Agricultural supply response to international food prices and price volatility: a cross-country panel analysis

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1. Introduction

Over the past quarter of the century, the world has experienced significant land use changes including the shrinkage of arable land, deforestation and degradation, the expansion of urban areas, and more recently, an increasing production of biofuels. This has implications for feeding the world's population, which is predicted to increase by a further 50% during the first half of this century. Thus, the allocation of the world's land resources over the coming decades is a vital research question. Empirical evidence shows that several countries have been expanding cropland by shifting away land from forest and pasture, mainly due to the higher crop prices (Timilsina et al., 2012). The allocation of cropland is crucial since it is directly linked to the pressing food security situation in many developing countries. The recent increases in agricultural commodity prices and the subsequent food versus biofuel trade-offs have made the food security situation more problematic. Understanding how global food commodity producers allocate cropland and how their decisions about crop production are affected by changes in prices and their volatility is therefore fundamental for designing policies related to global agriculture and food supply.

The literature on estimation of supply response to prices has a long history in agricultural economics (Houck & Ryan, 1972; Lee & Helmberger, 1985; Nerlove, 1956). Nevertheless, there are various reasons to reconsider the research on acreage allocation. The majority of the previous empirical literature investigating supply response focuses largely on particular crops and is concentrated in a few countries. 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 make the global and country level agricultural production equally sensitive to prices and their volatility as is the case at the individual producer level. Given that previous analyses at micro-level showed the supply effects of output price and price volatility at the micro and national levels (Bakhshi & Gray, 2012; Binswanger & Sillers, 1983; Fafchamps, 1992; Newbery & Stiglitz, 1981), it is rational to ask whether this effect ensues at the global scale as well. The analysis at global scale appears to be even more important as the impacts are likely to affect national and household level land allocations and crop 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 affect the global food supply.

This study, therefore, investigates the responsiveness of global cropland to changes in output prices and the uncertainty therein. The study provides a global short- and long-term acreage and yield elasticity which hints at how major agricultural commodity producers respond to the recent high food prices and volatility. Global scale agricultural supply studies suggest that the major proportion of the supply response to output price, in the short-run, is via acreage changes (e.g. Roberts & Schlenker, 2009). Thus, estimating acreage response at the global scale is vital, among others, to contest or affirm this very conception and in order to predict the food price and food supply effects of the newly emerging drivers such as biofuel demand and the financialization of crops.

The econometric approach of the present study is in line with a partial supply adjustment framework updated, among others, with dynamic response, alternative price expectation assumptions and introduction of price risk variables. The study applies state-of-the-art panel econometric methods to estimate global acreage response equations for key agricultural commodities: wheat, corn, soybeans and rice. These commodities play a crucial global role from both the demand and the supply side perspective. They are also partly substitutable both in production and in consumption. These crops together comprise three quarters of the global calories content (Roberts & Schlenker, 2009). The use of corn, soybeans and wheat as a feed for livestock and dairy purposes has also grown due to higher meat demand owing to the rapid economic growth in the emerging and developing economies. The rapidly growing market for biofuel is also another source of demand for corn. The four 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 the FAO (2012), they accounted for more than 75% and 85% of global cereal area and production in 2010, respectively. Soybeans does also contribute about a third of both the global area and production of total oil crops.

Using country-level data from 1961 to 2010, we estimated global acreage and yield responses to output and input prices, output price variability, and yield shocks as proxy for expectation of weather shocks. Since expected prices are not realized during planting, we model farmers' price expectations using price information available during planting. We alternatively used two price variables; international spot and futures prices at the planting time of the specific country, to proxy producers' expected harvest-period prices. The use of international and not local farm gate prices as proxy for expected prices implicitly assumes that international prices transmit to domestic prices even when countries are poorly integrated to the global agricultural market. Several empirical studies indicated large transmission elasticities between international prices and domestic prices for several developing countries (Greb et al., 2012; Ianchovichina, Loening, & Wood, 2012; Minot, 2010). Using international instead of domestic output and input prices circumvents the potential reverse causality from area or yield to prices since individual economies are more likely to be price takers in the global output and input markets. Nevertheless, the prices relevant to producers in forming harvest-period price expectations are country-specific in accordance with the planting patterns of each country. As a result, country-specific spot and futures prices were constructed using the crop-calendar of each country.

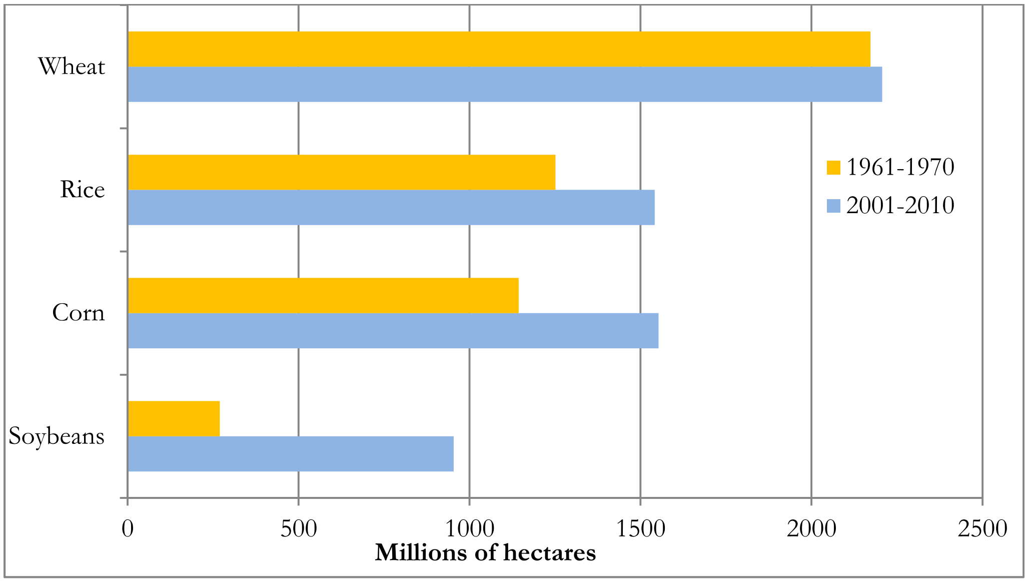
Depending on respective crop, the econometric results indicate that the short-run own price acreage elasticities range from about 0.07 to 0.30 and the corresponding yield elasticities are between 0.04 and 0.12. The coefficients of the price-risk variables are also statistically and economically significant for global wheat, corn and soybean acreages. The findings in this article suggest that while risk-aversion is the foremost behavior amongst the majority of wheat and corn producers, this is not the case for the majority of the global soybean producers. This is relevant for policy makers suggesting that "one size fits all" price-risk management tools may not be beneficial for all crop producers. In summary, the findings highlight the differences in acreage and yield responses to price levels and price-risks across crops, which may affect the ways in which policy makers at the international and domestic levels intervene to global agriculture and food production. These updated estimates of the responses of crop-specific acreages and yields to output prices and their variability, and their growth trends are essential to understanding the likely extensive and intensive margin changes because of changes in crop prices.

