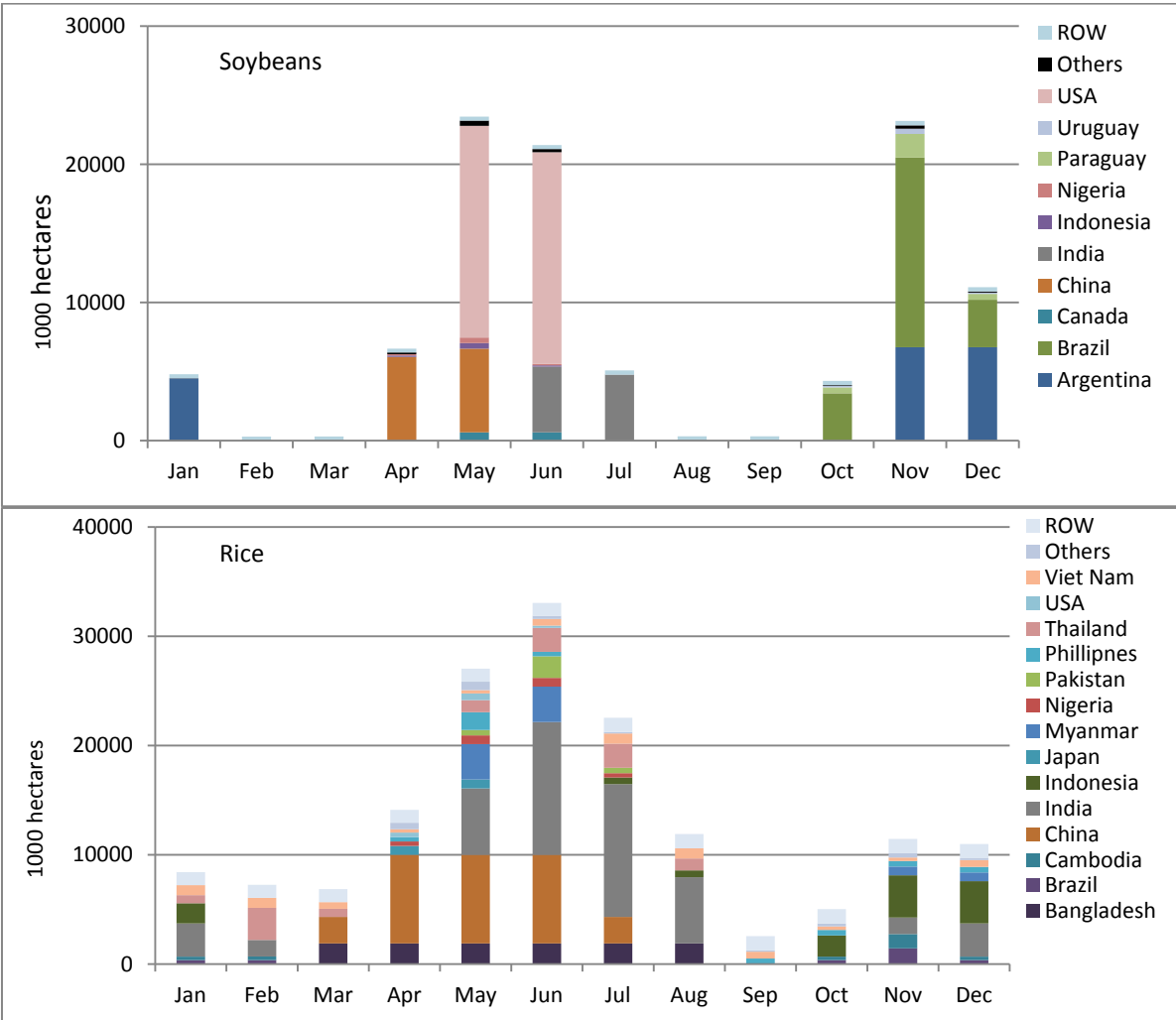
Figure 6. Monthly wheat and corn planting patterns for selected countries (2008)



Source: Author’s calculation using data from FAO (2012) and national sources

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.

