Worldwide Acreage and Yield Response to International Price Change and Volatility: A Dynamic Panel Data Analysis for Wheat, Rice, Corn, and Soybeans

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This article estimates a worldwide aggregate supply response for key agricultural commodities—wheat, rice, corn, and soybeans—by employing a newly-developed multi-country, crop-calendar-specific, seasonally disaggregated model with price changes and price volatility applied accordingly. The findings reveal that, although higher output prices serve as an incentive to improve global crop supply as expected, output price volatility acts as a disincentive. Depending on the crop, the results show that own-price supply elasticities range from about 0.05 to 0.40. Output price volatility, however, has negative correlations with crop supply, implying that farmers shift land, other inputs, and yield-improving investments to crops with less volatile prices. Simulating the impact of price dynamics since 2006, we find that price risk has reduced the production response of wheat in particular—and to a lesser extent, rice—thus dampening price incentive effects. The simulation analysis shows that the increase in own-crop price volatility from 2006–2010 dampened yield by about 1–2% for the crops under consideration.

Key words: Food prices, price volatility, global supply response, staple food commodities, supply elasticity.

JEL codes: O11, O13, Q11, Q13, Q18, Q24.

After approximately three decades of low and relatively stable prices of staple food commodities, the world has experienced a surge in the prices of many of these commodities since 2005. Such high prices are typically expected to bring about a supply response in which producers allocate more land to the agricultural sector and increase investment to improve yield growth (OECD 2008). These higher prices were, however, accompanied by higher volatility (Gilbert and Morgan 2010). Price volatility introduces

output price risk, which has detrimental implications for producers' resource allocation and investment decisions (Sandmo 1971; Moschini and Hennessy 2001). Because agricultural producers in many developing countries are often unable to deal with (Binswanger and Rosenzweig 1986) and are unprotected from (Miranda and Helmberger 1988) the consequences of price volatility, they are exposed to the effects of international agricultural market price instability to the extent it is transmitted to local markets. Yet Bellemare, Barrett, and Just (2013) point out that reducing commodity price volatility could provide larger relative benefits for wealthier rural households than for poorer ones.

This article analyzes the supply responsiveness of the world's key staple food commodities—namely, wheat, corn, soybeans, and rice—to changes in output prices

and volatility. The paper assesses how global food commodity producers allocate cropland and how their production decisions are affected by changes in price levels and volatility, which are fundamental questions for designing policies related to agricultural growth and food supply. Additionally, the article provides relevant information on how fast current scarcities in global food supply, which are indicated by high prices, can be overcome by increased production in the short term.

The literature on estimating supply response to prices has a long history in agricultural economics (Nerlove 1956; Houck and Ryan 1972; Lee and Helmberger 1985). Nevertheless, there are various reasons for the renewed interest in research on supply response. The majority of the previous empirical literature is concentrated on a few countries, and thus does not estimate the worldwide supply response to international prices. Furthermore, the impact of price volatility and price risk is rarely considered due to the small number of observations that limit the use of additional explanatory variables, or because price risk has not been considered as an important factor at the global level. Because prices of many agricultural commodities have been more volatile after 2005, there has emerged new interest in the impacts of price risk and volatility for (global) food security. The present article addresses this debate from the supply side perspective, that is, it attempts to assess the extent that price risks reduce production and supply response to increasing price levels.

Many existing econometric analyses focus on national supply responses to domestic prices. In contrast, this article investigates the worldwide aggregate supply response of the key world staples to international market prices. In so doing, the article makes the following major contributions. First, it provides updated short- and long-term supply elasticities that indicate how major agricultural commodity producers have responded to the recent increase in global food prices and volatility. This reveals to what extent the global agricultural system is responding to emerging global food scarcities. Second, given some empirical evidence suggesting that the largest share of the supply response to output price, in the short run, is through acreage adjustments (e.g., Roberts and Schlenker 2009), both acreage and yield responses are estimated to contest or

affirm this finding. Third, the paper evaluates whether the recent increases in prices and price volatility represent an opportunity or a challenge to agricultural producers in particular, and to the agriculture sector in general. To this end, we use simulation analyses to assess the overall impacts of the agricultural commodity price dynamics during the 2006–2010 period on the worldwide supply of the aforementioned key staple crops.

This article differs from related work by Haile, Kalkuhl, and von Braun (2014) in terms of methodology and research question. These authors employ several time series models to investigate annual and intra-annual global acreage response, whereas the current article uses a panel econometric modeling approach that makes use of data where international prices are assigned to the corresponding planting season of the respective country and crop. Thus, this article estimates global supply response of the aforementioned agricultural commodities employing a newly developed multi-country, crop- and calendar-specific, seasonally disaggregated panel data with price changes and price volatility applied accordingly. This is an alternative approach for modeling the heterogeneous seasonal planting patterns on the global scale, which has the advantage of using a larger number of observations without sacrificing the underlying nature of the monthly time resolution of production decisions. In addition, this article not only investigates acreage but also yield supply response to prices and price risk. The joint consideration allows us to infer about the global production response (as the product of acreage and yield response), which is relevant for policymakers. Finally, yet importantly, this article assesses the net impacts of the recent agricultural commodity price dynamics on acreage, yield, and production of the key interest crops.

Related Literature

This article builds on the extensive agricultural economics literature on the estimation of agricultural supply response. Elasticities from a supply response model refer to the speed and size of adjustments in desired output to expected output prices. Neither the desired output nor the expected price is observable, however. The empirical literature employs different types of proxies for

these variables, which could affect the results obtained. We provide a brief review of the literature with respect to the alternative proxies of these two variables.

In terms of the proxy for expected output prices, the literature does not provide unambiguous evidence regarding which expectation model to use for empirical agricultural supply response estimation (Nerlove and Bessler 2001; Shideed and White 1989). The widely applied expectation formation hypotheses in the supply response literature include the following themes: naïve expectation (Ezekiel 1938), where expected prices are assumed to be equal to the latest observed prices; adaptive expectation (Nerlove 1958), where farmers are assumed to revise their expectations depending on past errors; and rational expectation (Muth 1961), which assumes that expectations are consistent with the underlying market structure and that economic agents make efficient use of all available information. Other research has focused on modeling supply response using a quasi-rational price expectation (Holt and McKenzie 2003), which is consistent with price prediction from a reduced-form dynamic regression equation. Futures prices are also used as a proxy for price expectations (Gardner 1976).

Some authors criticize the naïve and adaptive expectation hypotheses, claiming that they are backward-looking (Nickell 1985); in other words, these hypotheses ignore that the dynamics of price expectations imposed by decision makers can influence future prices. Although it can be forward-looking, the rational expectation hypothesis implies that economic agents make efficient use of all available information, which may not be the case when some information is costly or difficult to process (Chavas 2000). Additionally, the rational expectation is not supported in some experimental and survey datasets (Nelson and Bessler 1992). The applicability of futures prices as a proxy is also dubious in supply analyses in countries where farmers are neither able to make any futures transactions nor have access to information from exchange markets. Moreover, some empirical evidence shows that heterogeneous expectations coexist among agricultural producers simultaneously (Chavas 2000).

Following Nerlove (1958), several empirical supply response models employ the adaptive expectation hypothesis and its variants. Askari and Cummings (1977) and later Nerlove and Bessler (2001) provide a thorough review of such literature; however, Yu, Liu, and You (2012), Vitale, Djourra, and Sidib (2009), and de Menezes and Piketty (2012) can be mentioned as recent examples. Moreover, Aradhyula and Holt (1989) employ the rational expectation hypothesis to investigate broiler supply in the United States, while Eckstein (1938) and Lansink (1999) apply it to estimate crop acreage elasticities using aggregate agricultural data and farm-level data, respectively. Moreover, other empirical applications show the relevance of the quasi-rational expectation approach in their supply models (Holt and McKenzie 2003; Nerlove and Fornari 1998). Last, but not least, Gardner (1976), Lin and Dsimukse (2007), Liang et al. (2011), and Hausman (2012) are a few of the studies that use harvesting time futures prices as a proxy for farmers' price expectations during the planting season.