The rest of the paper is organized as follows: the following section presents a brief overview of global acreage and output price dynamics. Section 3 provides the theoretical framework and the state-of-the-art on the empirical acreage response model. The empirical framework follows in section 4 and discusses the dynamic panel econometric methods and data used in this study. Section 5 presents and discusses the econometric results, and the last section concludes.

2. Overview of global cropland and price dynamics

The UK's Foresight program has identified competition for land as one of the drivers that affect global food and farming in the future (Smith et al., 2010). Since the beginning of human history, there have been land cover changes involving clearing of natural ecosystems for agriculture, pasture, urbanization and other purposes. While total cropland constituted less than a tenth of the global land cover in the 18th century (Beddow et al., 2010), about one third of the global land area is currently devoted to agricultural use (Hertel, 2011). There have been several changes in crop acreage allocation all over the world due to several factors. This cropland expansion along with increased productivity has been (and will be) needed in order to sustain the associated population growth. While there is little room for extensification (bringing in more land for crop cultivation) in South and East Asia, the Middle East, North Africa, and many advanced economies, extensification does have substantial potential to increase crop production in many other regions such as Sub-Saharan Africa, Latin America and the Caribbean (Bruinsma, 2003). The recent rise in agricultural commodity prices has also resulted in more competition for agricultural land. For instance, 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).

Fig. 1 shows that global average area cultivation has increased for all the four crops during the past 50 years. While the acreage increase is small for the case of global wheat (less than 2%), it has been substantial for soybeans (254%), corn (36%), and rice (23%). Moreover, global average corn acreage, which was about 90% of the global rice acreage over the decade 1961-1970, has surpassed the latter by about a million hectares during the recent decade. Some studies indicate that the emerging biofuel markets and Chinese soybean imports are the major drivers of the acreage increases for corn and soybeans (Abbott et al., 2011). The crop acreage changes have been met both by adding marginal land into cultivation and by bidding away from low-demand crops. To this end, a recent study has shown that over a quarter of the increase in area of the high-demand crops for the period 2004/2005 to 2010/2011 was composed of displaced low-demand crop area while the rest came from the expansion of marginal land (Haile et al., 2013). 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 to high and volatile agricultural commodity prices will be predominantly via land reallocations.



Source: Data from FAO (2012) and several national sources

Fig. 1. Changes in global average acreage for the four crops, 1961-1970 versus 2001-2010

The global dynamics depicted in Fig. 1 are typical of acreage changes of these crops in their major producer countries. Table 1 shows the size and global acreage share for the top six countries[1] for the years 1961 and 2010, as well as the average percentage change between these periods. In line with the global changes described above, average sown acreage in the top six cultivating countries has had the largest expansions for soybeans (335%), followed by corn (52%), rice (41%), and wheat (18%) over the 50 year period. Moreover, the global share of the combined acreage of all the four crops of these six countries has increased between the two periods.

Table 1. Acreage for selected crops of the six largest cultivating countries (in 2010), 1961 versus 2010

Crop	Country	1961		2010		% Δ
		Area (1000 ha)	Global share (%)	Area (1000 ha)	Global share (%)	%
Wheat	India	13570	6.55	29248.27	13.26	115.54
	EU	24505	11.83	25875.14	11.73	5.59
	China	25568	12.34	24256.09	10.99	-5.13
	USA	22541	10.88	21683.09	9.83	-3.81
	Russian Federation*	24000	11.58	22000	9.97	-8.33
	Australia	5958	2.88	13645	6.18	129.02
	Top Six Total	*116142*	*56.05*	*136708*	*61.96*	*17.71*
Corn	USA	26676.58	23.71	35690.18	21.56	33.79
	China	15215	13.52	32517.87	19.64	113.72
	Brazil	6885.74	6.12	12814.8	7.74	86.11
	India	4510	4.01	8488.6	5.13	88.22
	Mexico	6287.75	5.59	7860.705	4.75	25.02
	EU	8796.046	7.82	6620.871	4.00	-24.73
	Top Six Total	*68371*	*60.77*	*103993*	*62.81*	*52.10*
Soybeans	USA	11245.04	45.79	31324.41	30.44	178.56
	Brazil	240.919	0.98	23293.1	22.63	9568.44
	Argentina	0.98	0.00	18130.9	17.62	1849991.84
	India	11	0.04	9554.19	9.28	86756.27
	China	10006.58	40.75	8516.115	8.27	-14.89
	Paraguay	1.3	0.01	2671.06	2.60	205366.15
	Top Six Total	*21506*	*87.57*	*93490*	*90.84*	*334.72*
Rice	India	34690	30.07	42561.2	26.65	22.69
	China	27044.82	23.44	30116.86	18.86	11.36
	Indonesia	6857	5.94	13244.2	8.29	93.15
	Bangladesh	8483.52	7.35	11800	7.39	39.09
	Thailand	1100	0.95	11000	6.89	900.00
	Myanmar	4253.7	3.69	8100	5.07	90.42
	Top Six Total	*82429*	*71.45*	*116822*	*73.15*	*41.72*

Source: Data from FAO (2012) and national sources

Note: EU refers to the 27 European countries and the crop area size refers to the aggregated amount in these countries. *In the case of the Russian Federation, the wheat acreage in 1992 is used instead of acreage in 1961. The grey shaded rows indicate countries where the respective crop acreage has shrunk between 1961 and 2010.

Rice acreage was higher for all countries in 2010 compared to 1961. The same is true for soybeans, with the exception of China, and for corn, with the exception of the EU. The decline in China's soybean acreage is associated with a large increase in imports that in turn, at least partly, drives the

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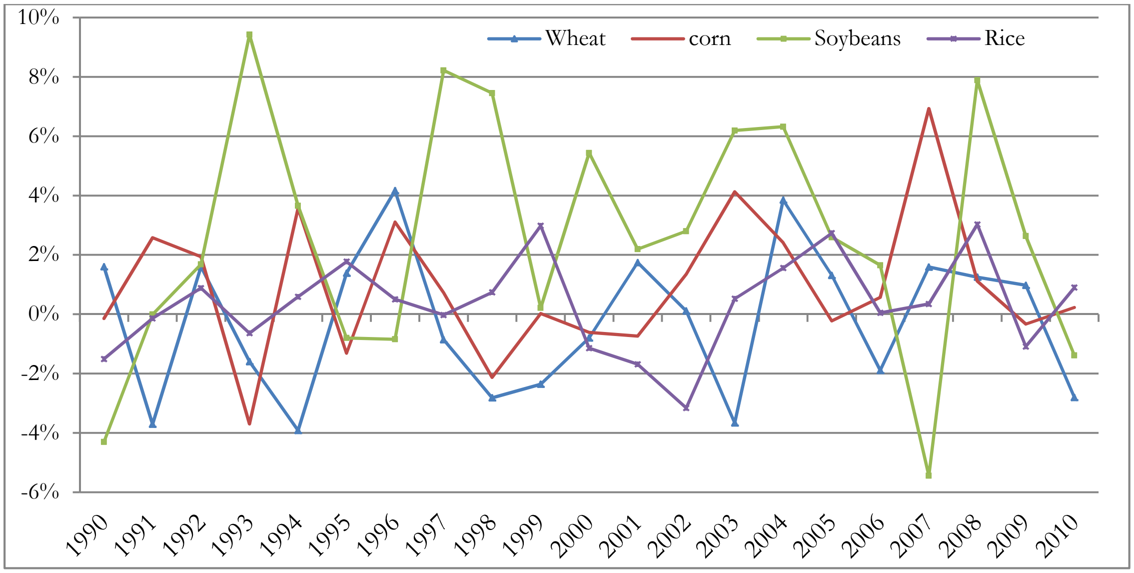
[1] In this study, we considered the European Union (EU)-aggregate data of the 27 countries- as a single country.