Figure 7. Monthly Soybean and rice planting patterns for selected countries (2008)



Source: Author’s calculation using data from FAO (2012) and national sources

Our crop calendar data has some limitations. First, the monthly disaggregation does not capture any planting changes over time. Early or delayed planting and harvesting may occur for several reasons such as climatic and agronomic factors, ownership of tractors, availability of inputs, technological change and other socio-economic reasons which are not predictable and which vary across countries and over time. As it is difficult to account for these complexities, the monthly data are best approximations for the respective months rather than accurate acreage values. The other limitation is that the crop calendar observations are specified at the national level despite planting and harvesting month variations within countries. Nevertheless, the crop calendar data set enables investigation of intra-annual and inter-national acreage responses to output prices and their variability. The disaggregated data is central to analyze the variability of agricultural response to output prices and price risk across seasons and months.

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

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

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

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

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

where ϕ is the shadow price of the land constraint. The first-order conditions (FOC) for the above equation which ensure an optimal interior solution are:

$$\frac{\partial L}{\partial l_i} = \frac{\partial \Pi}{\partial l_i} - \phi = 0$$

$$\frac{\partial L}{\partial \mathbf{x}} = \mathbf{p}' \frac{\partial \mathbf{y}}{\partial \mathbf{x}} - \mathbf{w}' = 0$$

$$\bar{l} - \sum_{i=1}^N l_i \geq 0 \quad \perp \quad \phi \geq 0$$

The first FOC implies that producers allocate land uses until there is no arbitrage from land reallocation. The optimized shadow price of land and the optimized factor input (second FOC) can be substituted in the first FOC equation to obtain the crop-specific profit functions from which we can solve the choice variable functions including the acreage allocation function:

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

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 price Uncertainty

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.⁴ 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, $\bar{\Pi}$ and variance, σ_{Π}^2)

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

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. The mean variance approach follows

⁴ Uncertainty regarding yields may also play a role in the allocation decision, and their formal integration into the model is similar to price risk. However, this is not dealt with here.

directly from maximizing expected utility for an exponential utility function of the form, $u(\Pi) = -\exp(-\alpha \Pi)$. Assuming that crop prices \mathbf{p} remain the only random variables in the model (input prices \mathbf{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:

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

$$\sigma_{\Pi}^2 = \mathbf{y}'\mathbf{\Omega}_p\mathbf{y}$$

where $\mathbf{\Omega}_p$ 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

$$E U^*(\mathbf{p}, \mathbf{w}, \mathbf{\Omega}_p, \mathbf{l}) = \text{Max}_{\mathbf{x}, \mathbf{l}} \left\{ E U(\Pi) \equiv \left[E[\mathbf{p}]'\mathbf{y}(\mathbf{x}, \mathbf{l}, \mathbf{z}) - \mathbf{w}'\mathbf{x} - \frac{1}{2}\alpha\mathbf{y}'\mathbf{\Omega}_p\mathbf{y} \right] \right\}$$

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:

$$L = \sum_i^n E[p_i]y_i(\mathbf{x}, l, \mathbf{z}) - \mathbf{w}'\mathbf{x} - \frac{1}{2}\alpha\mathbf{y}'\mathbf{\Omega}_p\mathbf{y} - \phi(\bar{l} - \sum_i^n l_i)$$

The necessary conditions for an interior solution are:

$$\frac{\partial L}{\partial l_i} = \{E[p_i] - \alpha\Omega_{pi}\mathbf{y}\} \frac{\partial y_i}{\partial l_i} - \phi = 0$$

$$\frac{\partial L}{\partial \mathbf{x}} = \{E[p_i] - \alpha\Omega_{pi}\mathbf{y}\} \frac{\partial \mathbf{y}}{\partial \mathbf{x}} - \mathbf{w}' = 0$$

$$\bar{l} - \sum_{i=1}^N l_i \geq 0 \quad \perp \quad \phi \geq 0$$

The optimal allocation of land to crop i at a specific period t is then given as

$$l_i^* = l_i^*(E[\mathbf{p}], \mathbf{w}, \mathbf{\Omega}_p, \bar{l}, \mathbf{z})$$

Unlike the land allocation functions resulting from the traditional price-certainty models, the corresponding functions from the mean-variance approach are affected by output price uncertainty. The FOC with respect to the acreage allocation, l_i indicates that higher own

price variance or higher positive covariance of the price of a given crop with other crops' prices requires a lower shadow price of land. Given a constant shadow price of land, ϕ this implies that acreage allocated to i th crop declines with higher variance or positive covariances of crop prices. 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 Ω_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).