The empirical agricultural supply response literature often uses acreage, yield, or production as a proxy for desired output supply. Several studies prefer to use acreage in modeling output supply response (Coyle 1993; Haile, Kalkuhl, and von Braun 2014) because acreage, unlike observed output, is not influenced by external shocks that occur after planting. However, acreage elasticities may only serve as a lower bound for the total supply elasticity (Rao 1989) because the latter also depends on how yield responds to prices. Accordingly, several studies estimate both acreage and yield responses to prices (Weersink, Cabas, and Olale 2010; Yu, Liu, and You 2012). When there is little interest in whether the supply response to output prices occurs via acreage or yield, total observed production is another proxy used to estimate output supply response in the literature (Coyle 1999). Because "external" weather and pest shocks—which usually happen after farmers make their production decisions and are hardly predictable for farmers to consider in their production decisions—influence this proxy, the estimated supply response may not reflect the actual response of farmers to prices.

There is, however, another proxy used in recent studies—total caloric production, which is the sum of the caloric value of specific crops (Roberts and Schlenker 2009, 2013). This proxy implicitly assumes that the crops in the caloric aggregate are perfectly

substitutable, which is less plausible because it assumes identical land and other input requirements for each crop. This ignores the possibility that producers switch crops as a result of changes in relative prices, which is supported by the literature that shows acreage expansion of "high demand" crops such as corn, by shifting out land from "low demand" crops (Abbott, Hurt, and Tyner 2011; Goodwin et al. 2012). Such aggregation excludes inter-crop acreage and other input shifts, which, by definition, implies that aggregate output elasticities are likely to be smaller than crop-specific elasticites. This conforms to several empirical studies that find statistically significant cross-price elasticities of crop acreages. Hendricks, Smith, and Sumner (2014), for instance, conclude that most of the acreage response to the prices of corn and soybeans in the United States occurs through substitution rather than through area expansion. Moreover, aggregating crops conceals any implications for, as well as the effects of, crop-specific policies with respect to changing intra-commodity price relations.

On the other hand, output supply can be estimated at the following levels: at a plot or farm-level, where farm size, soil quality, and other farm characteristics can be controlled for; at a household level, which enables a better understanding of farmers' supply behaviors; or at larger aggregation scopes such as national, regional, or global levels, which have methodological limitations to capture the effects of contextual factors but that still enable sufficient measurement of supply responsiveness. Still, estimating aggregate agricultural supply response to changing price incentives is essential because it has crucial implications for economic growth and poverty alleviation in economies with a sizable share of the agricultural sector in their national income.

Although several farm- and micro-level studies (e.g., Lansink 1999; Vitale, Djourra, and Sidib 2009; Yu, Liu, and You 2012), and quite a few studies at the national level (e.g., Barr et al. 2009; de Menezes and Piketty 2012) exist, global level studies are few. Nevertheless, cross-country analyses using a certain group of countries are conducted to determine the role of prices on agricultural supply. Peterson (1979), for instance, finds agricultural supply in developing countries to be fairly responsive to crop prices (estimated long run elasticities range between 1.25–1.66). On the other hand, Binswanger et al. (1987), using a sample of 58 countries from 1969–1978, find that agricultural supply responds weakly to price incentives but strongly to non-price factors. A more recent cross-country study by Subervie (2008), based on a sample of 25 developing countries between 1961 and 2002, finds a rather small but statistically significant aggregate supply elasticity of 0.04. Findings from Imai, Gaiha, and Thapa (2011), which use data from a panel of ten Asian countries, and other crop-disaggregated studies that find much larger supply elasticities, hint that such crop aggregation could result in the small supply elasticities.

The other scope is when supply is aggregated over all countries and crops. Two related studies by Roberts and Schlenker (2009, 2013) estimate the world's aggregated caloric supply and demand of staple crops—corn, wheat, soybeans, and rice—and find supply elasticity in the range of 0.06–0.12. These authors use lagged weather shocks, approximated by deviations of yield from trend, to identify the supply elasticity of agricultural commodities. Hendricks, Janzen, and Smith (2015) replicate Roberts and Schlenker's analysis and find little difference between their estimates that control for the realized yield shock and the estimates by Roberts and Schlenker that use weather shocks in the previous year as an instrument for potentially endogenous expected prices. These authors also suggest that using planted acreage as a dependent variable can reduce the endogeneity bias in the supply elasticity estimates. Along the lines of this suggestion, Haile, Kalkuhl, and von Braun (2014) aggregate the acreage of all countries to estimate crop-specific world supply elasticties that range between 0.03 for rice and 0.34 for soybeans.

This article subtly differs from the literature discussed above, in terms of both the level of aggregation employed for the dependent variables and the proxy used for expected prices. Besides using crop acreage, yield, and production as alternative proxies for the desired output supply, these variables are aggregated at the world level for each crop. Nevertheless, the aggregation retains the panel feature of the data, which enables us to control for heterogeneity across countries. For example, we make use of the country and crop-specific planting and harvesting seasons to assign the relevant proxy for price expectation in each country and for each crop.

This leads us to the second point of how our proxy for expected prices differs from that used in the literature. We use world planting season prices to proxy farmers' anticipated prices in each country; in other words, we estimate crop supply response to changes in world prices rather than to specific domestic prices. Thus, unlike the commonly understood agricultural supply response, which estimates how output supply responds to changes in the domestic prices that producers face within their own countries, we estimate production, area, and yield responses to changes in international prices. These two supply response estimates are identical under the assumption of complete transmission of international prices to domestic producer prices. However, they could be different in the case of incomplete price transmission—an argument that is supported by the literature (e.g., Kalkuhl 2014). Finally, with the exception of Subervie (2008), none of the cross-country panel studies discussed above and, to our knowledge, no worldwide aggregated supply response study except Haile, Kalkuhl, and von Braun (2014) has accounted for price volatility (price risk) in the respective supply models.

Conceptual Framework

The supply response literature has gone through several important empirical and theoretical modifications, from which two major frameworks have been developed. The first approach is the Nerlovian partial adjustment model, which allows both the speed and the level of adjustment from actual toward desired output to be analyzed. The second is the supply function approach, which is derived from the profit-maximizing framework. This second 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 many countries. Moreover, our main interest lies in the output supply function. Thus, the econometric approach of the present article is in line with the partial adjustment framework, enhanced with dynamic response, alternative price expectation assumptions, and the introduction of price-risk variables.

Models of the supply response of a crop can be formulated in terms of output, area,

or yield response. For instance, the desired output of a certain crop in period t is a function of expected output prices and a number of other exogenous factors (Braulke 1982):

$$(1) \qquad Q_t^d = \beta_1 + \beta_2 p_t^e + \beta_3 Z_t + \varepsilon_t$$

where Q_t^d denotes the desired output in period t; p_t^e refers to expected prices of the crop under consideration and of other competing crops; Z_t 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 crop production with zero expected mean; and β_t are the parameters to be estimated. Usually output (determined by area and yield) adjustments are delayed for one or two agricultural production cycles due to lacking resources. To account for such time lags in agricultural supply response, it is important to apply a dynamic approach. Supply response is usually a two-stage process. Because harvest-time prices are not realized during the time of planting, producers, in the first stage, make acreage allocation decisions conditional on expected prices. As in the production equation above, the desired area to be cultivated for a certain crop at time t (A_t^d) is determined by expected own and competing crop prices and other non-price factors:

$$(2) \qquad A_t^d = \alpha_1 + \alpha_2 p_t^e + \alpha_3 Z_t + \varepsilon_t.$$

Given the acreage allocation for each crop, farmers then determine crop yield based on other inputs and climate conditions. During the growing period, they may make revisions to their production practices by adjusting input quantity, input quality, and crop protection. Hence, the desired yield of each crop is defined similarly to equations (1) and (2) except that the output price vector includes only the crop's own price.