dramatic soybean acreage expansion in the Latin American countries. The three largest soybean producer countries in Latin America, Brazil, Argentina and Paraguay, contributed close to 45 percent of the global soybean cultivation in 2010, up from merely half a percent in 1961. India has experienced expansion in sown acreage for all the four crops during this period. Besides, India's global acreage share for these crops was higher in 2010 compared to 1961, except for a slight decline in the case of rice. Meanwhile, the global acreage share of rice has increased for other Asian countries including Indonesia, Thailand, Myanmar, and Viet Nam.

Fig. 2 depicts the annual change of global acreage for the four crops since 1990. Although the growth in global crop acreages does not seem to show any clear trend, visual inspection shows that the year-to-year acreage changes for soybeans, corn and wheat have become more variable since about 2002, relative to the preceding 5 years. The growth of wheat and rice acreages has been relatively more stable compared to that of soybeans and corn in the recent two decades. Global soybean acreage has been steadily growing since about the mid-1990s except for a decline of about 5.4% in 2007. Cultivation of corn has also shown consistent upward trend in the recent decade except for a slight decline in 2009.



Source: Data from FAO (2012) and several national sources

Fig. 2. Annual changes in global acreages of the four crops

Fig. 2 also shows that periods of major global corn acreage increases have usually been to the detriment of soybean acreage, and vice versa. For instance, a close to 5% decline in global soybean cultivation in 2007 was accompanied by an increase of about 7% in corn acreage. This is because the two crops are typically planted in similar seasons, have similar land requirements and are good substitutes for animal feed. When data starting from the 1960s is included into Fig. 2, we can see that the annual acreage changes of these crops were relatively stable in the 1980s and 1990s, compared to the 1970s and the recent decade. While previous literature indicated that the volatility of agricultural commodity prices has shown a similar development during this period (e.g. Huchet-Bourdon, 2011; Sumner, 2009), it is worthwhile to empirically investigate whether price volatility actually is one of the key factors behind these acreage variations.

The levels of agricultural investment have been low for about three decades since the early 1970s. This has been attributed to the prevailing low international agricultural commodity prices. However, agricultural commodity prices have shown dramatic upward movement since the middle of the previous decade. High food prices pose an incentive for net food sellers to produce more food. Whenever agricultural output prices are on an upward trend relative to input prices, farm income will grow, encouraging agricultural investment. Price volatility, however, is a challenge for producers, and evidence shows that the recent increase in price trends is accompanied by higher volatility (Gilbert & Morgan, 2010). Volatility introduces risks that affect the investment decisions of a risk-averse agent (von Braun & Tadesse, 2012). Since agricultural producers in many developing countries are neither able to deal with (Binswanger & Rosenzweig, 1986) nor protected from (Miranda & Helmberger, 1988) the consequences of price volatility, they are substantially exposed to the effects of international agricultural market price instability. The world price volatility of selected crops, as measured by the moving standard deviation of monthly logarithmic prices, has been higher in the recent decade relative to earlier periods (Table 1).

Table 2. Volatility of international prices for selected crops

Period	Wheat	Corn	Soybeans	Rice
1961-1970	0.06	0.07	0.08	0.10
1971-1980	0.16	0.12	0.18	0.19
1981-1990	0.09	0.13	0.12	0.13
1991-2000	0.13	0.13	0.08	0.14
2001-2011	**0.17**	**0.15**	**0.15**	**0.13**
2006-2011	**0.21**	**0.19**	**0.16**	**0.16**

Note: Price volatility is measured by the standard deviation of logarithmic monthly prices using the World Bank international prices. The figures in each row refer to average values over the respective decade.

Table 1 also shows that the volatility of soybean and rice prices was slightly higher in the 1970s. Moreover, the literature indicates that international agricultural commodity prices have been more volatile over the past three decades than during the pre-1973 periods (Dehn et al., 2005). Thus, the main contribution of this study is to investigate the effect of international price volatility on crop production, with an emphasis on cropland allocation at the global level. The study involves cross-country panel data and recent developments in panel econometrics in order to test for several assumptions on variable acreage responses to prices and volatility, as well as to control for a time trend. The study also provides updated estimates of various price elasticities for crop-specific acreages and yields, and their growth trends that are essential to understanding the likely extensive and intensive margin changes resulting from changes in crop prices.

3. Theoretical and analytical developments

3.1. Theoretical model

The supply response literature has gone through several important empirical and theoretical modifications, out of which two major frameworks have been developed. The first approach is a Nerlovian partial adjustment model, which allows analyzing both the speed and the level of adjustment from actual towards desired output. The second is the supply function approach, derived from the profit-maximizing framework. This approach requires detailed input prices and simultaneous estimation of input demand and output supply equations. However, input markets, in particular land and labor markets, are either missing or imperfect in several developing countries. Moreover, our main interest lies in the acreage supply function. Thus, the econometric approach of the present study is in line with the partial adjustment framework, enhanced with dynamic response, alternative price expectation assumptions and the introduction of price risk variables.

There has been a wide variety of applications of the Nerlovian model certain modifications of the original framework. Alternative expectation assumptions such as futures prices as additional information used for price expectation formation (Gardner, 1976), expected net returns rather than prices alone (Chavas & Holt, 1990; Davison & Crowder, 1991), and acreage value rather than prices or returns (Bridges & Tenkorang, 2009) have been used. Risk variables have also been included to capture the behavioral aspects of farmers (Liang et al., 2011; Lin & Dimukse; 2007). Furthermore, econometric developments have allowed more recent work to use panel data while time series data have often been used to capture the dynamics of agriculture production in earlier studies.