Since expected prices are not directly observable, 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 (uncertainty) using a measure of international price instability. We measured price risk as the standard deviations of the changes in the logarithmic output prices of the previous 12 months. Although they were

dropped from the econometric models due to high multicollinearity, the co-variances between expected harvest crop prices were used as additional variables to capture price risk. Similar to other studies (Chavas & Holt, 1990; Coyle, 1992), we calculated covariances of crops i and j , $covt(p_{ij})$ as the sum of squares of the prediction errors of the previous three harvesting periods with declining weights of 0.5, 0.33 and 0.17.

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:

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

where l_i denotes the acreage planted to the i -th crop (1=wheat 2 = corn, 3 = soybeans, and 4 = rice; in thousand hectares), p_j is the expected price for the j -th crop, $\Omega(p)_{jk}$ is the (co)variance 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:

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

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. Since some crops are substituted into rotations relatively easier than others, the rate of change in aggregate cropland may have different acreage allocation effects for different crops. Including the lagged total cropland into the acreage demand equations will capture this effect. The system of individual crop acreage equations specified above does not only link acreage allocations to lags in adjustment of total cropland but also maintains the possibility for estimation of lagged acreages of individual crops (Coyle, 1993). Accordingly, we included lagged own crop acreages rather than the total crop land in our analysis.

Acreage response equations are usually given as functions of crop revenues per acre rather than in terms of output prices. This has the underlying assumption that crop yields are predetermined and that they can provide more information regarding production technologies. However, we assume that crop yields may vary with the level of crop protection, variable inputs and land management. In fact, Coyle (1993) rejected specification of acreage response models in terms of revenues per hectare in favor of a specification using output prices.⁵

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 acreage for all countries were obtained from the Food and Agricultural Organization of the United Nations (FAO) and the United States Department of Agriculture (USDA). The international spot market output prices, crude oil prices and fertilizer price indices 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.

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 (GIEWS) of the FAO, the Office of the Chief Economist (OCE) of the USDA is the source of the crop-calendar for the advanced economies. It is further modified with expert knowledge on planting and harvesting periods from Bayer CropScience AG. 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 multangular probability distribution is used to apportion values to each month in case of multiple planting and harvesting months.

⁵ Moreover, while global price data that reasonably reflect national domestic prices is available, it is difficult to find global yield data as yield remarkably varies across countries.

The acreage and harvest data for the rest of the world is evenly distributed across all months.

The spot and futures crop prices, crude oil price and fertilizer price indices used in our estimation were all in real terms - deflated by the U.S. Consumer Price Index (CPI). The price of crude oil as well as fertilizer price indices are used as proxies for production costs which otherwise would not be captured. In global scale studies, it is not easy to get variable inputs with reasonably comparable prices across all countries. The crude oil price, as defined by the World Bank, refers to the average spot prices of Brent, Dubai and West Texas Intermediate, with equal weights. The fertilizer price index is also constructed using the prices of natural Phosphate Rock, phosphate, potassium and nitrogenous fertilizers.

5. Results and Discussion

In the following section, we discuss several regression results to highlight the relationship between acreage, prices and price uncertainty. A standard approach to estimate such acreage response model is the seemingly unrelated regressions (SUR). However, we chose single equation methods of estimation. This is primarily for three reasons: a misspecification in one of the acreage equations in the system generally results in inconsistent estimates for the other equations (Coyle et al., 2008); the Breusch-Pagan test does not show significant correlation of residuals across the acreage equations⁶; and the explanatory variables are highly correlated across the equations. Thus, the gains from SUR will be small and single equation estimations are more robust.

We have conducted the standard statistical unit root tests, augmented Dickey-Fuller and Phillips-Perron tests (Dickey & Fuller, 1979; Phillips & Perron, 1988), for each time series in the acreage response models of all four crops. The unit root test results indicated that the entire price and the annual global acreage variables of all crops are non-stationary series and are integrated of the order 1. However, the price volatility as well as the monthly or the intra-annual acreage variables of all four crops were found to be stationary series⁷. 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, $I(0)$. Thus, we

⁶ For instance the Breusch-Pagan test of independence of residuals in the annual acreage response model has a chi-squared statistic of 5.23 with P-value = 0.52.

