Impacts of climate and price changes on global food production

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Abstract

Agriculture is one of the key drivers and victims of climate change. Climate-resilient agriculture is therefore vital for achieving enhanced food security—which is a crucial component of the sustainable development goals (SDGs). This paper provides answers to questions that are prerequisite for policies that address agriculture and climate change. We analyze the determinants of global average crop production for maize, wheat, rice, and soybeans over the period 1961–2013. We find strong and statistically significant supply elasticities for all four crops with respect to own crop prices. Our results also underscore the relevance of output price volatility for the supply of these key global agricultural staple crops—especially on production of wheat and maize. Comparing the standardized effect sizes of own price and price volatility estimates, the effects are on par for wheat production while the price volatility effect is only a fifth of the own price effect on maize production. In agreement with previous studies, we also find that climate change has significant adverse effects on production of the world's key staple crops. More importantly, this study finds that weather extremes—both in terms of temperature and precipitation shocks— during the growing months have significant adverse impacts on the production of the abovementioned food crops. Price and weather extremes do not only adversely affect average global food production, they also positively contribute to the year-to-year fluctuations of food availability. Thus, combating climate change using both mitigation and adaptation technologies is crucial for global production and hence food security.

Keywords: *Food supply, climate change, price volatility, staple crops, global*

JEL codes: *Q11, Q15, Q54*

1. Introduction

Food insecurity remains to be a critical challenge to the world's poor today. According to recent estimates by the Food and Agriculture Organization of the United Nations (FAO) one in nine people in the world and about a quarter of those in sub-Saharan Africa are unable to meet their dietary energy requirements in 2014-15 (FAO 2015). The focus of this study is not food insecurity and hunger per se. It instead addresses one major component of food security, that is, food production. Although a range of factors influence global food security (FAO, 1996), cereal production plays a major role (Parry *et al.*, 2009). In this paper, we seek to empirically evaluate the impacts of population growth, changes in climate and weather extremes, and price changes on global food production. This paper estimates global average effects of climate change and other variables on production of the world's principal staple crops, namely wheat, rice, maize, and corn. These crops are crucial for the fight against global food insecurity since they are major sources of food in several parts of the world, comprising three-quarter of the food calories in global food production (Roberts & Schlenker, 2009). Maize, wheat, and rice, respectively, are the three largest cereal crops cultivated around the world. According to data from FAO (2012), they make up more than 75% and 85% of global cereal area and production in 2010, respectively. About one-third, of both the global area and production, of total oil crops is attributed to soybeans. Our analysis pools data from 31 major crop producer countries or regions for the 1961–2013 period. The study regions account for greater than 90% of global production of each of these crops in any year since 1991.

Tackling against food insecurity and hunger is a more difficult task in the face of rising global population, climate change, and high and volatile food prices. Increasing global population, which is projected to reach almost 10 billion in 2050, entails that more food needs to be produced. From the demand perspective rising global population makes food insecurity more challenging. Population growth and the subsequent urbanization compete for land with food production, whereas with growing population come more labor and technology that potentially boost food production. The second factor is the threat to food insecurity brought about by climate change and weather extremes. Under a business as usual scenario climate change may increase child stunting by about a quarter in Sub-Saharan and by nearly two-thirds in South Asia by 2050 (Lloyd *et al.*, 2011). The other factor contributing to problems of food insecurity and hunger is an increase in the level and volatility of food prices. In fact, rising population and climate change are the major causes of high and volatile food prices (von Braun & Tadesse, 2012). Policy responses towards climate change and population growth will therefore directly affect price changes.

Considering these key drivers of food insecurity simultaneously to estimate their impact on global food production is our key contribution to the literature. Previous studies that have addressed a similar research question can be grouped in to three: studies that address impact on crop production of 1) climate change only, 2) price changes only, and 3) climate and price change. The first strand of studies considers crop production to be a technical relationship between yield per hectare and climate change variables and fail to account for the potential for farmers to adapt to climatic changes through adjustments in area allocation, input use, crop choice, and other agronomic practices. The studies that investigate crop production using economic variables (input and output price changes) without considering climate change implicitly assume that the effect of climate variables can be fully captured by economic variables. Although farmers respond to climate changes through adjustments to their price expectations – thereby adjusting acreage or input use, not all climate and weather variations are predictable in advance such that farmers respond appropriately. The third group of studies—including the present study—investigates the impact of not only climate variables but also economic variables on crop production.