Models of the supply response of crops can be formulated in terms of yield, area, or output response. For instance, the desired area to be planted for a certain crop in period t is a function of expected output prices, and a number of other exogenous factors (Braulke, 1982):

$$A_t^d = \beta_1 + \beta_2 P_t^e + \beta_3 Z_t + \varepsilon_t \tag{1}$$

where A^d is the desired cultivated area in period t, P^e is the expected price of the crop under consideration and of other competing crops, Z is a set of other exogenous variables including fixed and variable input prices, climate variables, and technological change, ε_t accounts for unobserved random factors affecting the area under cultivation with zero expected mean, and β_i are the parameters to be estimated.

Since full adjustment of the desired allocation of area may not be complete in the short run, the actual adjustment in area will only be a fraction δ of the desired adjustment:

$$A_t = \delta A_t^d + (1-\delta)A_{t-1} + v_t \qquad (2)$$

where A_t is the actual area planted of the crop at time t, δ is the acreage adjustment coefficient that ranges between 0 and 1, and v_t is again a spherical error term.

The harvest time prices are not observed during the time of planting. Thus, the farmers make expectations about output prices based on their knowledge of past and present prices as well as other relevant observable variables. In the traditional Nerlovian model, such price expectation is modeled in an adaptive manner whereby farmers learn and adjust their expectations as a fraction of the deviation between their expected price and the actual price in the previous period, t–1:

$$P_t^e = \gamma P_{t-1} + (1-\gamma)P_{t-1}^e + \omega_t \qquad (3)$$

where P_{t-1} is the output price at the time decisions are made, γ is the price expectation coefficient that ranges between 0 and 1, and ω_t is a random error with zero expected mean.

Equations (1), (2), and (3) contain the long-term equilibrium and expected variables that are not observable. However, after some algebraic manipulation we obtain a reduced form equation containing only observable variables for estimation purposes:

$$A_t = a_1 + a_2 P_{t-1} + a_3 A_{t-1} + a_4 A_{t-2} + a_5 Z_t + a_6 Z_{t-1} + e_t \qquad (4)$$

where

$$a_1 = \beta_1 \delta\gamma,\ a_2 = \beta_2 \delta\gamma,\ a_3 = (1-\delta) + (1-\gamma),\ a_4 = -(1-\delta)(1-\gamma);\ a_5 = \beta_3 \delta,\ a_6 = \beta_3 \delta(1-\gamma)$$

and

$$e_t = v_t - (1-\gamma)v_{t-1} + \delta\varepsilon_t - (1-\delta)\varepsilon_{t-1} + \beta_2 \delta\omega_t$$

The reduced form is a distributed lag model with lagged dependent variables. The estimated coefficients for each explanatory variable of equation (4), given logarithmic specification, provide the short-run price elasticities. Dividing the short-run elasticities by the adjustment coefficients gives us the respective long-run elasticities. The long-run acreage response is greater than the short-run supply response if both the price expectation and acreage adjustment are smaller than one. A close to unity adjustment coefficient implies fast adjustment of actual acreage to desired acreage. On the other hand, if the adjustment coefficient is close to zero, the adjustment takes place slowly.

3.2. *Review of recent applications*

There have been several empirical applications of the above model with respect to the estimation of supply response to price movements in several countries. Askari & Cummings (1977) and later Nerlove & Bessler (2001) have provided a thorough analysis of the literature in this regard. Although we do not make an attempt to exhaustively revise the empirical literature, we briefly review some recent applications of this framework and its variants in several different parts of the world.

Using panel data for the period 1970/1971 to 2004/2005 across the states of India, Mythili (2008) estimates short and long-run supply elasticities for a set of crops in the country. Panel econometric estimation based on a pooled cross-sectional data over this period shows that Indian farmers respond to price incentives in the form of both acreage expansion and yield improvement. The study also indicates that acreage adjustment to desired levels is slow in India. Another recent study by Kanwar & Sadoulet (2008) has also applied a variant of the Nerlovian model to estimate output response of cash crops in India using panel data for the period 1967/1968 to 1999/2000 across 14 states in the country. They also apply dynamic panel estimation techniques using expected profit instead of expected prices and find that expected profit has statistically significant positive impact on five out of seven cash crop acreages. A recent study by Yu et al. (2012) has applied similar framework to estimate the acreage and yield response of different winter and summer season crops for the province of Henan in China. Using data from 108 counties in the province for the period 1998-2007, the study found variable responses to output prices of acreage and yield across crops. Similar recent empirical applications in Asia include supply response estimations by Yu & Fan (2011) for rice production in Cambodia, Mostofa et al. (2010) for vegetable production in Bangladesh, and Imae et al. (2011) for several agricultural commodities for a panel of ten Asian countries.

Other applications in a similar framework have also been conducted for Latin American countries. A national soybean supply response model by de Menezes & Piketty (2012) using state-level data in Brazil for the period 1990-2004 found that soybean supply is price elastic. Another Brazilian acreage response study by Hausman (2012) also found stronger response to crop prices for soybean acreage but weak response in case of sugar cane. Furthermore, Richards et al. (2012) estimated soybean supply response equations for three Latin American countries using data from the middle of the 1990s. Their econometric results show significant soybean acreage response to own output prices in all these countries with stronger response in Brazil, followed by Bolivia and Paraguay.

Studies in Africa also show responsive agricultural output to crop prices, albeit with lower magnitude as compared to responses in most advanced economies. For instance, Vitale et al. (2009) use farmer level data for the period 1994-2007 in Southern Mali in order to estimate a supply response model for major staple crops in the region. This study reports statistically significant acreage responses with respect to own-crop prices and, in most cases, to cross-prices as well. Muchapondwa (2009) estimates aggregate agricultural supply response models for Zimbabwe for the period 1970-1999. The study found short-run price elasticity of supply consistent with theory; however, the long-run elasticity is only significant at 10% and is atypically smaller than the short-run value. Other supply response studies in Africa include Subervie (2008) on aggregate agricultural commodity for many African and other developing countries, Leaver (2004) on tobacco supply in Zimbabwe, and Molua (2010) and Mkpado et al. (2012) for rice supply in Cameroon and Nigeria, respectively.

There are also several econometric studies on the advanced economies. For the US, for instance, Huang & Khanna (2010) model the supply response of specific agricultural commodities to own and cross-prices whereas Roberts & Schlenker (2010) estimate the aggregate supply response of calories to world food prices. Supply response models by Sanderson et al. (2012) for wheat and by Agbola & Evans (2012) for rice and cotton acreages are two examples of such studies on Australia. Slightly modified versions of such a partial adjustment framework were also applied for econometric estimation of crop production and acreage in some provinces of Canada. These include studies by Coyle et al. (2008) for the estimation of acreage and yield response models for wheat, barley and canola in Manitoba and by Weersink et al. (2010) for the estimation of acreage responses of corn, soybeans and winter wheat in Ontario.

These and other empirical studies investigate supply responses to prices at the micro, national or at most regional scale while there is a lack of equivalent research at the global level. The present paper tries to fill this gap by estimating country-specific and global crop supply responses to output prices and price risk using dynamic panel econometric methods.