⁷ Results of the unit-root tests can be available upon request.

included the first order difference of the I(1) variables in the annual model. However, if either the dependent or the independent variable or both is stationary, which is the case in the intra-annual specifications of the present study, then the regression is misspecified by differencing the series. By first differencing, we are imposing the constraint that the parameter on the lagged variable is one, which may not be true if the series is stationary. In such circumstances, including lagged values of the dependent and independent variables as regressors helps avoid the problem of spurious regression. In this case, a set of parameters for which the error term is stationary exists and the t-statistics for the individual coefficient estimates will have the usual asymptotic normal distribution. Our intra-annual model specifications 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) are specified as logarithms in the econometric models of the proceeding discussion. Hence, the estimated coefficients can be interpreted as short-run elasticities. Depending on the disaggregation method, annual as well as monthly acreage elasticities are estimated. As the price covariance terms cause problems of high multicollinearity and turned out to be insignificant, we omitted them. Since the lagged endogenous variable implies autocorrelation in our econometric estimations, we employed the Newey-West autocorrelation adjusted standard errors.

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 changes in output price expectation. 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 unpredictability of prices.

Table 1. Annual acreage response estimates

| <i>Variables</i> | <i>Wheat</i> | <i>Corn</i> | <i>Soybeans</i> | <i>Rice</i> |
|------------------------------|---------------------|----------------------|---------------------|--------------------|
| <i>Acreage (t-1)</i> | -0.252** (0.111) | -0.281** (0.117) | -0.381* (0.201) | -0.22 (0.145) |
| <i>Wheat price</i> | 0.069** (0.034) | -0.100*** (0.027) | 0.036 (0.057) | -0.054* (0.028) |
| <i>Corn price</i> | 0.004 (0.032) | 0.174*** (0.034) | -0.149* (0.082) | 0.039 (0.026) |
| <i>Soybean price</i> | 0.012 (0.033) | -0.014 (0.030) | 0.244*** (0.075) | 0.004 (0.023) |
| <i>Rice price</i> | | | | 0.027* (0.016) |
| <i>Fertilize price index</i> | -0.028** (0.014) | 0.012 (0.011) | -0.037 (0.026) | 0.014 (0.009) |
| <i>Own price volatility</i> | 0.015 (0.377) | -0.985** (0.429) | -0.142 (0.484) | -0.283* (0.171) |
| <i>Time trend</i> | 0.0 (0.000) | 0.0 (0.000) | 0.0 (0.000) | 0.0* (0.000) |
| <i>Constant</i> | 0.776 (0.566) | -0.562 (0.474) | 0.401 (0.474) | 0.504* (0.300) |
| <i>N</i> | 48 | | | |

Notes: Figures in parentheses are autocorrelation adjusted standard errors.

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

Table 1 shows the global annual acreage response results. 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. We alternatively considered harvest time futures prices, observed in the months when planting decisions are made, as proxy for expected prices at planting time. 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. We failed to find a significant area-price relationship using these futures prices, which could imply that several agricultural producers do not make use of futures prices information in forming price expectations. Indeed, futures prices are good proxy for expected prices for those producers in countries where the domestic price is strongly linked to the futures prices, i.e. where the maturity basis is constant. Although the farmers in advanced economies widely participate in

the futures markets and the futures prices are linked to the cash prices, this is not so in several developing countries. As some studies applied and indicated that futures prices are good proxy for price expectations at planting time in some developed countries (e.g. Lin & Dimukse, 2007), expansion of futures markets could benefit more producers by supplementing the existing information set utilized in price expectation formation.

The proceeding discussion relies on the results obtained from the specifications with spot prices⁸. The regression estimates show that all the acreage responses to own prices are statistically significant and consistent with economic theory. The short-run acreage responses to own prices range from 0.03 (rice) to 0.24 (soybeans), 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 results also show that the statistically significant cross-price acreage coefficients are consistent with economic theory: a negative area response to competing crop prices. In this regard, expectations about wheat prices seem to be important for all but soybean crop acreages. Expectation of higher wheat prices encourages cultivation of more land for wheat production. The cross price coefficients suggest that shifting away land from corn and rice cultivation contributes to this additional land for wheat production. Besides encouraging more land to corn cultivation, the results also show that higher corn prices lead to less land for soybean production. Own price volatility reduces global corn and rice acreage significantly, the respective estimated coefficients are -0.99 for corn and -0.28 for rice. Fertilizer prices are statistically significant only for the global wheat acreage in the annual model. As described above both the dependent variable, sown area, and its lagged independent variable are first-differenced to avoid spurious results due to unit root. The coefficients of the lagged acreage are statistically significant and negative for all crops except for rice. The interpretation is that a higher acreage growth in a certain year is associated by a lower growth in the coming year. This may be indicative of the cyclical (cobweb) nature of agricultural production.