It is important to emphasize that we use international prices instead of domestic prices for our empirical analysis. Given a price transmission elasticity η, we can substitute the domestic log price p_t^e by the transmitted international price $p_t^e = \eta p_t^{e,int}$ in equations (1) and (2). This substitution

provides

$$(1') \quad Q_t^d = \beta_1 + \beta_2 \eta p_t^{e,int} + \beta_3 Z_t + \varepsilon_t$$
$$= \beta_1 + \tilde{\beta}_2 p_t^{e,int} + \beta_3 Z_t + \varepsilon_t$$

and

$$(2') \quad A_t^d = \alpha_1 + \alpha_2 \eta p_t^{e,int} + \alpha_3 Z_t + \varepsilon_t$$
$$= \alpha_1 + \tilde{\alpha}_2 p_t^{e,int} + \alpha_3 Z_t + \varepsilon_t$$

which are structurally equivalent to equations (1) and (2). The estimated supply response elasticities $\tilde{\beta}_2$ and $\tilde{\alpha}_2$, however, implicitly consider the imperfect transmission of prices from international to domestic markets. Hence, the supply response concept used in this paper is an aggregate response that consists of two parts: the (imperfect) transmission of global prices to domestic producer prices and the genuine supply response to expected (domestic) producer prices—the latter being typically estimated in conventional supply response models.[1]

Data

The econometric model relies on a comprehensive database covering the period 1961–2010. The empirical model uses global and country-level data to estimate global production, acreage, and yield responses for the world's key staple crops. Data on planted acreage are obtained from several relevant national statistical sources, whereas harvested acreage, production, and yield for all countries are obtained from the Food and Agriculture Organization of the United Nations (FAO).[2] Area harvested serves as a proxy for planted area if data on the latter are not available from the relevant national agricultural statistics. International spot market output prices, as well as different types of fertilizer prices and price indices, are obtained from the World Bank's commodity price database. All commodity futures prices are from the Bloomberg database. The 32 countries or regions included in this article, with the rest of world (ROW) aggregated as

a separate entity, are reported in table A1 in the online appendix.[3]

A producer may choose to cultivate different crops at planting time (Just and Pope 2001). Therefore, it is worthwhile to consider price, price risk, and other information available to the farmer during the planting season. Accordingly, we use crop calendar information to identify the major planting seasons of each country in order to construct country-specific spot and futures prices, measures of price risk and yield shocks, and input prices.[4]

Because actual prices are not realized during planting, we model farmers' price expectations using the relevant spot and futures world price information available during planting. Since they contain more recent price information for farmers, own and competing crop spot prices observed in the month before the start of planting are used in the empirical model. Alternatively, harvest-time futures prices quoted in the months prior to planting are used. Using these two price series to formulate producers' price expectations makes our supply response models adaptive as well as forward-looking. Because the planting pattern varies across countries and crops, both the futures and spot prices of each crop are country-specific. For countries in the ROW, we use annual average spot and futures prices.

The degree of transmission of international prices to national markets, η, can vary among countries (so do the "genuine" supply elasticities α_2 and β_2). Comparisons of the global and national supply response elasticities from the literature suggest that price transmission from world to domestic prices is imperfect or absent in some countries. Consequently, producers' responses to international price changes and volatility—that is, the focus of this article—is expected to be smaller. Nevertheless, empirical evidence shows that world prices are a significant source of variation in domestic prices (Mundlak and Larson 1992). Recent empirical literature also shows that domestic markets are integrated to world markets mostly through the adjustment of domestic prices to deviations from the long-run domestic-world

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[1] We thank an anonymous reviewer for this suggestion.
[2] Data sources are available in table A.2 in the online appendix.

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[3] Countries with a global acreage share of less than 0.5% are grouped in the rest-of-world category.
[4] The crop calendar for emerging and developing countries is obtained from the Global Information and Early Warning System (GIEWS) of the FAO, and the crop calendar for the advanced economies is from the Office of the Chief Economist (OCE) of the United States Department of Agriculture (USDA).

Table 1. International Price Volatility and Levels for Wheat, Corn, Soybeans, and Rice

| Period | Price volatility | | | | Price level | | | |
	Wheat	*Corn*	*Soybeans*	*Rice*	*Wheat*	*Corn*	*Soybeans*	*Rice*
1961–1970	0.062	0.069	0.082	0.104	258	220	467	594
1971–1980	0.157	0.122	0.175	0.194	267	210	502	598
1981–1990	0.089	0.135	0.121	0.125	182	140	320	331
1991–2000	0.131	0.127	0.080	0.136	149	113	256	285
2001–2010	0.153	0.142	0.148	0.127	191	133	323	328
2001–2005	0.113	0.107	0.132	0.086	160	111	273	236
2006–2011	0.214	0.193	0.163	0.160	227	169	384	423

Note: Price volatility is measured by the standard deviation of logarithmic monthly prices using World Bank international prices. Prices are in real 2005 U.S. dollars per metric ton. The figures in each row refer to average values of the annualized volatilities and prices over the respective decade.

price relationship (Baquedano and Liefert 2014; Kalkuhl 2014). Estimating the country-specific transmission elasticity would allow us to decompose the supply response for each country into its transmission component (η) and its "genuine" supply response (α_2 and β_2). As this, however, is empirically cumbersome and requires long price series that are difficult to obtain for the country coverage of this article, we empirically estimate the global average response to international price changes, disregarding possible heterogeneity in the price transmission and the "genuine" supply response.

We include own and cross volatility of international spot prices to capture output price risk. For price volatility, we use the standard deviation of the log returns (that is, first differences instead of levels of log prices) in order to use the de-trended price series. The price-risk measures show country-specific output price variability in the 12 months preceding the start of the planting season of each crop in each country. Table 1 presents international price volatility along with the respective average real prices for all four crops. The volatility of world prices of these crops, as measured by the moving standard deviation of monthly logarithmic prices, was higher in the recent decade relative to earlier periods, although not as high as in the 1970s. Being wary of any possible high degree of collinearity between each crop's price level and volatility that might be a concern for our empirical estimation, we compute both Pearson's and Spearman's rank correlation coefficients. The correlation coefficients are positive and statistically significant in all cases, with wheat and corn

exhibiting the highest Pearson's (Spearman's rank) correlation—between own price and own-price volatility—coefficients of 0.51 (0.53) and 0.45 (0.56), respectively. Further, collinearity diagnostic analyses among all price and volatility variables, such as the variance inflation factor (VIF), indicate that multicollinearity is not a serious problem in our data.[5]

We include yield shocks calculated as deviations from country and crop-specific trends in our empirical supply models. Our presumption is that these deviations from the respective yield trends, which may be a result of weather shocks, pest infestations, or other factors, could serve as proxy for producers' yield expectations. Following Roberts and Schlenker (2009), the yield shocks are the jackknifed residuals from separate yield-on-trend regressions for each crop in each country. A positive deviation entails good yield expectations, implying a positive effect on crop supply. For countries in the ROW, we pool the crop yields across the remaining countries to generate yield shocks for each crop.

Fertilizer price indices are used as proxies for production costs in this article. Given the weights used by the World Bank, the fertilizer price index contains the prices of natural phosphate rock, phosphate, potassium, and nitrogenous fertilizers. The fertilizer price indices are also crop- and country-specific depending on the planting pattern of each

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[5] The Pearson's and Spearman's rank correlation coefficients, and further collinearity diagnostic test results computed using the Philip Ender's-collin procedure are available in the supplementary appendix online.

crop in each country. The fertilizer price index in the month prior to the start of planting is used.