4. The econometric model and data

4.1. Empirical model

Given the above theoretical model and assuming there are K countries observed over T periods, the acreage demand equations of the four crops can be specified most generally as:

$$A^i_{k,t} = \sum_{p=1}^{p} \pi_i A^i_{k,t-p} + \sum_{j=1}^{4} \alpha_{ij} P^j_{k,t_k} + \sum_{j=1}^{4} \varphi_{ij} vol(p)^j_{k,t_k} + \lambda_1 w^i_{k,t_k} + \lambda_2 YS^i_{k,t_k} + \lambda_3 f^i(t) + \mu^i_t + \eta^i_k + u^i_{k,t} \qquad (5)$$

where A^i denotes the cultivated acreage of the *i-th* crop (1=wheat 2 = corn, 3 = soybeans, and 4 = rice), A^i_{t-p} is lagged acreage used as a proxy for soil conditions or land constraints, P denotes either spot or futures prices that are used as a proxy for expected own and competing crop prices at planting time, $vol(p)^j$ is a matrix of the volatility measures for own and competing crop prices, w refers to prices of variable inputs (e.g. fertilizer), YS refers to a yield shock for each crop, potentially capturing producers' expectations of weather conditions, $f(t)$ is a time trend which may vary across countries or continents and captures trends in area cultivation stemming from technological change and population growth, μ captures year-fixed effects to account for some structural changes or national policy changes with global influence, η denotes country-fixed effects, and u denotes the error term. The subscript k denotes the country: this implies that the lag lengths of the relevant futures and spot prices to form price expectations as well as the price volatility, input price and yield shock variables are country-specific. As mentioned above, the seasonality of agricultural cultivation in different countries enables us to construct such country specific variables. The lag length p is assumed to ensure the stochasticity of the idiosyncratic error term. All variables (except the price volatility measures, which are rates; and yield shock measures, which are negative as well as positive) are in logarithmic form.

Since actual prices are not realized during planting, we model farmers' price expectations using price information available during planting. We alternatively use two price variables, spot and futures prices, to proxy producers' expected harvest period prices. It is possible for the producer to choose cultivating a different crop at planting time (Just & Pope, 2001). Therefore, it is worthwhile to consider the price and risk information during the planting season. Accordingly, we gathered crop calendar information to identify the major planting seasons of each country. The spot prices are the crop prices in the month immediately before planting, containing more recent price information for farmers. They are also closer to the previous harvest period, possibly conveying new information about the future supply situation. The futures prices refer to the harvest period futures prices quoted in the months prior to planting. The use of these two price series to formulate producers' price expectations makes the acreage response model in this study adaptive as well as forward-looking. Since the crop calendar varies across countries, both the futures and spot prices of each crop in the above specification are country-specific. For countries in the rest of the world, we use the annual average spot prices and annual average generic futures prices, respectively. We also include own and cross price volatility in order to capture price-risks. Price volatility is measured, as is customary in agricultural economics, as the standard deviation of logarithmic prices. We alternatively calculate price volatility as the standard deviation of price returns, i.e. the standard deviation of changes in logarithmic prices. The price-risk measures are also country-specific referring to the crop price variability in the twelve months preceding the beginning of the planting period for each country[2].

In this study, we measure yield shocks as deviations from country and crop-specific trends. Our proposition is that these deviations from the respective yield trends are largely due to weather shocks and this could serve as proxy for expected weather conditions. Following Roberts & Schlenker (2009), we calculate yield shocks by taking the jackknifed residuals from fitting separate yield trends for each crop in each country. A positive deviation implies favorable weather conditions and hence we expect a positive effect on crop production. For countries in the rest of the world, we pool the yield across the remaining countries to generate yield shocks for each crop. We include lagged own crop acreages in order to capture soil conditions or land constraints as well as acreage adjustment costs for rotating crops. Moreover, the country-specific fixed effects control for all time-invariant heterogeneities across countries.

Given the dynamic nature of agricultural supply response, the panel dataset may contain nonstationary variable series. Hence we conduct panel unit root tests, the results of which are reported in Table 2. For we have an unbalanced panel dataset in this study, we use the Maddala and Wu (1999) Fisher-type panel unit root test. The results suggest that unit roots exists in the levels of nearly all the time series variables whereas first order differences of these variables are stationary (Table 2).

Table 3. Panel unit root test results, P-values

Variable	**H_0: unit root**		**Variable**	**H_0: unit root**	
	Level	Difference		Level	Difference
Wheat area	0.008	0.000	Wheat spot price	0.999	0.000
Maize area	0.192	0.000	Maize spot price	0.999	0.000
Soybean area	0.033	0.000	Soybean spot price	1.000	0.000
Rice area	0.992	0.000	Rice spot price	0.021	0.000
Wheat yield	0.492	0.000	Wheat futures price	1.000	0.000
Maize yield	1.000	0.000	Maize futures price	0.999	0.000
Soybean yield	0.549	0.000	Soybean futures price	0.999	0.000
Rice yield	0.999	0.000	Oil price	1.000	0.000
			Fertilizer price	1.000	0.000

Note: The Dickey-Fuller results of the Fisher's panel unit root test are reported here (the Phillips-Perron option gives similar results).

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[2] The standard deviation of price returns are used as price-risk measures in the econometric models.

Applying Ordinary Least Squares (OLS) estimation to a dynamic panel data regression model such as in Equation (5) above results in a dynamic panel bias due to the correlation of the lagged dependent variable with the country fixed effects (Nickell, 1981). Since current acreage is a function of the fixed effects (η_k), it is obvious that lagged acreage is also a function of these country fixed effects. This violates the strict exogeneity assumption and hence the OLS estimator is biased and inconsistent. An intuitive solution to this problem is to transform the data and remove the fixed effects. The within group or fixed effects (FE) estimator does exactly this and wipes out the fixed effect terms. However, under the within group transformation, the lagged dependent variable remains correlated with the error term. Therefore, the FE estimator is biased and inconsistent and the bias diminishes only as the time period gets larger[3]. While the correlation between the lagged dependent variable and the error term is positive in the simple OLS regression, the estimated coefficient of the lagged dependent variable is biased downwards in the case of the FE estimator.