This article differs from the literature, especially from those in the last group mentioned above, in terms of both the level of aggregation employed for the dependent variable and the proxy used for expected prices. More importantly, we investigate the effect on production variance of changes in both weather and price fluctuations. Key findings of this study indicate that population density has a non-linear effect on the production of all crops. As expected crop production responds positively to increasing prices – elasticity ranging between 0.2 for wheat to about 1.0 for rice – but negatively to own crop price volatility. With respect to climate variables, increasing mean growing season temperature does not seem to be the major problem for crop production. Instead, rising temperature becomes a problem to crop production after some critical level, indicating the commonly found bell-shaped relationship. In the case of soybean production, for instance, an increase in growing season temperature turns out to have statistically significant and negative impact on soybean production beyond 32.6 degrees. The results also highlight that seasonal temperature variations have negative effects on crop production. Although production fluctuation of all crops has a decreasing trend over time, it increases with both price and weather extremes.

2. Theoretical framework

This section discusses the channels though which our key variables of interest affect global food production. Models of supply response of a crop can be formulated in terms of output, area, or yield response. According to Just and Pope (1978, 1979), the mean and variance of production can be estimated from a stochastic production function of the type:

$$(1) \qquad Q_{it} = f(X_{it}, \varphi) + h_{it}(X_{it}, \phi)\varepsilon_{it}$$

where Q_{it} denotes crop production of country i in period t; X_{it} is vector of climate and price change variables; $f(.)$ and $h_{it}(.)$ are the deterministic and stochastic components of the production function respectively; φ and ϕ are vectors of parameters to be estimated; and ε_{it} is a random error with zero mean and constant or unitary variance.

The stochastic production function given by equation (1) can be expressed for a certain crop in an explicit form with heteroskedastic errors that allow for the estimation of variance effects as

$$(2) \qquad Q_{it} = f(X_{it}, \varphi) + u_{it} \qquad E(u_{it}) = 0,\ E(u_{it}u_{is}) = 0, for\ \ i \neq s$$

$$(3) \qquad E({u_{it}}^2) = exp[W'_{it}\phi]$$

The first stage in evaluating the effect of explanatory variables on crop production involves estimation of Equation (2) with heteroskedastic disturbances. The residuals from this stage can be used to estimate the marginal effects of variables determining production variance. The vectors of independent variables (X and W) in the two stages can be the same or different. In this study, we include all climate and weather change; price and price volatility; and population density variables in the first stage, whereas the second stage includes variables that capture short-term climate and price change variables (weather extremes and price volatility).

Climate and weather extremes

The impact of climate change on crop production has been widely studied (IPCC, 2001, 2007). Changes in climate and weather affect crop production in several ways. High temperature can reduce critical growth periods of crops; promote crop disease; and increase sensitivity of crops to insect pests, thereby affecting crop development and potential yield (CCSP, 2008; Jones & Yosef, 2015). Growing period temperature that exceeds a certain threshold level can damage reproductive tissues of plants and also increase pollen sterility (Roberts & Schlenker, 2009; Thornton & Cramer, 2012). Furthermore temperature variability can affect crop production through yield losses (McCarl *et al.*, 2008). These authors also indicate that climate change affects not only the mean of crop production but also its variability.

The other climate change variable that affects crop production is precipitation. Low rainfall in arid and semi-arid regions dictates the formation of shallow soils, which are poor in organic matter and nutrients. Inter- and intra-annual variability in rainfall is a key climatic element that determines the success of agriculture in many countries (Sivakumar *et al.*, 2005). Some empirical evidence shows that the effect on year-to-year variability of crop production of precipitation is larger than that of temperature (Lobell & Burke, 2008). Low or excessive rainfall can affect crop production both through yield and acreage effects. Farmers will adjust their acreage allocation to a crop depending on – onset and magnitude of –planting time rainfall (Sacks *et al.*, 2010). It is therefore important to control for both planting and growing period mean precipitation and for standardized precipitation anomaly index (SPAI) in these seasons. The literature suggests that the relationship between crop yield and climate and weather variables is better represented by a bell-shaped curve (Shaw, 1964). The definitions and measurements of these variables are given in subsequent sections.