Econometric Model

Given the abovementioned theoretical model, and assuming there are K countries observed over T periods, the supply functions of the four crops can be specified most generally as

$$(3) \quad Q_{ikt} = \pi_1 Q_{ik,t-1} + \Sigma_{j=1}^4 \alpha_{ij} p_{jk,t_{i,k}}$$
$$+ \Sigma_{j=1}^4 \varphi_{ij} vol(p)_{jk,t_{i,k}} + \lambda_{i1} w_{ik,t_{i,k}}$$
$$+ \lambda_{i2} YS_{ik,t_{i,k}} + \mu_{it} + \eta_{ik} + \mu_{ikt}$$

where Q_{ikt} denotes the total production (or area under cultivation) of crop i (1 = wheat, 2 = corn, 3 = soybeans, and 4 = rice), $p_{jk,t_{i,k}}$ denotes either spot or futures prices that are used to proxy expected own and competing crop prices at planting time, $vol(p)_{jk,t_{i,k}}$ is a measure of volatility for own and competing crop prices, $w_{ik,t_{i,k}}$ refers to prices of variable inputs (such as fertilizer), $YS_{ik,t_{i,k}}$ refers to a yield shock for each crop, μ_{it} are time dummies to account for some structural changes or national policy changes, η_{ik} denote country-fixed effects to control for time-invariant heterogeneity across countries, and μ_{ikt} is the idiosyncratic shock. π_i, α_{ij}, φ_{ij}, λ_{i1}, and λ_{i2} are parameters to be estimated. The parameter α_{ij} can, for instance, be interpreted as an own-price supply elasticity if $j = i$, and as a cross-price supply elasticity if $j \neq i$. The subscript k denotes the country. The subscripts i and k on t imply that the lag lengths of the relevant futures and spot price, output price volatility, input price, and yield shock variables are country- and crop-specific.

As discussed above, the seasonality of agricultural cultivation in various countries enables us to construct international prices that are country-specific variables at the seasonally appropriate time in terms of each country's crop calendar. This approach is more precise than assuming all countries face the same yearly output price. This is particularly important given that planting decisions in the early months of the calendar year (or marketing year) in some countries affect the annually averaged price and would cause an endogeneity problem in any global

supply response model that uses annual data. Likewise, if planting decisions take place later in the calendar or marketing year, an average annual price will contain past prices that dilute the information signal that more recent planting-time prices could convey.[6] Using the lagged annual average price is not a good remedy because producers adjust their price expectations with more recent information (Just and Pope 2001).

As described in the conceptual model, the yield equation is specified similarly to equation (3) except that the output price and price volatility vectors do not include price and volatility of competing crops. There is a subtle difference between the yield deviation measures that we use as proxies for yield expectations in the acreage and yield response models. These measures are derived from the harvesting period prior to planting in the acreage response models, but from the harvest of the previous year in the yield response models. Consequently, the deviations in the yield response models are lagged whereas they need not be lagged in the acreage response models if the prior harvest is in the year of planting. We therefore exclude these variables from the regressions of the production and yield response functions because they are, by definition, correlated with the respective lagged dependent variables.[7] All quantity, output, and input price variables (except for price volatilities, which are rates) are specified as logarithms in the econometric models. Hence, the estimated coefficients can be interpreted as short-run elasticities.

Applying ordinary least squares (OLS) estimation to a dynamic panel data regression model such as in equation (3) above results in a dynamic panel bias because of 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

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[6] See Haile, Kalkuhl, and von Braun (2014) for global intra-annual planting and harvesting patterns.
[7] The yield shock variables are not statistically significant in the acreage response models, and we omit them from the final regression.

the data and remove the fixed effects. However, under the within-group transformation, the lagged dependent variable remains correlated with the error term, and therefore the fixed-effects (FE) estimator is biased and inconsistent. 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 downward in the case of the FE estimator (Roodman 2009a, 2009b).

Therefore, we need an estimator that provides an estimate of the true parameter that lies in the range of the OLS and the FE estimate for the coefficient on the lagged dependent variable. Anderson and Hsiao (1982) suggest using the instrumental variable (IV) method to estimate the first difference model. This technique eliminates the fixed-effect terms by differencing instead of within transformation. Since the lagged dependent variable is correlated with the error term, this method uses the second lagged difference as an IV. Although this method provides consistent estimates, Arellano and Bond (1991) developed a more efficient estimator, called difference generalized method of moments (GMM), 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 2009a). Blundell and Bond (1998) further developed a strategy named system GMM to overcome dynamic panel bias. 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, 2009a). The estimator in the difference GMM model can have poor finite sample properties in terms of bias and precision when applied to persistent series or random-walk types of variables (Roodman 2009b). Moreover, the system GMM estimator allows substantial efficiency gains over the difference GMM estimator provided that initial conditions are not correlated with fixed effects (Blundell and Bond 1998). Thus, we use the system GMM method to estimate our dynamic supply models.

Several statistical tests are done to check the consistency of our preferred GMM estimator. First, the Arellano-Bond test for autocorrelation is used to test for serial correlation in levels. The test results, reported in the next section, indicate that the null hypothesis of no second-order autocorrelation in residuals cannot be rejected for nearly all production, acreage, and yield models, indicating the consistency of the system GMM estimators. Second, the Hansen test results cannot reject the null hypothesis of instrument exogeneity. We also conduct a test for the validity of the Blundell-Bond assumption using the difference-in-Hansen test of the two-step system GMM. The test statistics give p-values greater than 10% in all cases, suggesting that past changes are good instruments of current levels and that the system GMM estimators are more efficient. Furthermore, the standard error estimates for all specifications are robust in the presence of any pattern of heteroskedasticity and autocorrelation within panels. The Windmeijer (2005) two-step error bias correction is incorporated. Following Roodman (2009a, 2009b), we also "collapsed" the instrument set in order to limit instrument proliferation.

Results

Tables 2 and 3 present the GMM results of the production/acreage and yield response functions, respectively. For each respective crop, we estimate the supply models using pre-planting month spot prices and harvest period futures prices (except for rice) as a proxy for expected prices at planting time.[8] We fail to find a significant supply-price relationship using futures prices (except for soybeans), which could imply that many agricultural producers do not make use of information on futures prices when forming their price expectations. Indeed, futures prices are good proxies for expected prices for producers in countries where domestic prices are strongly linked to the futures prices—that is, where the maturity basis is constant. Although farmers in advanced economies participate widely in futures markets and the futures prices are linked to the cash prices, this is not the case in many developing countries. Thus, we reported the results obtained from the specifications with spot prices.

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

Table 2. Estimates of Production and Acreage Response

Variable	Production				Acreage			
	Wheat	*Corn*	*Soybeans*	*Rice*	*Wheat*	*Corn*	*Soybeans*	*Rice*
Lagged dep. var.	0.961***	0.964***	0.928***	0.625***	0.990***	0.978***	0.932***	0.747***
	(0.013)	(0.030)	(0.036)	(0.089)	(0.005)	(0.033)	(0.029)	(0.045)
Lagged dep. var. (2)				0.356***				0.244***
				(0.099)				(0.039)
Wheat price	0.106**	−0.015	−0.205***		0.075***	0.009	−0.034***	
	(0.046)	(0.057)	(0.058)		(0.027)	(0.014)	(0.012)	
Corn price	0.034	0.226**	−0.054		−0.002	0.069***	−0.118***	
	(0.052)	(0.113)	(0.066)		(0.032)	(0.025)	(0.025)	
Soybean price	−0.028	0.050	0.365**		−0.047	−0.038*	0.146**	
	(0.054)	(0.062)	(0.166)		(0.029)	(0.020)	(0.074)	
Rice price	−0.020	−0.135**	−0.061	0.058***				0.024**
	(0.023)	(0.068)	(0.065)	(0.025)				(0.010)
Wheat price volatility	−0.628**	0.074	0.511***		−0.350***	0.123	−0.110	
	(0.281)	(0.283)	(0.162)		(0.124)	(0.146)	(0.151)	
Corn price volatility	0.159	0.287	−0.374**		0.249*	0.135	0.134	
	(0.438)	(0.252)	(0.175)		(0.123)	(0.095)	(0.147)	
Soy price volatility	0.366	−0.608	0.013		0.279**	−0.108	0.228**	
	(0.234)	(0.559)	(0.411)		(0.106)	(0.128)	(0.092)	
Rice price volatility				−0.197**				−0.064
				(0.106)				(0.062)
Fertilizer price	−0.068**	−0.010	0.040**	−0.014	−0.013	−0.017	0.013	−0.003
	(0.023)	(0.018)	(0.018)	(0.019)	(0.011)	(0.014)	(0.029)	(0.013)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,174	1,444	1,371	1,332	1,162	1,418	1,371	1,332
F-test of joint significance: *p*-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(1): *p*-value	0.015	0.013	0.020	0.101	0.100	0.004	0.010	0.002
Test for AR(2): *p*-value	0.162	0.152	0.055	0.317	0.880	0.292	0.945	0.767
Diff-in-Hansen test: *p*-value	1.000	0.991	0.991	0.753	1.000	0.980	0.970	0.980

Note: All regressions are two-step system GMM and treat the lagged dependent variable as predetermined. Two-step robust standard errors, incorporating the Windmeijer (2005) correction, are in parentheses. Yield deviations are included in the acreage response models as additional control variables. Asterisks *, **, and *** represent the 10%, 5%, and 1% levels of significance. All the production and area response models are weighted by the global crop acreage share of the respective country. Sensitivity analyses, where we estimated elasticities using panels excluding countries in the ROW group, provide consistent results. Rice price and volatility are excluded in the non-rice acreage response models because land for rice cultivation is not usually suitable for these crops; however, competition in production is possible through input substitution.