Therefore we need an estimator that gives an estimate of the true parameter that lies in the range of the OLS and the FE estimate for the coefficient on lagged acreage. Kiviet (1995) and later Bun and Kiviet (2003) suggest that using a bias-corrected FE estimator that performs FE estimation and then corrects the results for the bias solves this problem. Although Bruno (2005a) extends these bias approximations in order to accommodate unbalanced panels, they are not applicable in the presence of endogenous or even only weakly exogenous regressors other than the lagged dependent variable (Bruno, 2005b). Anderson and Hsiao (1982) suggest instrumental variable (IV) method to estimate the first differenced model. This technique eliminates the fixed effect terms by differencing instead of within transformation. Since the lagged dependent variable is correlated with the respective error term, this method uses the second lagged difference as an IV. Although this provides consistent estimates, Arellano and Bond (1991) argue that it is inefficient for it does not make use of all the available moment conditions. Arellano and Bond (1991) develop the so-called feasible efficient GMM estimator method in order to estimate a dynamic panel difference model using all suitably lagged endogenous and other exogenous variables as instruments in the GMM technique (Roodman, 2009). The feasible efficient GMM, also called difference GMM, transforms equation (5) into a first difference equation:

$$\Delta A_{k,t}^{i} = \sum_{p=1}^{p} \pi_i \Delta A_{k,t-p}^{i} + \Delta \mathbf{X}'^{i}_{k,t_k} \boldsymbol{\lambda} + \sum_{j=1}^{4} \alpha_{ij} \Delta P_{k,t_k}^{j} + \sum_{j=1}^{4} \varphi_{ij} \Delta vol(p)_{k,t_k}^{j} + \Delta \mu_t^{i} + \Delta u_{k,t}^{i} \qquad (6)$$

where $\mathbf{X'}$ is a matrix of all time-variant variables in Equation (5) with coefficient λ.

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[3] Since the time period is relatively large in our dataset, we estimate our crop acreage models using the FE estimator as a robustness check. The results are highly consistent with those of the difference GMM, which is our preferred estimator.

At any time t, if u_t are not serially correlated, the lagged dependent variable(s) are uncorrelated with the first differenced dependent variable (ΔA_t). Thus, the lagged dependent variables can be used as valid instruments for the differenced Equation (6) at time $t+2$. The GMM estimators for the parameter set $\Psi = (\pi, \lambda, a, \varphi)'$ are computed as:

$$\hat{\Psi} = \left\{ (\mathbf{Y}'\mathbf{Z}) \mathbf{B}_{\mathbf{K}} (\mathbf{Z}'\mathbf{Y}) \right\}^{-1} (\mathbf{Y}'\mathbf{Z}) \mathbf{B}_{\mathbf{K}} (\mathbf{Z}'\mathbf{Y}) \qquad (7)$$

where **Y** refers to a matrix of all time-variant lagged differences of independent variables including the lagged dependent variable and time dummies; **Z** is a vector of lagged level values of all independent variables and other predetermined variables that could serve as instrument variables; and $\mathbf{B}_{\mathbf{K}} = (\mathbf{Z}'\mathbf{H}\mathbf{Z})^{-1}$ is the GMM weighting matrix where **H** is an estimate of individual specific covariance matrix of the transformed errors on a minimally arbitrary assumption about the errors. This GMM estimation retains the error component with panel-specific random terms. First differencing the variables does also remove the panel-specific effects and maintains purely random terms. In the process of first-differencing, the GMM estimation adjusts for unit root variable series and makes use of the stationary differenced series (Table 2).

Blundel and Bond (1998) further develop a strategy named system GMM to overcome dynamic panel bias described above. Instead of transforming the regressors to purge the fixed effects and using the levels as instruments, the system GMM technique transforms the instruments themselves in order to make them exogenous to the fixed effects (Roodman, 2009). However, the Blundell-Bond method is appropriate for random walk-type variables whereas the dependent variables, acreage or yield, in this study are not such type of variables. Thus, the Arellano-Bond technique is used to estimate the dynamic panel model described in this study.

4.2. Data

The econometric model relies on a comprehensive database covering the period 1961-2010. The empirical model utilizes global and country-level data in order to estimate global acreage responses for the world's key crops. While data on planted acreage were obtained from several relevant national statistical sources[4], harvested acreages for all countries were obtained from the Food and Agricultural Organization of the United Nations (FAO) and the United States Department of Agriculture (USDA). International spot market output prices, crude oil prices as well as different types of fertilizer prices and price indices were obtained from the World Bank's commodity price database. All commodity

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[4] Data sources can be made available upon request.

futures prices were obtained from the Bloomberg database. Table 4 reports the countries or regions analyzed in this study and their respective typical planting months.

Table 4. Sample countries and planting months for each crop

Country	**Planting months for the main harvest season**				**Remark**
Africa	***Wheat***	***Corn***	***Soybeans***	***Rice***	
Egypt	*Nov*	*Apr-May*	*Apr-May*	*Apr-Jun*	
Ethiopia	*May-Jun*	*Mar-May*	*Mar-May*	*Mar-May*	Rice acreage data is available from 1993
Nigeria	*May-Jun*	*Mar-Sep*	*Apr-Jun*	*Apr-Jul*	
South Africa	*Apr-Jun*	*Oct-Jan*	*Oct-Dec*	*Sep-Dec*	
Asia					
Bangladesh	*Nov-Jan*	*Jun-Aug*	*Jun-Aug*	*Jan-Aug*	Soybean acreage data available from 2005
Cambodia	*n.a.*	*May-Jun*	*May-Jun*	*Jun-Dec*	
China	*Sep-Nov*	*Apr-Jun*	*Apr-May*	*Mar-Jul*	
India	*Oct-Dec*	*Jun-Aug*	*Jun-Aug*	*May-Aug*	
Indonesia	*n.a.*	*Jun-Aug*	*May-Aug*	*Oct-Jan*	
Japan	*Sep-Nov*	*Mar-May*	*Mar-May*	*Apr-May*	
Kazakhstan	*May*	*Apr-Jun*	*Apr-May*	*Apr-Jun*	Data applicable since 1992
Myanmar	*Sep-Nov*	*Sep-Nov*	*Oct-Dec*	*May-Jun*	
Pakistan	*Oct-Dec*	*Apr-Aug*	*Apr-Aug*	*May-Jul*	
Philippines	*n.a.*	*Apr-Jun*	*Apr-Jun*	*Apr-Jun*	
Sri Lanka	*n.a.*	*Oct-Nov*	*Sep-Nov*	*Sep-Dec*	
Thailand	*Sep-Nov.*	*Apr-Jun*	*Apr-Jun*	*May-Aug*	Wheat acreage data available from 1986
Uzbekistan	*Sep-Oct*	*Apr-Jun*	*n.a.*	*Apr-Jun*	Data applicable since 1992
Viet Nam	*n.a.*	*Jan-Oct*	*Apr-Jun*	*Jan-Dec*	
South America					
Argentina	*Jun-Sep*	*Sep-Dec*	*Nov-Jan*	*Sep-Dec*	
Brazil	*Apr-May*	*Sep-Dec*	*Sep-Nov*	*Oct-Dec*	
Mexico	*Oct-Dec*	*May-Jul*	*Apr-Jul*	*Apr-Jul*	
Paraguay	*Apr-Jun*	*Jul-Sep*	*Oct-Dec*	*Oct-Dec*	
Uruguay	*May-Aug*	*Aug-Dec*	*Oct-Dec*	*Oct-Dec*	
Middle East					
Iran	*Sep-Nov*	*Apr-May*	*Apr-Jun*	*May-Jun*	
Turkey	*Sep-Nov*	*Apr-May*	*Apr-Jun*	*Apr-Jun*	
Europe					
EU-27	*Sep-Nov*	*Apr-May*	*May-Jun*	*Apr-May*	Quantity data such as acreage and yield are pooled across the 27 member countries
Russian Federation	*May*	*Apr-Jun*	*Apr-May*	*Apr-May*	Data applicable since 1992
Ukraine	*Aug-Oct*	*May*	*Apr-May*	*Apr-May*	Data applicable since 1992
North America					
Canada	*May-Jun*	*May-Jul*	*May-Jun*	*n.a.*	
USA	*Sep-Nov*	*Apr-May*	*May-Jun*	*Apr-Jun*	
Australia					
Australia	*May-Jul*	*Oct-Dec*	*Nov-Jan*	*Oct-Nov*	
Other					
ROW	*Jan-Dec*	*Jan-Dec*	*Jan-Dec*	*Jan-Dec*	Quantity data such as acreage and yield are pooled across all the remaining countries