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 resultant disaggregated

⁸ Results where we used futures prices as proxy for expected prices can be available upon request.

data 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 understand 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 (Table 2); the second estimates month-specific elasticities that differ from month to month (Table 3). While the latter turns out to fit the data better, the former allows a more direct comparison with the annual regression.

5.2.1. Monthly supply elasticities

The advantage of estimating month-independent supply elasticities is to have a rough estimation of acreage response to prices given the price information of the month(s) prior to planting time. To account for the effect of seasonality that may arise due to climatic and geographic conditions which may affect cultivation in each specific planting month, monthly dummies are included.⁹ Since our disaggregation of (mainly wheat) acreage data into planting months shows a structural break in 1992 due to the breakdown of the Soviet Union, we further include a dummy for this year.

Table 2. Monthly supply response estimates

| <i>Variable</i> | <i>Wheat</i> | <i>Corn</i> | <i>Soybeans</i> | <i>Rice[†]</i> |
|---------------------------|---------------------|---------------------|---------------------|-------------------------|
| <i>Acreage (t-12)</i> | 0.837*** (0.029) | 0.842*** (0.042) | 0.961*** (0.011) | 0.628*** (0.022) |
| <i>Wheat price</i> | 0.068** (0.027) | 0.031 (0.020) | 0.018 (0.031) | -0.007 (0.012) |
| <i>Corn price</i> | 0.021 (0.028) | 0.113** (0.055) | -0.085** (0.036) | -0.002 (0.013) |
| <i>Soybean price</i> | -0.057** (0.026) | -0.015 (0.021) | 0.111*** (0.030) | 0.007 (0.012) |
| <i>Rice price</i> | -0.023 (0.017) | -0.028** (0.013) | 0.011 (0.024) | 0.016** (0.007) |
| <i>Wheat price vol.</i> | -0.894** (0.425) | 0.269 (0.279) | 0.307 (0.606) | -0.321* (0.183) |
| <i>Corn price vol.</i> | 1.014** (0.501) | 0.286 (0.330) | 0.057 (0.651) | 0.128 (0.188) |
| <i>Soybean price vol.</i> | 0.635* (0.336) | -0.184 (0.331) | 0.696 (0.572) | 0.297* (0.154) |
| <i>Rice price vol.</i> | -0.151 (0.306) | 0.072 (0.276) | -0.786** (0.368) | 0.095 (0.126) |
| <i>Trend</i> | 0 (0.001) | 0.001 (0.001) | 0.002** (0.001) | 0.003*** (0.000) |
| <i>Constant</i> | 2.596** (1.316) | -0.634 (1.234) | -3.848* (2.095) | -1.062 (0.694) |
| <i>N</i> | | 588 | | 587 |

Notes: Figures in parentheses are autocorrelation adjusted standard errors. Monthly dummies were also included for each crop regression.

[†]The rice price is the average price of the previous 12 months.

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

⁹ The coefficients of monthly dummies are not reported for the sake of brevity

Table 2 summarizes the monthly regression results. In this case, we assume that producers base their expectations on the spot prices during the pre-planting months. Since rice is cultivated throughout the year in several countries, we take the one period lagged annual average price rather than a spot price in a specific month. The dependent own acreage variables are the values corresponding to the same month of the previous year.

In comparison to the annual model, there are some interesting differences. Aside from the wheat acreage where the coefficients are in the same order of magnitude, the monthly acreage responses to own crop prices are slightly lower than their annual counterparts for the other crops. This implies that price expectation formation matters in the sense that more price information improves producers' response to output prices. Nevertheless, the monthly acreage responses are in agreement with the annual acreage responses to prices: positive area response to own prices and negative response to competing crop prices. The fact that acreage, on global average, adjusts monthly to changes in international monthly prices prior to planting time attests that the prices preceding the planting period of these crops contain relevant information that the producers base 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 the planting period whereas the spot price in the month immediately before the planting period is more important for wheat farmers. The results suggest that doubling of these respective own spot prices leads to – on a global average- acreage increases of between 7% for wheat and 11% for both corn and soybean crops in the short-run. The global monthly rice acreage is the least responsive to own prices (elasticity: 0.02). In addition to the responses to own crop prices, the monthly acreage specification findings reveal that higher crop prices result in lower land allocation for competition crop production. In particular, global wheat producers negatively respond to expected soybean prices whereas expectations of corn and rice crop prices are more important for global soybean and producers respectively.