Price change and volatility

Higher output prices are typically expected to bring about a positive supply response in which producers allocate more land to the agricultural sector and increase investment to improve yield growth (OECD, 2008). Although conceptually higher prices may also lead to expansion of acreage under cultivation of a crop to a less fertile land, and hence reducing yield, several empirical studies have shown that the positive effect outweighs (Haile *et al.*, 2016; Miao *et al.*, 2016). Crop price volatility, on the other hand, acts as a disincentive for crop production because it introduces output price risk. Price risk has detrimental implications for producers' resource allocation and investment decisions (Moschini & Hennessy, 2001; Sandmo, 1971). This is especially true for agricultural producers in developing countries as they are often unable to deal with (Binswanger & Rosenzweig, 1986) and are unprotected from (Miranda & Helmberger, 1988) the consequences of price volatility.

The farmer has to make his optimal crop production decision subject to output prices, which are not known at the time when planting and input-use decisions are made. Thus, expected rather than observed output prices are used for decision making. The literature hints that a farmer may choose to cultivate a different crop at planting time if new and relevant information is obtained (Just & Pope, 2001). Therefore, it is worthwhile to consider price, price risk, and other information during the planting season to model price expectations of farmers. Input prices may also affect crop production through their effects both on yield and on acreage. For a farmer who produces a single crop, an increase in input prices, for instance fertilizer prices, discourages application of inputs and therefore unambiguously reduces crop production. However, in the case of multiple crop production higher input prices may induce a farmer to shift his input application to a crop that requires less of that input. Moreover, farmers may also substitute other inputs, such as land, for fertilizer if the latter gets more expensive. The effect of input prices on production is therefore an empirical question. We also include population density and its squared term for two reasons. On the one hand, population density can serve as a proxy for wages or physical labor. Similar to the explanation for fertilizer, the effect on crop production of availability of cheaper labor is ambiguous. Population density also serves as a proxy for urbanization and possible land degradation, both of which have negative impacts on crop production. The net effect of population density on crop production therefore depends on the relative magnitude of these effects on yield and acreage.

It is worth to mention here that we use international crop prices to proxy farmers' anticipated prices in each country; in other words, we estimate crop production response to changes in world prices rather than to specific domestic prices. These two supply response estimates—responses to domestic or world prices—are identical under the assumption of complete price transmission from international markets to domestic markets. In the case of incomplete price transmission, however, our estimates should be interpreted as average production response to country-and crop-calendar specific global price changes and volatility.[1]

3. Empirical framework

Given the above theoretical framework, we model the country-specific average production of crop c in country i and at time t as

$$(4) \quad Q_{cit} = \alpha_c + \boldsymbol{\beta}_c \boldsymbol{PR}_{cit} + \boldsymbol{\gamma}_c \boldsymbol{CL}_{cit} + \boldsymbol{\theta}_c \boldsymbol{POP}_{cit} + \boldsymbol{\lambda}_c \boldsymbol{T}_{cit} + \eta_{ci} + u_{cit}$$

where Q_{cit} denote production of crop $c \in$ (wheat, corn, soybeans, rice); $\boldsymbol{PR}$, $\boldsymbol{CL}$, $\boldsymbol{POP}$, and $\boldsymbol{T}$ denote vectors of variables measuring prices, climate change, population density, and time trend, respectively; η_{ci} denote country-fixed effects to control for time-invariant heterogeneity across countries, and u_{ict} is the disturbance term. While α_c is the overall constant term, $\boldsymbol{\beta}_c$, $\boldsymbol{\gamma}_c$, $\boldsymbol{\theta_c}$, $\boldsymbol{\lambda}_c$, are vectors of parameters to be estimated. For the empirical estimation we include the logarithmic values of the dependent variable and output and fertilizer prices.