In general, production, acreage, and yield responses to own prices are positive and statistically significant, which is consistent with economic theory. The results suggest that higher output prices induce producers to increase acreage and to invest in improving crop yields, implying that global food supply response to prices appears to occur through both acreage and yield changes. The production responses to own prices

are larger than the respective acreage and yield responses (with the exception of the wheat yield response). The acreage and yield own-price elasticities are mostly similar in their order of magnitude.

The results show that soybeans and corn have the largest production responses to own-crop prices, followed by wheat and rice. Conditional on other covariates, a 10% rise in the expected own-crop price induces a

Table 3. Estimates of Yield Response

Variable	Wheat	Corn	Soybeans	Rice
Lagged dep. var.	0.920***	0.960***	0.925***	0.724***
	(0.032)	(0.020)	(0.034)	(0.133)
Lagged dep. var. (2)				0.272
				(0.165)
Own-crop price	0.166***	0.094**	0.146***	0.043**
	(0.055)	(0.039)	(0.045)	(0.018)
Own-price volatility	−0.336**	−0.366**	−0.467**	−0.148**
	(0.168)	(0.170)	(0.226)	(0.070)
Fertilizer price	−0.069**	−0.008	−0.050**	−0.020
	(0.026)	(0.021)	(0.020)	(0.017)
Time dummies	Yes	Yes	Yes	Yes
N	1,174	1,444	1,371	1,332
F-test of joint significance: p-value	0.000	0.000	0.000	0.000
Test for AR(1): p-value	0.002	0.001	0.000	0.016
Test for AR(2): p-value	0.046	0.425	0.079	0.574
Diff-in-Hansen test: p-value	0.950	0.749	0.933	0.751

Note: All regressions are two-step system GMM and treat the lagged dependent variable as predetermined. Two-step robust standard errors, incorporating the Windmeijer (2005) correction, are in parentheses. Asterisks *, **, and *** represent the 10%, 5%, and 1% levels of significance.

production increase of about 4% for soybeans, 2% for corn, 1% for wheat, and 0.6% for rice in the short run. These production responses typically reflect the acreage and yield adjustments. An equivalent increase in the respective international crop prices induces farmers to increase their land allocation to soybean and corn cultivation by about 1.5% and 0.7%, respectively. The yields of soybeans and corn also respond to higher international own-crop prices in an order of magnitude similar to their respective acreage responses; the short-run elasticities are 0.15 and 0.09, respectively. Global wheat acreage and yield also respond to output prices, with short-run elasticities of 0.08 and 0.17, respectively. In line with the production response results, rice has relatively weaker acreage and yield responses to own prices. Rice cultivation in some areas requires capital investment (such as canals and sluices) to ensure flooding at the time of planting. These investments are long-term decisions, implying that short-run price responses are inevitably low.

Additionally, the statistically significant cross-price elasticities have negative signs consistent with economic theory. Higher wheat prices are negatively correlated with soybean production, and corn producers respond to higher international rice prices by lowering corn production. The cross-price elasticities show that corn and soybeans compete for land at a global level, with a stronger corn price effect on soybean acreage than vice versa. In addition, higher international wheat prices lead to less land for soybean production.

Unlike own-crop price levels, own-price volatility does not have a uniform effect on the supply of all crops. Price volatility seems to affect wheat and rice production most. The results reveal that an increase in the volatility of international wheat and rice prices leads producers to allocate less land to these crops and to reduce yield-improving investments, resulting in a decline in wheat and rice production. To some extent, the negative wheat acreage response to own-price volatility could be offset if prices of competing crops such as corn and soybeans also exhibit such volatility. For corn, the negative supply impact of own-price volatility is due mainly to declining yields. Corn producers react to rising own-crop prices by using more inputs to improve productivity, whereas corn price risk induces producers to shift inputs away from corn production. For soybean acreage, on the other hand, the estimated coefficient of own-price volatility has a statistically positive sign. This result is consistent with previous national-level studies that find either insignificant or positive effects of price volatility on soybean acreage (e.g., de Menezes and Piketty 2012). The majority of soybean producers in the world are large commercial holders who are likely to be well-informed about price developments.

Table 4. Standardized Effect Sizes of Price and Volatility on Supply for Each Crop

	Wheat price	Corn price	Soybean price	Rice price	Wheat price volatility	Corn price volatility	Soy price volatility	Rice price volatility	Fertilizer price
Production response									
Wheat	**0.045**	0.012	0.011	−0.008	**−0.025**	0.005	0.016		**−0.044**
Corn	−0.005	**0.061**	0.015	**−0.042**	0.002	0.006	−0.019		−0.005
Soybeans	**−0.065**	−0.015	**0.108**	−0.019	**0.016**	**−0.008**	0.000		**0.020**
Rice				**0.021**				**−0.008**	−0.008
Acreage response									
Wheat	**0.035**	−0.001	−0.020		**−0.015**	**0.008**	**0.013**		−0.009
Corn	0.004	**0.025**	−0.015		0.005	0.004	−0.005		−0.011
Soybeans	**−0.013**	**−0.040**	**0.053**		−0.004	0.003	**0.009**		0.008
Rice				**0.010**				−0.003	−0.002
Yield response									
Wheat	**0.132**				**−0.025**				**−0.084**
Corn		**0.054**				**−0.016**			**−0.009**
Soybeans			**0.109**				**−0.037**		**−0.062**
Rice				**0.038**				**−0.015**	−0.028

Note: The effect sizes that are statistically significant at the 10% level or less are typed in bold.

Thus, they may be willing and able to absorb price risks.

It is worth mentioning here that the coefficients of the price volatility variables—measured by the standard deviation of log price returns—are not elasticities, and hence are not directly comparable with the price elasticity estimates. We compute the standardized effect sizes of price and volatility on the respective supply responses to shed light on the relative magnitude of effect sizes between mean and volatility responses (Table 4). The effect sizes in table 4 show the global supply response for a one standard deviation change in price and volatility for each crop. In the case of effect sizes for wheat, the negative impact of own-price volatility on production and area is roughly half of the positive impact of own-price increase. Own-price volatility is also an important factor for the yields of all four crops, with effect sizes ranging between 19% and 34% of the yield responses to own-crop prices.

In addition to output prices, input prices are important factors in farmers' production decisions, as shown by fertilizer price elasticities. A higher international fertilizer price not only has a negative effect on wheat production, but also reduces the yields of all crops (although not statistically significant in the case of corn and rice). A doubling of international fertilizer price indices results in a 1% to 7% reduction in crop productivity.

The lagged dependent variables are both statistically and economically relevant in all crop supply models.[9] The estimated coefficients indicate producers' inertia, which may reflect adjustment costs of crop rotation, crop-specific land (and other quasi-fixed and fixed inputs), technology, and soil-quality requirements. The coefficients of the lagged dependent variables may also, however, reflect unobservable dynamic factors, and interpretation should be made with caution (Hausman 2012). The estimated coefficients of the lagged dependent variables are close to one, indicating that agricultural supply is much more responsive to international output prices in the longer term than in the short term.