In contrast to annual crop acreage specification, price risks seem to be more relevant to wheat producers in the intra-annual acreage model. While higher fluctuations of own crop price discourage producers to allocate more land for wheat production, this could be counterbalanced if prices of competing crops such as corn and soybeans exhibit such fluctuations as well. Fertilizer prices seem not to be statistically significant in the monthly

global acreage specifications. The estimated lagged acreage planted variables were both statistically and economically relevant in determining current cultivations of all crops. With regard to the time trend, the global acreages of soybeans and rice have increasing trend implying, annual average growth rates of about 0.2% for soybeans and 0.3% for rice acreages.

5.2.2. Seasonal supply elasticities

For the second intra-annual regression we estimate the acreage response in typical planting months depending on prices in the preceding month as well as individual crop area allocation in the same month of the previous year. We present results for those months where cultivation of each crop is predominant in the global setting (see Figure 3 above). Table 3 shows the results for these selected months.

Table 3. Month-specific elasticities for typical planting months

| <i>Variable</i> | <i>Wheat</i> | | | <i>Corn</i> | | | <i>Soybeans</i> | | | <i>Rice</i> | | |
|-------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | <i>April</i> | <i>May</i> | <i>Nov.</i> | <i>April</i> | <i>May</i> | <i>Nov.</i> | <i>May</i> | <i>June</i> | <i>Nov.</i> | <i>May</i> | <i>June</i> | <i>Nov.</i> |
| <i>Acreage (t-12)</i> | 0.506*** (0.097) | 0.468*** (0.106) | 0.822*** (0.092) | 0.334*** (0.118) | 0.346*** (0.126) | 0.640*** (0.096) | 0.792*** (0.104) | 0.804*** (0.056) | 0.923*** (0.043) | 0.662*** (0.063) | 0.680*** (0.063) | 0.556*** (0.110) |
| <i>Wheat price</i> | 0.134*** (0.048) | 0.303** (0.120) | 0.014 (0.027) | -0.044 (0.044) | -0.015 (0.031) | 0.047 (0.043) | 0.061 (0.049) | 0.025 (0.056) | 0.141 (0.100) | | | |
| <i>Corn price</i> | -0.05 (0.045) | -0.144 (0.110) | -0.018 (0.028) | 0.111* (0.060) | 0.095** (0.044) | -0.116* (0.060) | -0.156** (0.063) | -0.13 (0.078) | -0.068 (0.157) | | | |
| <i>Soybean price</i> | 0.048 (0.034) | 0.023 (0.043) | 0.028 (0.038) | 0.05 (0.041) | 0.02 (0.025) | 0.039 (0.050) | 0.178*** (0.057) | 0.222*** (0.054) | 0.013 (0.148) | | | |
| <i>Rice price</i> | | | | | | | | | | 0.019* (0.010) | 0.022** (0.010) | -0.01 (0.020) |
| <i>Own price vol.</i> | -0.627 (0.468) | -1.807 (1.089) | -0.252 (0.301) | -0.675 (0.758) | -0.082 (0.422) | 0.937 (0.822) | 0.158 (0.728) | -0.169 (0.700) | 0.659 (0.750) | 0.113 (0.179) | 0.131 (0.165) | -0.213 (0.292) |
| <i>Fertilizer price</i> | -0.023 (0.024) | -0.069** (0.032) | -0.004 (0.014) | -0.006 (0.028) | -0.008 (0.020) | 0.022 (0.018) | -0.039 (0.024) | -0.034 (0.029) | -0.005 (0.067) | 0 (0.010) | -0.006 (0.011) | 0 (0.015) |
| <i>Time trend</i> | 0.002** (0.001) | 0.005*** (0.001) | 0.002 (0.001) | 0.007*** (0.001) | 0.008*** (0.001) | 0 (0.001) | 0.003 (0.002) | 0.006*** (0.002) | 0.004 (0.004) | 0.001*** (0.000) | 0.002*** (0.000) | 0.002 (0.001) |
| <i>Constant</i> | -0.66 (2.053) | -6.18*** (1.973) | -1.24 (1.562) | -8.47*** (1.982) | -8.66*** (1.448) | 3.46** (1.638) | -4.90 (3.340) | -11.0*** (3.878) | -7.74 (7.269) | 0.43 (0.576) | -0.51 (0.663) | 0.46 (2.035) |
| <i>R-squared</i> | 0.88 | 0.62 | 0.944 | 0.871 | 0.941 | 0.739 | 0.949 | 0.985 | 0.993 | 0.927 | 0.949 | 0.82 |