The second stage involves estimating the variance component of the stochastic production function as

$$(5) \quad VQ_{cit} = \alpha'_c + \boldsymbol{B}_c \boldsymbol{W}_{cit} + \lambda'_c \boldsymbol{T}_{cit} + \eta'_{ic} + e_{cit}$$

where VQ_{cit} is production variance of each crop; $\boldsymbol{W}_{cit}$ is a vector of weather and price volatility variables that potentially affect production variance ($\boldsymbol{B}_c$ is a vector of the respective parameters to be estimated); and $e_{cit}$is an idiosyncratic error term. All remaining variables are as defined above, with the prime symbol indicating that estimated values can be different. Following Just and Pope (1978) and the theoretical model above, the logarithmic squared residuals ($ln\left[\hat{u}_{cit}{}^2\right]$) from the mean production equation (4) can be used as a measure of production variance for the respective crop. Because we specify the mean equation in logarithm, we need to take the antilogarithm of the residuals before squaring them.

The price vector $\boldsymbol{PR}$ in equation (4) includes input and output prices in levels and output price variability. The proxy for input prices is a fertilizer price index lagged by one-year and that contains world prices of natural phosphate rock, phosphate, potassium, and nitrogenous fertilizers. The output price refers to both prices of own crop at planting season and one-year lagged index of competing crop prices. The cross crop prices used for computing the index are the other three crops that are not under consideration in a given specification. We weight prices of each crop by the calorie per metric ton content of each crop to compute the index.[2] This vector also includes seasonal own crop price volatility to capture output price risk. In order to use the de-trended price series, we calculate own crop price variability—of the de-trended price series—in the 12 months preceding the start of the planting season of each crop in each country. The climate vector $\boldsymbol{CL}$ in equation (4) includes mean temperature and squared deviation of maximum and minimum temperature values during growing periods of each crop. This enables us to capture the effects of seasonal changes in average and variance of temperature on crop production. To capture extreme (low or high) temperature effects, we further include average number of growing season frost days and dummy variables to capture if growing season temperature increases above a threshold temperature level above which crop growth is severely affected.[3] Because the literature suggests that higher minimum (maximum) temperatures can lead to a reduction in rice (maize) yields (HLPE, 2012), we test for the effect of growing period minimum and maximum temperatures in rice and maize equations, respectively. For precipitation we include both planting and growing season mean precipitation along with their squared terms, anticipating an increase (a decline) in crop production with an increase in average (excessive) rainfall. In addition, we control for rainfall shock variables, which are squared deviations of current planting and growing season rainfall from the respective long run mean rainfall values and standardized by the respective historical standard deviations. These variables capture the effects of seasonal unexpected precipitation extremes such as droughts and flooding both on crop acreage and yield. In the weather vector $\boldsymbol{W}$ of equation (5), we include some of the climate variables that potentially capture short-term temperature and precipitation changes, such as seasonal temperature variation and excessive precipitation measures as well as the variables that proxy for rainfall anomaly—that is, as measured by SPAI. The vector $\boldsymbol{POP}$ contains population density and its squared term to capture any non-linear effect of population growth as a proxy both to wage and to urbanization growth. The last vector $\boldsymbol{T}$ in both the mean and variance equations contains country-specific linear and quadratic time trends to control for the effect of technological progress with the possibility of decreasing marginal return.

We estimate a log-linear model of crop production allowing for heteroscedastic variance. This is appropriate since production of the crops follow log-normal distribution. The log-linear specification of production on climate change variables is also especially important in studies (such as the present study) that attempt to estimate the average impact of climate change on global crop production. In a log specification, a given change in a climate change variable results in the same percent impact on production (Lobell *et al.*, 2011b). We use fixed effects (FE) model for our cross-country panel data, both for the mean and variance equations. First, the FE model controls for time-invariant heterogeneity across countries, such as soil quality and agroecology that would otherwise result in omitted variable bias. Employing FE model when both the linear and quadratic terms of climate change variables are included has additional merit. It uses both within- and between-country differences to estimate marginal impacts. Thus, the FE model with quadratic weather terms enables to capture adaptation mechanisms such as changing sowing date or crop variety by allowing the marginal effect to vary with climate change (Lobell *et al.*, 2011b). Because we include input, own, and competing prices, this model also allows us to capture other forms of climate change adaptations such as switching crop or applying less or more inputs including labor and fertilizer.