Robustness Checks

We have conducted several statistical tests to check the consistency of our preferred GMM estimator, and a number of additional sensitivity checks to investigate the sensitivity of our results to alternative estimators.[10] Results are generally robust in terms of the significance and sign of the control variables in most specifications.

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[9] Rice cultivation requires capital investment to ensure flooding at the time of planting, which is a long-term investment. To account for such dynamics, we include a second lag of the dependent variable as a control variable.

[10] The alternative model results are provided in the online appendix.

The coefficients on the lagged dependent variable of our preferred GMM estimator are mostly close to unity, suggesting remaining residual serial correlation. To this end, we conducted the Arellano-Bond test for first and second-order autocorrelated disturbances in the first-differenced equation. The p-values reported for AR(1) and AR(2) indicate that, as expected, there is high first-order autocorrelation, and no evidence for significant second order autocorrelation. However, for any remaining serial correlations and whenever the p-values of AR(2) are below 0.15—for instance, in the production and yield response models for soybeans and in the latter model for wheat—we use second- and higher-order lags of the predetermined variable as instruments. Moreover, the coefficients of the lagged dependent variable can be statistically distinguished from unity in most cases (see supplementary material in the online appendix). Another useful check for the validity of the dynamic panel estimates is to determine if the estimated coefficient on the lagged dependent variable lies between the values obtained from OLS and FE estimators. All our preferred system GMM specifications result in an estimated autoregressive coefficient that lies between the two bounds; the first two columns of tables A5–A16 in the online appendix present these results.

We also report the two-step difference GMM estimates, which are mostly consistent with their system GMM counterparts. Nevertheless, the autoregressive coefficient of the difference GMM (in most cases) lies below the lower credible bound as given by the FE estimator. In addition, as discussed in the empirical model, the difference GMM estimator does not account for the high persistence of the dependent variable. Although we do not reject the null hypothesis of the validity of the overidentifying restrictions in all the difference and system GMM estimators, the Diff-in-Hansen test results indicate the validity of the additional moment restriction necessary for system GMM.

Several things changed during the time period covered by our empirical data, including the information technology available to form price expectations, general inflation, and market- and government-based institutions to provide risk management. Thus, we have checked whether our estimated parameters are stable over the estimation period by estimating our supply response models with 20- and 30-year rolling windows. Additionally, we include interaction of the price variables with a dummy variable for the period after 1985—dividing the data period equally—and the period dummy to test if these additional variables are statistically different from zero. We also estimate the system GMM model on the subsample of our data after 1985, the results of which are reported in the online appendix. In general, the results of the recursive rolling estimation and the "Chow" test hint that the estimated coefficients are mostly stable over time and do not significantly change between the two periods, respectively.[11] Moreover, the results from the estimations using the subsample data are mostly consistent with our preferred model results.

In summary, our empirical results align with previous work showing that agricultural supply is inelastic in the short run. Table 5 summarizes selected countries' supply elasticities as estimated by the Food and Agricultural Policy Research Institute (FAPRI) and other studies; these estimates do not capture the effects of price volatility on supply. The supply elasticity from Roberts and Schlenker (2009) is aggregated for all four crops in terms of their caloric content. Apart from the soybean supply elasticities, which are of the same order of magnitude, our estimated elasticities are smaller than the weighted average of the national-level estimates. Despite the positive response of national crop supply to international prices, this discrepancy may hint that supply responses to domestic prices are relatively stronger.

Simulation Results

We use the estimated coefficients of our preferred GMM estimator in tables 2 and 3 to analyze whether the recent increase in prices and price volatility is an opportunity or a challenge to the world food supply, in terms

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[11] The results for the Chow test and the estimates from the rolling window regression are provided in the supplementary appendix online. For the sake of brevity, we provide the graphs of the own-price coefficients along with the 95% confidence interval using the 30-year rolling window estimates. The 95% confidence interval contains the "average" estimated coefficient—indicating that the supply responses to own prices do not statistically change (over time) from the point estimate for the entire period—except for yield response of corn where the estimated parameter lies outside of the 95% confidence level in a few cases.

Table 5. Summary of Existing Own-price Supply Elasticities (without Considering Volatility)

Country	Wheat	Corn	Soybeans	Rice
Egypt	0.25	0.09	0.03	0.16
South Africa	0.09	0.28	0.03	0.03
China	0.09	0.13	0.45	0.16
India	0.29	0.21	0.36	0.11
Pakistan	0.23	0.28	0.29	0.29
Argentina	0.41	0.7	0.32	0.24
Brazil	0.43	0.42	0.34	0.07
Turkey	0.20	0.14		0.47
Iran	0.08	0.01	0.01	0.01
EU	0.12	0.08	0.19	0.24
Russia	0.19	0.31		
Canada	0.39	0.18	0.32	
United States	0.25	0.17	0.30	0.35
Australia	0.33	0.23		0.17
Weighted average (weighted by area share)	**0.18**	**0.14**	**0.31**	**0.07**
Roberts and Schlenker (2009), Global		0.11		
Roberts and Schlenker (2013), Global	0.10	0.27	0.55	0.03
Haile, Kalkuhl, and von Braun (2014)	0.09	0.18	0.37	0.02
This article	**0.11**	**0.23**	**0.37**	**0.06**

Source: Food and Agricultural Policy Research Institute (FAPRI), FAPRI Elasticity Database, http://www.fapri.iastate.edu/tools/elasticity.aspx. Because FAPRI only reports rice acreage elasticities for the United States, for the other crops we used elasticities from Lin and Dismukes (2007). We also use average acreage elasticities for "other Africa" for unreported elasticities for Egypt and South Africa. Price elasticities for individual countries refer to acreage responses to domestic producer prices, while global price elasticities for this article refer to responses to world market prices.

of acreage and yield changes. To this end, we calculate the differences in the predicted outcome variables under the realized prices and under a counterfactual scenario where all output prices and volatility, as well as fertilizer prices after 2006, are set equal to their 1980–2005 mean values. We consider only the direct short-term impacts and neglect the influence of the auto-regressive term, which would further exacerbate the changes in the long-run. The results of these simulations are shown in figures 1 and 2.

The net impact of increasing own and competing crop prices is about a 2% increase in the area under cultivation of both wheat and corn. The effect is higher (6%) for rice, as we include only own prices in the rice acreage. However, the effect of higher prices of competing crop prices on soybean acreage offsets that of higher own prices, resulting in a negligible net effect. In contrast, increasing the fertilizer price reduces acreage by nearly comparable amounts, except for soybeans, where it has a positive effect.[12]

The coefficient for volatility is statistically insignificant for corn, but higher volatility affects wheat acreage negatively and soybean acreage positively. The overall impact of the 2006–2010 output and input price dynamics on acreage is estimated to be, on average, positive for corn, soybeans, and rice, and slightly negative for wheat. The different price dynamics have greater impacts on yields, but because of strong opposing effects, the net impact is similar in magnitude to the impact on acreage allocation decisions. The increase in own-crop price volatility during the same period has dampened yield by about 1–2% for the crops under consideration.