Note: n.a. (not applicable) refers to either no acreage is devoted to the respective crop or data is not available and hence is not used for the econometric analysis.

We make use of the crop-calendar information in Table 4 in order to construct country-specific spot and futures prices, measures of price-risk and yield shocks, and input prices. While the crop calendar for emerging and developing countries is obtained from the General Information and Early

Warning System (GIEWS) of the FAO, information from the Office of the Chief Economist (OCE) of the USDA is used for the advanced economies. It is further modified with expert knowledge on planting and harvesting periods from Bayer CropScience. Area harvested serves as a proxy for planted area if data on the latter are not available from the relevant national agricultural statistics. Fertilizer price indices are used as proxies for production costs in this study. The fertilizer price index is constructed using the prices of natural phosphate rock, phosphate, potassium and nitrogenous fertilizers.

5. Results and discussion

Tables 5 and 6 present the GMM results of the acreage and yield response functions respectively. There is a subtle difference between the yield deviation measures that we use in the acreage and yield response models in order to proxy weather expectations or conditions. While, for the former, they are derived from the harvest period prior to planting, they are derived from the harvest of the previous year for the latter. Accordingly, the deviations in the yield response models are lagged whereas they need not be lagged in the former if the prior harvest was in the year of planting. We, therefore, exclude the lagged dependent variable from the regression of the yield response functions since it is by definition correlated with the lagged yield deviation. The standard error estimates for all specifications are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels. The test results in the lower part of the tables indicate that the null hypothesis of no second-order autocorrelation in residuals cannot be rejected for all acreage and yield models, indicating the consistency of the GMM estimators. We consider several models with different orders of time trend polynomial. Area and yield elasticity estimates are reasonably stable across model specifications with different order of polynomial time trends[5].

For each respective crop, the first column uses pre-planting month spot prices whereas the second column (except for rice)[6] uses harvest period futures prices as proxy for expected prices at planting time. Crop acreage and yield responses to own prices are positive and statistically significant, consistent with economic theory. The results are robust across the two specifications. Wheat acreage responds to competing crop futures prices besides the response to own output price. While the response of wheat acreage to corn futures prices has an unexpected positive sign, its response to soybean futures prices is negative and thus consistent with economic theory. Moreover, an increase in

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[5] We use linear time trend in the reported results

[6] Rice futures markets have relatively shorter time series data and local prices are unlikely to be strongly correlated with futures prices in several countries.

corn price, both spot and futures, tends to reduce the global soybean acreage. The proceeding discussion relies on the results obtained from the specifications with spot prices (reported under columns marked (1)), unless stated otherwise.

The results show that wheat acreage responds positively to own output price. When the expected price of wheat rises by 10 percent, farmers respond by increasing their land allocated to wheat cultivation by about 1 percent. The long run wheat acreage own-price elasticity is larger than the short run, and is equal to 0.68. However, the positive response of wheat acreage to a rise in own price levels may be overshadowed by own crop price volatility. The results reveal that a 1 percent increase in the volatility of wheat prices leads to a 0.41 percent decline in the average global wheat acreage. Considering the specifications with futures prices, global wheat acreage tends to respond to the volatility of corn and soybean prices as well. More specifically, the negative wheat acreage response to own-price volatility could be offset by a similar increase in the volatility of the competing corn prices. Expectations about weather conditions, measured by yield shocks, also have the *a priori* expected statistically significant effect on wheat acreage.

Table 5. Estimates of global acreage response

Variable	**Wheat**		**Corn**		**Soybeans**		**Rice**
	(1)	(2)	(1)	(2)	(1)	(2)	(1)
Lagged own area	0.856***	0.895***	0.981***	0.982***	0.922***	0.897***	0.682***
	(0.050)	(0.050)	(0.029)	(0.026)	(0.029)	(0.030)	(0.109)
Wheat spot price	0.099***		-0.043		-0.145**		
	(0.031)		(0.058)		(0.068)		
Wheat futures price		0.112***		0		-0.092	
		(0.038)		(0.053)		(0.076)	
Corn spot price	-0.001		0.087**		-0.171*		
	(0.031)		(0.037)		(0.100)		
Corn futures price		0.119**		0.053		-0.223**	
		(0.047)		(0.069)		(0.106)	
Soy spot price	-0.019		0		0.319***		
	(0.032)		(0.072)		(0.115)		
Soy futures price		-0.129**		-0.062		0.294**	
		(0.055)		(0.040)		(0.111)	
Rice spot price							0.065**
							(0.032)
Wheat price volatility	-0.411**	-0.433**	-0.194	-0.165	0.214	0.164	
	(0.195)	(0.205)	(0.221)	(0.252)	(0.282)	(0.299)	
Corn price volatility	0.416	0.602**	-0.443**	-0.332*	-0.258	-0.527	
	(0.270)	(0.267)	(0.243)	(0.227)	(0.520)	(0.494)	
Soy price volatility	-0.24	-0.236*	0.336*	0.362	0.208	0.569	
	(0.146)	(0.118)	(0.186)	(0.238)	(0.394)	(0.396)	
Rice price volatility							-0.19
							(0.210)
Fertilizer price	-0.009	-0.029	-0.047*	-0.022	0.037	0.056	-0.021
	(0.018)	(0.018)	(0.027)	(0.030)	(0.030)	(0.035)	(0.018)

Weather expectation	0.019**	0.014	-0.009	-0.016*	0.029*	0.026	0
	(0.009)	(0.010)	(0.008)	(0.008)	(0.017)	(0.023)	(0.011)
Time trend	-0.001	-0.001	0.003*	0.003*	0	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	1130	1126	1155	1151	1100	1096	1332
Test for AR(1): p-value	0.001	0.001	0.076	0.075	0.007	0.006	0.018
Test for AR(2): p-value	0.423	0.413	0.419	0.390	0.235	0.241	0.313

Note: Robust standard errors in parenthesis; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Columns marked (1) and (2) for the respective crop report results of which we use spot and futures prices, respectively.