Because we use international prices to measure input and output prices as well as crop price volatility, these variables may be exogenous to crop production for a small country. Yet, large producers may influence international output and input prices in that year (through trade) and we therefore need to account for possible endogeneity of fertilizer prices as well as the level and volatility of crop prices. To this end, we apply the described FE panel data estimator while instrumenting all the price variables in each crop model. The literature suggests some potential instrument variables including lagged climate change and crop stock variables (Miao *et al.*, 2016; Roberts & Schlenker, 2013). We additionally use one-year lagged net-trade of each crop. Stock and net-trade for soybeans are not used because of missing data for several countries and years. These variables are theoretically valid IVs because they affect domestic crop production only through their effects on prices. Based on results of weak- and over-identification statistical tests different sets of the instrument variables are used in the different specifications.[4]

Because the mean equation is specified with heteroscedastic variance, we need to account for this in order to obtain more precise or efficient estimates. We estimate the mean production model with two stage least squares (2SLS) that are both robust to arbitrary heteroscedasticity and intra-country correlations. There are more number of IVs than endogenous variables in our model, in other words the model is overidentified. In this case, a two-step general method of moments (GMM) IV estimator – with cluster-robust standard errors – yields more efficient estimates than 2SLS estimates (Baum *et al.*, 2007). Thus, the IV-GMM estimator is our preferred method.

4. Data and descriptive statistics

We obtain production data for each of wheat, rice, maize, and soybeans for the period 1961-2013 from FAO. We include country-level crop production data for 30 major producer countries and pooled production data for the 27 countries of the European Union (EU, as of 2010) as a single entity. Because we include four countries (Russian Federation, Ukraine, Kazakhstan, and Uzbekistan) from the former Soviet Union region, the minimum number of units in our panel data becomes 27. Although the period of analysis is the same across all four crops, the total number of observations in the panel data differs because some countries do not produce a certain crop. Yet, the focus countries and regions constitute about 82% for wheat, 90% for maize, 93% for rice, and 98% for soybeans of the global average production of each crop for the entire period of 53 years. We obtain country-level data on ending stock and trade for each crop from the Foreign Agricultural Service (FAS) of the US Department of Agriculture (USDA).

International market output prices and fertilizer index are obtained from the World Bank's commodity price database. All prices are converted to real 2010 US dollar prices by deflating each price with Consumer Price Index (CPI) of the United States. We use crop calendar information to identify the major planting seasons of each country in order to construct country-specific seasonal price and price variations. We obtain crop calendar information from the Global Information and Early Warning System (GIEWS) of the FAO for emerging and developing countries, whereas the Office of the Chief Economist (OCE) of the USDA provides such information for advanced economies. Six climate variables, mean precipitation, minimum, mean and maximum temperature, average number of wet and frost days (all in a monthly resolution) are obtained from the Climatic Research Unit (CRU) Time-Series (TS) Version 3.22 of the University of East Anglia. We constructed several climate change indicators from these six variables, including crop-specific seasonal mean and squared climate variables for each country. In case of the EU we constructed regional climate variables as an average value of the top five major producers of each crop using their respective cropland share as weights. Data on country-level population density, which refers to FAO and World Bank estimates of people per square km of land area, are obtained from the World Bank. The summary statistics of total crop production of crops and of all variables for maize production estimation are reported in table 1.[5]

Table 1. Summary statistics of all crop production and production variance and of dataset for maize production analyses.

Variables	Mean	SD	Min	Max
Dependent variables				
Maize production (1000 mt)	15547.2	42629.0	0.1	353699.4
Wheat production (1000 mt)	14303.6	26639.1	0.0	150341.0
Soybean production (1000 mt)	4014.3	12810.1	0.0	91417.3
Rice production (1000 mt)	15373.7	34802.4	0.0	205936.2
Variance of maize production (log)	2.48e-04	1.59	-6.61	9.50
Variance of wheat production (log)	6.77e-04	0.91	-5.44	4.22
Variance of soybean production (log)	-0.031	2.60	-8.54	7.21
Variance of rice production (log)	-2.29e-09	1.08	-8.24	4.61
Independent variables				
Maize sowing prices ($/mt)	251.2	111.4	95.3	644.9
Competing crop price index ($/mt)[a]	388.5	134.7	216.0	862.3
Maize price volatility	0.10	0.03	0.0	0.20
Fertilizer price index	66.7	34.4	33.8	196.9
Population density (people/squared km)	112.6	163.3	1.4	1203.0
Maximum growing temperature (°C)	28.6	4.7	9.3	37.1
Mean growing temperature (°C)	23.0	4.6	4.7	30.0
Squared sowing temperature deviation (°C)	357.9	225.7	42.3	1398.8
Squared growing temperature deviation (°C)	269.0	146.7	56.3	718.2
Growing cold stress (dummy var = 1 if < 10°C)	0.2	0.4	0.0	1.0
Growing heat stress (dummy var = 1 if >32°C)	0.3	0.5	0.0	1.0