Analogously, we calculate the production impact of the recent price dynamics from the acreage and yield simulations by the identity that production equals acreage times yield. Thus, we rely on the two-stage decision process where acreage and yield decisions are temporally decoupled. Figure 2 depicts the respective results. According to these results, the overall net impact of the 2006–2010 price dynamics on production is about a 3% increase for corn, a 1.5% increase for soybeans, negligible for rice, and about a

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[12] One explanation for this is that soybeans require less nitrogen fertilizer than the other crops, which makes it more attractive when fertilizer prices are high.
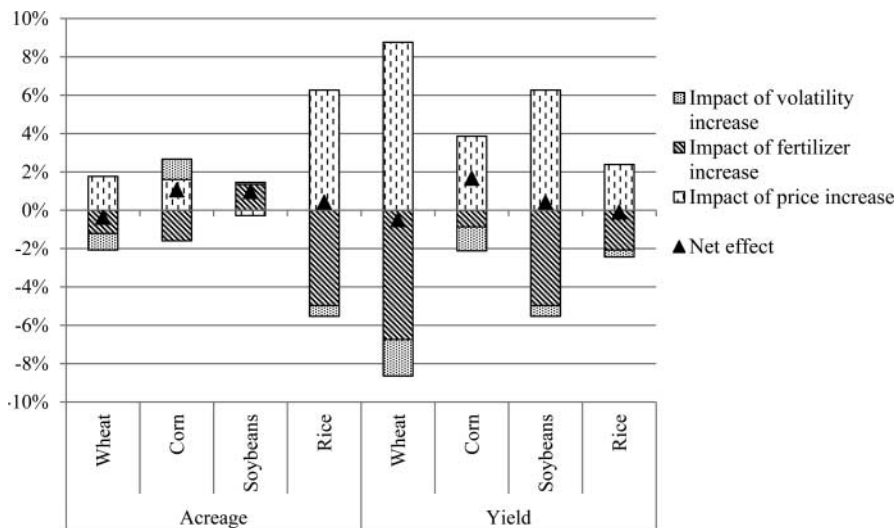
Figure 1. Impacts of the 2006–2010 price dynamics on acreage and yield

Note: The figure shows the impact of output and fertilizer prices, and output price volatility, on acreage and yield compared with a counterfactual scenario where these values were set to their long-term average. The net effect is calculated as the sum of the three components. The depicted rates refer to the net impacts during the five-year period 2006–2010. These changes are the direct short-term response, and they are the lower bounds for the longer-term effects as the coefficients of the autoregressive term are positive and closer to unity.
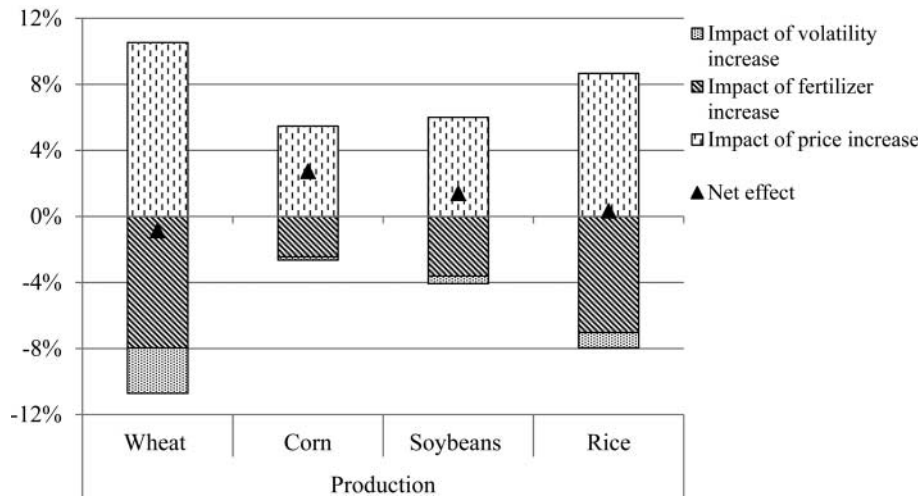
Figure 2. Impacts of the 2006–2010 price dynamics on production

Note: See simulation assumptions detailed in figure 1.

1% decrease for wheat. Decomposing the overall effect into output price, fertilizer price, and price volatility effects reveals interesting results. The net impact of increasing own and competing crop prices ranges from about a 6% increase in the production of corn and soybeans to about 11% for wheat. In contrast, the effect of higher fertilizer price is a reduction in production that ranges from about 2% for corn to about 8% for wheat. The effect of own and competing crop price volatility is about a 3% and a 1% decrease on the production of wheat and rice, respectively, and a negative but negligible effect on the production of corn and soybeans.

In summary, the simulation results show that more volatile output prices and higher input prices have weakened the extent to which rising international agricultural commodity prices have increased output production since the middle of the last decade.

Conclusions

Uncertainty is a quintessential feature of agricultural commodity prices. Besides the traditional causes of price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices (Tadesse et al. 2014). Using cross-country panel data for the period 1961–2010, this article investigates the global supply impacts of international price levels and volatility. Estimation of the recent supply response to input and output price levels and output price volatility is a necessary step in predicting the future global food supply effects of developments in output price levels and volatility. In addition to responding to price changes by reallocating acreage, producers react to expected price changes by making decisions that affect yields.

The results underscore the relevance of output price volatility for the supply of the key global agricultural staple crops. Although higher risk in prices is usually associated with higher returns, economic theory shows that output price risk is detrimental to producers (Sandmo 1971). Coefficients for the price-risk variables are statistically and economically significant in the supply response models for wheat and rice and in the yield response models for all crops. Besides inducing producers to shift land away from wheat and rice cultivation, higher output price volatility weakens their incentive to invest in yield improvement. For corn, own-crop price volatility has little or no impact on acreage allocation, but it has a negative impact on yield.

Consequently, reducing agricultural price volatility is likely to increase food supply in the world and, more importantly, in developing countries. Some agricultural producers, however, do not shy away from making investments in order to obtain the higher returns associated with higher price risks. Such producers need not be hurt by output price volatility. The findings of this article suggest that this is the case for the majority of soybean producers in the world, indicated by the statistically significant positive coefficient of own-price volatility in the acreage response model. This result is relevant for policy makers because it suggests that a one-size-fits-all approach to price volatility management—such as through stockholding or public price risk insurance systems—may not be appropriate.

This article explains why the current high food prices have not brought about a large increase in global agricultural supply as one might expect. The estimated short-run supply elasticities are generally small. Agricultural supply does not, in the short-run, increase on a par with output price increases. In other words, agricultural producers need more time to make necessary production adjustments and investments to increase supply. Furthermore, this article assesses how much the increased latent output price uncertainty represented by price volatility weakens the global positive supply response.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

References

Abbott, P.C., C. Hurt, and W.E. Tyner. 2011. What is Driving Food Prices in 2011? Farm Foundation Issue Reports. Available at http://www.farmfoundation.org/news/articlefiles/1742-FoodPrices_web.pdf.

Anderson, T.W., and C. Hsiao. 1982. Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics* 18 (1): 47–82.

Aradhyula, S.V., and M.T. Holt. 1989. Risk Behavior and Rational Expectations in the U.S. Broiler Market. *American Journal of Agricultural Economics* 71 (4): 892–902.

Arellano, M., and S. Bond. 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies* 58 (2): 277–97.

Askari, H., and J.T. Cummings. 1977. Estimating Agricultural Supply Response

with the Nerlove Model: A Survey. *International Economic Review* 18 (2): 257–92.

Baquedano, F.G., and W.M. Liefert. 2014. Market Integration and Price Transmission in Consumer Markets of Developing Countries. *Food Policy* 44: 103–14.

Barr, K.J., B.A. Babcock, M.A. Carriquiry, A.M. Nassar, and L. Harfuch. 2009. Agricultural Land Elasticities in the United States and Brazil. *Applied Economic Perspectives and Policy* 33 (3): 449–62.

Bellemare, M., C. Barrett, and D. Just. 2013. The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics* 95 (4): 877–99.

Binswanger, H., M.C. Yang, A. Bowers, and Y. Mundlak. 1987. On the Determinants of Cross-country Aggregate Agricultural Supply. *Journal of Econometrics* 36 (1–2): 111–31.

Binswanger, H.P., and M.R. Rosenzweig. 1986. Behavioural and Material Determinants of Production Relations in Agriculture. *The Journal of Development Studies* 22 (3): 503–39.

Blundell, R., and S. Bond. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* 87 (1): 115–43.

Braulke, M. 1982. A Note on the Nerlove Model of Agricultural Supply Response. *International Economic Review* 23 (1): 241–44.

Chavas, J.P. 2000. On Information and Market Dynamics: The Case of the U.S. Beef Market. *Journal of Economic Dynamics and Control* 24 (5–7): 833–53.

Coyle, B.T. 1993. On Modeling Systems of Crop Acreage Demands. *Journal of Agricultural and Resource Economics* 18 (1): 57–69.

———. 1999. Risk Aversion and Yield Uncertainty in Duality Models of Production: A Mean-variance Approach. *American Journal of Agricultural Economics* 81 (3): 553–67.

de Menezes, T.A., and M.-G. Piketty. 2012. Towards a Better Estimation of Agricultural Supply Elasticity: The Case of Soya Beans in Brazil. *Applied Economics* 44 (31): 4005–18.