Although we fail to find a significant relationship between corn area and competing crop price levels, global corn acreage does respond to own crop price and to international fertilizer prices. In addition, global corn area responds to own and competing crop (soybean) price volatilities. While producers react to rising corn prices by increasing land for corn cultivation, corn price risk induces risk averse producers to shift land away from corn production. Considering the soybean acreage response results, on the other hand, the estimated coefficients on the volatility of all crop prices are statistically insignificant, with a positive sign for own price volatility. This may imply that output price risk does not have a negative impact on soybean acreage and that, unlike wheat and maize producers, soybean producers are less risk averse. This is consistent with previous national level studies that find either insignificant or positive effects of price variability on soybean acreage supply (e.g. de Menezes & Piketty, 2012). The response of global soybean acreage to own price is stronger relative to the other crops, with a short run acreage elasticity of 0.32 and a corresponding long-run elasticity of 4.1. Global rice acreage also responds to its own international price, with elasticity of 0.07 in the short-run and 0.20 in the long run.

The lagged acreage variables were both statistically and economically relevant in determining all crop acreages. The estimated coefficients indicate producers' inertia that may reflect adjustment costs in crop rotation and crop specific land and soil quality requirements. However, the coefficients of the lagged dependent variables might also reflect unobservable dynamic factors and interpretation should be made with caution (Hausman, 2012).

The results in Table 6 also indicate that higher output prices induce producers to invest in crop yield improvement, implying that global food supply response to prices appears to occur via both acreage and yield changes. As it does to wheat acreage, output price volatility tends to reduce wheat yield. In spite of their modest crop acreage effects, higher international fertilizer prices are detrimental to improving the yields of nearly all crops. Likewise, in line with our expectation, the yield effects of weather condition are both statistically and economically relevant for all crops. Better weather conditions or expectations of such weather conditions, measured by lagged yield deviations from the

Table 6. Estimates of global yield response

	Wheat		Corn		Soybeans		Rice
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)
Own spot price	0.169***		0.05		0.162***		0.034**
	(0.033)		(0.033)		(0.058)		(0.017)
Own futures price		0.166***		0.026		0.180**	
		(0.044)		(0.031)		(0.075)	
Own price volatility	-0.483**	-0.477**	-0.107	-0.1	-0.09	0.059	-0.023
	(0.181)	(0.187)	(0.135)	(0.135)	(0.181)	(0.167)	(0.053)
Fertilizer price	-0.057***	-0.062**	-0.014	0	-0.042*	-0.061**	-0.026**
	(0.017)	(0.025)	(0.022)	(0.019)	(0.022)	(0.028)	(0.012)
Weather condition/	0.078***	0.071***	0.108***	0.105***	0.145***	0.150***	0.084***
expectation	(0.015)	(0.018)	(0.022)	(0.023)	(0.035)	(0.036)	(0.010)
Time trend	0.018***	0.019***	0.026***	0.026***	0.016***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)
N	1147	1145	1412	1412	1340	1338	1332
Test for AR(1): p-value	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Test for AR(2): p-value	0.118	0.117	0.703	0.750	0.067	0.073	0.278

Note: Robust standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

trend, have positive crop yield effects. Besides, the estimated coefficients on the time trends suggest that the average global crop yield of these staple food commodities has been consistently growing at an annual rate of between 1 and 3 percent. However, the global acreages devoted to these crops do not show any clear annual growth rate except for a 0.3 percent growth of corn acreage.

6. Conclusions

Uncertainty is a quintessential feature of agricultural commodity prices. Besides the traditional causes for price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices (von Braun & Tadesse, 2012). In addition to the effects of climate changes, the unpredictable nature of output prices results in notable variations in supply. 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 substantial implications for global food supply as well as for the agribusiness sector such as input supply industries.

Using cross-country panel data for the period 1961-2010, this paper investigates the global supply impacts of output prices and their volatility. Besides providing updated estimates of supply responses to own and competing price expectations, it also estimates growth trends that are informative to policy in understanding the likely extensive and intensive margin changes because of crop price changes.

Estimation of acreage response to input and output prices as well as output price volatilities is a necessary step but not sufficient to predict the global food supply effect of possible developments in output prices and their volatility. In addition to the acreage allocation response that agricultural producers make towards price changes, they also react to expected changes in terms of yield response. While yield responses to own output prices are positive, the response towards output price volatilities is modest. Thus, besides via acreage changes, the global food supply response to expected prices comes from yield changes.

The results underscore the relevance of output price volatility on the supply of the key global agricultural staple crops. Although higher risk in prices is usually associated with higher return, it is a well-known finding in economic theory that output price risk is detrimental to producers (Sandmo, 1971). Coefficients for the price-risk variables are statistically and economically significant for global wheat and corn acreages. Besides inducing wheat producers to shift land away from wheat cultivation, higher output price volatility does also weaken the incentive to invest in yield improvement. Having little or no yield impact, own output price volatility has a negative impact on corn area and a positive but statistically insignificant impact on soybean area. Thus, the hegemonic view that output price volatility is a disincentive for pure agricultural producers relies on the behavioral assumption of risk aversion of the producers. This assumption is likely to hold for the majority of crop producers in developing and developed countries, albeit to a lesser extent in the latter case. Consequently, reducing agricultural price volatility is more likely to expand land for cultivation of staple crops and hence, to increase food supply in the world and more importantly in developing countries. However, there are agricultural producers who do not shy off from making investments in order to obtain higher returns associated with higher price risks. Such producers need not be hurt by output price volatility. The findings of this study suggest that this is the case for the majority of soybean producers in the world whereas risk-aversion is the foremost behavior among the majority of wheat and corn producers. This is relevant for policy makers, suggesting that "one-size fits all" type of price volatility management tools would not benefit all producers. Nevertheless, reducing agricultural price volatility is more likely to expand land for the cultivation of staple crops and hence, to increase food supply in many developing countries since it is likely that agricultural producers in such countries are averse to output price uncertainty

By aggregating area and yield data at country and regional levels, we may conceal the likely crop supply effects of farm and household level factors such as local transaction costs, farm and household characteristics. However, we are able to control for heterogeneities across countries and across time with greater transparency and parsimony than farm or household level supply response estimations.

Although the use of international instead of local farm gate prices as proxy for expected prices implies that the domestic market is less important, it is likely and empirically verified that international prices transmit to domestic prices even when countries are poorly integrated to the global agricultural market. It is plausible that each country is a small economy in the global market, and therefore the use of international prices rather than domestic prices avoids the likely reverse causality problem between supply and output prices. Nevertheless, country-specific prices were constructed based on each country's planting and harvesting patterns in order to proxy price expectations of producers in each country. Our estimates serve both as complements to micro level supply models and as verifications of whether involved household and farm level estimations add up to patterns that are apparent in the aggregate national and regional data.

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