N

49

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

The month specific acreage response estimations show several interesting results. First of all, 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). Additionally, 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 0.30 in May to nearly zero in November. Similarly, short-run own-price acreage elasticities range from 0.11 (corn in April), 0.22 (Soybeans in June), and 0.02 (rice in June) to fairly price insensitive acreages in winter (November). In accordance with both the annual and the intra-annual results above, the month-specific cross-price acreage elasticity shows that the global soybean cultivation (in spring) competes for land with corn cultivation. It is also during the spring that the global wheat and soybean acreages respond to fertilizer prices. One explanation for this negative relationship could be that when fertilizer prices are high, acreage expansion is more profitable than increasing intensification. We also conducted a separate regression where we used average crude oil prices as additional explanatory variables (results are not reported here for reasons of brevity).¹⁰ The effect of crude oil prices is not clear since it implies lower production cost on the one hand and higher output prices due to higher demand for biofuel on the other hand. The results indicate that the latter effect outweighs in case of corn and soybeans where the global acreage of these crops positively respond to higher crude oil prices.

The estimated coefficients of the lagged area were both statistically and economically relevant in determining the acreage at any particular planting month of all crops. As opposed to the acreage responses to output and input prices, the lagged own acreage coefficients are relatively larger during the winter months. This may affirm the already implied relative rigidity of acreage allocation during the winter. Similar to the above results, the estimated coefficients indicate that global soybean acreage has the largest producers' inertia that may reflect adjustment costs in crop rotation and crop specific land and/or soil quality requirements. However, the coefficients of the lagged dependent variables might also reflect

¹⁰ Results are available upon request.

unobservable dynamic factors and interpretation should be made with caution (Hausman, 2012).

This seasonally variable global acreage response may be partly explained by the lower availability of land during spring as it is the dominant planting season for all of these four crops although less so for wheat. The differences of the coefficients across the months do also reflect differences across the countries where sowing takes place in the respective months and captures characteristics such as global market integration or domestic institutions and government policy interventions. The time trend estimates do also show that more and more land has been allocated for these crops during the spring season. The results demonstrate that the global acreage of all these crops has been consistently growing at an annual rate of between 0.1% and 0.8% during spring. On the other hand, neither of the crop acreages shows any significant time trend during the winter.

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 country-specific crop calendar in order to apportion annual acreage values into respective planting months and 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 vary across crops and exhibit season variability. Global acreage responds to monthly as well as to annual price changes, the latter being slightly stronger. Generally, corn and soybean acreages are more responsive to prices with annual short-run own-price

elasticities of 0.17 and 0.24, respectively, than wheat (0.07) and rice (0.03). 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.

Acreage response to price changes, however, leads to further acreage response through the auto-regressive term. The long-run acreage responses to prices are, in equilibrium, larger than the short-run responses. In the annual acreage model, for instance, long-run price elasticities of wheat, soybeans and rice are about three times larger than the short-run elasticity estimates. The long-run price elasticity of corn acreage is also slightly larger than the short-run value. Thus, we might observe a higher acreage increase in the long-term due to global price increases than what the short-term elasticities suggest.¹¹

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 seasonal 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 owing to greater land competition in spring. This may also reflect other country-specific reasons including national policies that limit the flexibility of crop acreage adjustments.

Results from this study suggest that the effects on aggregate supply response of price uncertainty, measured by own price volatility, for the major global field crops are not robust across models and vary across commodities. Own price volatility has negative effect on annual global corn and rice acreages. Furthermore, both the own and competing crop price fluctuations are statistically significant and economically relevant to global wheat acreage allocation in the intra-annual model. The results indicate that, on average, global wheat acreage declines in response to higher own price volatility. On the other hand, expansion of land for wheat production is more likely in response to higher instability in corn and soybean prices. In summary, own crop price volatility seems to have a negative impact on wheat, corn and rice acreages but no or little impact on soybean area. It is a well-known finding in economic theory that price uncertainty is a disincentive to agricultural producers under the

¹¹ The Long run and short run elasticities are reported in Table A2 in the appendix.

underlying risk aversion assumption. The findings in this article support that the behavioral assumption of risk-aversion is likely to hold for the majority of wheat, corn and rice producers in the world. However, the results from all model specifications seem to display that the majority of the global soybean farmers are not unwilling to take price risks to acquire the associated higher returns of agricultural investments. This is relevant for policy makers suggesting that reducing output price volatility leads to an expansion of agricultural land and hence crop production; however, it may have unexpected and possibly undesirable outcome for some crops.