Ezekiel, M. 1938. The Cobweb Theorem. *The Quarterly Journal of Economics* 52 (2): 255–80.

Gardner, B.L. 1976. Futures Prices in Supply Analysis. *American Journal of Agricultural Economics* 58 (1): 81–4.

Gilbert, C.L., and C.W. Morgan. 2010. Food Price Volatility. *Philosophical Transactions of the Royal Society B: Biological Sciences* 365 (1554): 3023–34.

Goodwin, B.K., M. Marra, N. Piggott, and S. Mueller. 2012. Is Yield Endogenous to Price? An Empirical Evaluation of Inter- and Intra-seasonal Corn Yield Response. Paper presented at AAEA annual meeting, Seattle WA.

Haile, M.G., M. Kalkuhl, and J. von Braun. 2014. Inter- and Intra-seasonal Crop Acreage Response to International Food Prices and Implications of Volatility. *Agricultural Economics* 45 (6): 693–710.

Hausman, C. 2012. Biofuels and Land Use Change: Sugarcane and Soybean Acreage Response in Brazil. *Environmental and Resource Economics* 51 (2): 163–87.

Hendricks, N.P., A. Smith, and D.A. Sumner. 2014. Crop Supply Dynamics and the Illusion of Partial Adjustment. *American Journal of Agricultural Economics* 96 (5): 1469–91.

Hendricks, N.P., J.P. Janzen, and A. Smith. 2015. Futures Prices in Supply Analysis: Are Instrumental Variables Necessary? *American Journal of Agricultural Economics* 97 (1): 22–3.

Holt, M.T., and A.M. McKenzie. 2003. Quasi-rational and Ex-ante Price Expectations in Commodity Supply Models: An Empirical Analysis of the U.S. Broiler Market. *Journal of Applied Econometrics* 18 (4): 407–26.

Houck, J.P., and M.E. Ryan. 1972. Supply Analysis for Corn in the United States: The Impact of Changing Government Programs. *American Journal of Agricultural Economics* 54 (2): 184–91.

Imai, K.S., R. Gaiha, and G. Thapa. 2011. Supply Response to Changes in Agricultural Commodity Prices in Asian Countries. *Journal of Asian Economics* 22 (1): 61–75.

Just, R.E., and R.D. Pope. 2001. The Agricultural Producer: Theory and Statistical Measurement. In *Handbook of Agricultural Economics, vol. 1A*, ed. B.L. Gardner and G.C. Rausser, 629–741. Amsterdam, The Netherlands: North-Holland.

Kalkuhl, M. 2014. How Strong Do Global Commodity Prices Influence Domestic Food Prices? A Global Price Transmission Analysis. Discussion Paper on Development Policy No. 191, Center for Development Research, Bonn University, Germany.

Lansink, A.O. 1999. Area Allocation Under Price Uncertainty on Dutch Arable Farms. *Journal of Agricultural Economics* 50 (1): 93–105.

Lee, D.R., and P.G. Helmberger. 1985. Estimating Supply Response in the Presence of Farm Programs. *American Journal of Agricultural Economics* 67 (2): 193–203.

Liang, Y., J. Corey Miller, A. Harri, and K.H. Coble. 2011. Crop Supply Response Under Risk: Impacts of Emerging Issues on Southeastern U.S. Agriculture. *Journal of Agricultural and Applied Economics* 43 (2): 181–94.

Lin, W., and R. Dismukes. 2007. Supply Response Under Risk: Implications for Counter-cyclical Payments' Production Impact. *Applied Economic Perspectives and Policy* 29 (1): 64.

Miranda, M.J., and P.G. Helmberger. 1988. The Effects of Commodity Price Stabilization Programs. *The American Economic Review* 78 (1): 46–58.

Moschini, G., and D.A. Hennessy. 2001. Uncertainty, Risk Aversion, and Risk Management for Agricultural Producers. In *Handbook of Agricultural Economics, vol. 1A*, ed. B.L. Gardner and G.C. Rausser, 88–153. Amsterdam, The Netherlands: North-Holland.

Mundlak, Y., and D. Larson. 1992. On the Transmission of World Agricultural Prices. *World Bank Economic Review* 6 (3): 399–422.

Muth, J.F. 1961. Rational Expectations and the Theory of Price Movements. *Econometrica: Journal of the Econometric Society* 29 (3): 315–35.

Nelson, R.G., and D.A. Bessler. 1992. Quasirational Expectations: Experimental Evidence. *Journal of Forecasting* 11 (2): 141–56.

Nerlove, M. 1956. Estimates of the Elasticities of Supply of Selected Agricultural Commodities. *Journal of Farm Economics* 38 (2): 496–509.

———. 1958. Adaptive Expectations and Cobweb Phenomena. *The Quarterly Journal of Economics* 72 (2): 227–40.

Nerlove, M., and D.A. Bessler. 2001. Expectations, Information and Dynamics. In *Handbook of Agricultural Economics, vol. 1A*, ed. B.L. Gardner and G.C. Rausser, 155–206. Amsterdam, The Netherlands: North-Holland.

Nerlove, M., and I. Fornari. 1998. Quasirational Expectations, an Alternative to Fully Rational Expectations: An Application to U.S. Beef Cattle Supply. *Journal of Econometrics* 83 (1): 129–61.

Nickell, S. 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica* 49 (6): 1417–26.

———. 1985. Error Correction, Partial Adjustment and All that: An Expository Note. *Oxford Bulletin of Economics and Statistics* 47 (2): 119–29.

Organisation for Economic Co-operation Development. 2008. Rising Food Prices: Causes and Consequences. Paris, France. Available at http://www.oecd.org/trade/agricultural-trade/40847088.pdf.

Peterson, W.L. 1979. International Farm Prices and the Social Cost of Cheap Food Policies. *American Journal of Agricultural Economics* 61 (1): 12–21.

Rao, J.M. 1989. Agricultural Supply Response: A Survey. *Agricultural Economics* 3 (1): 1–22.

Roberts, M.J., and W. Schlenker. 2009. World Supply and Demand of Food Commodity Calories. *American Journal of Agricultural Economics* 91 (5): 1235–42.

———. 2013. Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the U.S. Ethanol Mandate. *American Economic Review* 103 (6): 2265–95.

Roodman, D. 2009a. How to Do Xtabond2: An Introduction to Difference and System GMM in Stata. *Stata Journal* 9 (1): 86–136.

———. 2009b. A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics* 71 (1): 135–58.

Sandmo, A. 1971. On the Theory of the Competitive Firm Under Price Uncertainty. *The American Economic Review* 61 (1): 65–73.

Shideed, K.H., and F.C. White. 1989. Alternative Forms of Price Expectations in Supply Analysis for U.S. Corn and Soybean Acreages. *Western Journal of Agricultural Economics* 14 (2): 281–92.

Subervie, J. 2008. The Variable Response of Agricultural Supply to World Price Instability in Developing Countries. *Journal of Agricultural Economics* 59 (1): 72–92.

Tadesse, G., B. Algieri, M. Kalkuhl, and J. von Braun. 2014. Drivers and Triggers of International Food Price Spikes and Volatility. *Food Policy* 47: 117–28.

Vitale, J.D., H. Djourra, and A. Sidib. 2009. Estimating the Supply Response of Cotton and Cereal Crops in Smallholder Production Systems: Recent Evidence from Mali. *Agricultural Economics* 40 (5): 519–33.

Weersink, A., J.H. Cabas, and E. Olale. 2010. Acreage Response to Weather, Yield, and Price. *Canadian Journal of Agricultural Economics* 58 (1): 57–72.

Windmeijer, F. 2005. A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators. *Journal of Econometrics* 126 (1): 25–51.

Yu, B., F. Liu, and L. You. 2012. Dynamic Agricultural Supply Response Under Economic Transformation: A Case Study of Henan, China. *American Journal of Agricultural Economics* 94 (2): 370–76.