Mean number of growing frost days	0.9	2.3	0.0	14.6
Mean number of growing wet days	10.1	6.8	0.1	27.8
Mean sowing precipitation (mm)	94.4	70.3	0.7	451.9
Mean growing precipitation (mm)	110.3	80.2	1.3	368.9
Sowing rainfall shock (mm)	522.3	1963.2	0.0	28457.8
Growing rainfall shock (mm)	441.3	1166.1	0.0	13750.6
Sowing rainfall anomaly (index)	-0.00015	0.26	-2.24	2.40
Growing rainfall anomaly (index)	-0.00004	0.33	-1.26	1.46

Notes: [a]Prices of wheat, rice, and soybeans constitute the competing crop price index.

We present the time series of global mean growing-season temperature and precipitation for all four crops in Fig. 1 from 1961 to 2013. The graph (qualitatively) shows an increasing trend in growing season temperature for all crops, whereas there is no clear trend in the average global precipitation (except a slight decline for wheat). A more formal statistical test of this qualitative illustration is given in table 2, where we test if there is any difference between global mean temperature and precipitation variables for the periods 1961-1986 and 1987-2013.

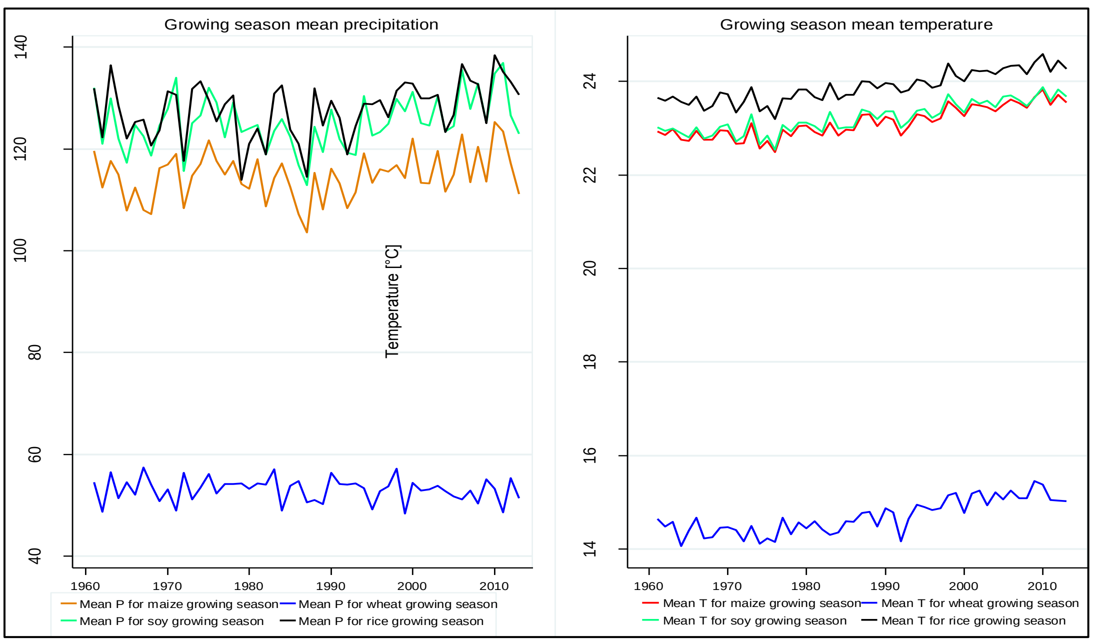

Fig. 1. Global average trend of growing season mean temperature and precipitation of the four crops

Table 2. Mean differences between aggregated mean trends of temperature and precipitation variables for the periods 1961-1986 and 1987-2013.