The short-term supply analysis provides a first step for establishing a global short-term supply model that predicts area planted (and, thus, 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 which 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.

Appendix

Table A1. Countries for which we compiled crop calendar, and acreage data sources

| Countries | Data sources |
|---------------------|--|
| <i>Argentina</i> | http://www.siaa.gov.ar/index.php/series-por-tema/agricultura http://64.76.123.202/site/agricultura/index.php |
| <i>Australia</i> | http://www.daff.gov.au/abares/data |
| <i>Bangladesh</i> | FAO, USDA |
| <i>Brazil</i> | http://seriesestatisticas.ibge.gov.br/lista_tema.aspx?op=0&no=1 |
| <i>Cambodia</i> | http://www.maff.gov.kh/en/ FAO, USDA |
| <i>Canada</i> | http://www5.statcan.gc.ca/cansim/a34?lang=eng&mode=tableSummary&id=0010010&p2=9 |
| <i>China</i> | China Statistical Yearbook 2010 |
| <i>Egypt</i> | FAO, USDA |
| <i>Ethiopia</i> | FAO, USDA |
| <i>EU27</i> | http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/themes |
| <i>India</i> | http://eands.dacnet.nic.in/latest_2006.htm |
| <i>Indonesia</i> | FAO, USDA |
| <i>Iran</i> | FAO, USDA |
| <i>Japan</i> | http://www.maff.go.jp/e/tokei/kikaku/nenji_e/nenji_index.html |
| <i>Mexico</i> | http://www.siap.gob.mx/index.php?option=com_wrapper&view=wrapper&Itemid=350 |
| <i>Myanmar</i> | FAO, USDA |
| <i>Nigeria</i> | FAO, USDA |
| <i>Pakistan</i> | http://www.finance.gov.pk/survey/chapter_12/02-Agriculture.pdf |
| <i>Paraguay</i> | FAO, USDA |
| <i>Philippines</i> | FAO, USDA |
| <i>South Africa</i> | http://www.daff.gov.za/docs/statsinfo/Abstract_2011.pdf , FAO, USDA |
| <i>Sri Lanka</i> | http://www.statistics.gov.lk/agriculture/index.htm , FAO, USDA |
| <i>Thailand</i> | FAO, USDA |
| <i>Turkey</i> | http://www.turkstat.gov.tr/VeriBilgi.do?alt_id=45 |
| <i>Uruguay</i> | Uruguayan Department of Livestock, Agriculture, and Fisheries (http://portal.gub.uy/) |
| <i>USA</i> | http://www.ers.usda.gov/data-products |
| <i>Viet Nam</i> | FAO, USDA |

Table A2. Short- and long-run own price elasticities of crop acreages

| <i>Model</i> | <i>Crop</i> | | <i>Short Run</i> | <i>Long Run</i> |
|-----------------------|-------------|--------------|------------------|-----------------|
| Annual | Wheat | | 0.07 | 0.18 |
| | Corn | | 0.17 | 0.22 |
| | Soybeans | | 0.24 | 0.84 |
| | Rice | | 0.03 | 0.10 |
| Monthly | Wheat | | 0.07 | 0.43 |
| | Corn | | 0.11 | 0.70 |
| | Soybeans | | 0.11 | 2.82 |
| | Rice | | 0.02 | 0.05 |
| Month-specific | Wheat | <i>April</i> | 0.13 | 0.26 |
| | | <i>May</i> | 0.3 | 0.56 |
| | Corn | <i>April</i> | 0.11 | 0.17 |
| | | <i>May</i> | 0.1 | 0.15 |
| | Soybeans | <i>May</i> | 0.18 | 0.87 |
| | | <i>Jun</i> | 0.22 | 1.12 |
| | Rice | <i>May</i> | 0.02 | 0.06 |
| | | <i>Jun</i> | 0.02 | 0.06 |

Notes: The long-run elasticities are the short-run elasticities divided by $(1-\beta_1)$ where β_1 is the estimate for the lagged dependent variable. In the case of the annual model, we took the lagged coefficients from the regression of data series before first differencing.

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