Variable	**Mean difference**	**t-stat**
Mean growing temperature: (M)	-0.519***	(-9.582)
Mean growing temperature: (W)	-0.560***	(-8.705)
Mean growing temperature: (S)	-0.523***	(-9.684)
Mean growing temperature: (R)	-0.517***	(-9.616)
Mean growing precipitation: (M)	-1.166	(-0.920)

Mean growing precipitation: (W)	0.823	(1.288)
Mean growing precipitation: (S)	-1.704	(-1.195)
Mean growing precipitation: (R)	-2.932*	(-1.974)
Mean sowing precipitation: (M)	-2.203	(-0.027)
Mean sowing precipitation: (W)	41.677	(0.981)
Mean sowing precipitation: (S)	-132.671	(-0.821)
Mean sowing precipitation: (R)	-80.038	(-1.047)
N=53: N1 = 26, N2 = 27		
Notes: t-statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001; H_0: (Mean of the variable during 1961-1986) - Mean of the variable during 1987-2013)=0; M = maize, W = wheat, S = soybeans, R = rice		

The test results confirm that global mean growing season temperature of all crops during 1987-2013 is statistically higher than the corresponding mean values during the earlier 26 years. The mean growing season temperature increase (which is above 0.5 for each crop) is equivalent to a rate of about 0.18°C per decade. This is close to the per decade rate (0.2°C) of global warming expected over the next three decades (IPCC, 2007). On the other hand, global mean growing and sowing season precipitation and rainfall shock of nearly all crops (except a slight increase for rice at growing season) do not exhibit any statistically significant trend. Lobell *et al*. (2011a) reach to a similar conclusion that there is no consistent shift in the distribution across countries of precipitation trends between the periods 1960–1980 and 1980–2008 (p. 618).

5. Results and discussions

The estimation results for mean crop production are presented in tables 3–6 for maize, wheat, soybeans, and rice, respectively.[6] In the first two models of each of these tables, we estimate the empirical model in equation (4) using country fixed-effects while assuming all variables (including price variables) as exogenous. As we see in tables 3–6, model **FE’** includes price index of competing crops besides own crop price. Model specifications **FEIV** and **FEIV’**, on the other hand, are country-fixed effects panel data IV estimations that account for endogeneity of all input and output price-related variables. The last column reports standardized effect sizes of the **FEIV’** estimation results to shed light on the relative importance of included explanatory variables, which are measured in various ways, on global supply response for each crop. The estimation results are qualitatively consistent across the four alternative models with a few exceptions.

We test for the underlying assumptions for the validity of our IV estimation methods. The test for overidentification using the Hansen *J* statistic shows that we cannot reject the hypothesis that the IVs are valid at any reasonable significance level. We consider several tests, including Kleibergen-Paap rk statistics of the first-stage regression, to check if the IVs are strongly correlated with the endogenous variables. The joint *F*-test strongly rejects the null hypothesis that our IVs do not jointly statistically significantly explain the included endogenous variables at any reasonable level of significance. The test results also indicate that the excluded IVs pass the

Kleibergen-Paap (2006) *rk* tests for underidentification and weak instrument. The results from the country fixed-effects IV model can therefore be reliable. The following discussions rely on the results obtained from the panel data IV estimator that also includes cross-price index (that is, **FEIV'**) for each crop production estimation. Similarly, the estimation results for the stochastic component of crop production in table 5 use the predicted residuals from this model to construct the respective dependent variables.

Table 3. Determinants of global maize production (dependent variable: log (mean production))

	FE	**FE'**	**FEIV**	**FEIV'**	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.170***	0.118***	0.431***	0.802***	0.250***
	(0.019)	(0.016)	(0.069)	(0.086)	
Cross-price index		0.156***		-0.540***	-0.126***
		(0.032)		(0.163)	
Own price volatility	-0.469**	-0.673***	-2.184***	-2.190***	-0.046***
	(0.199)	(0.213)	(0.496)	(0.622)	
Fertilizer price index	0.047**	-0.002	-0.208***	-0.126*	-0.035*
	(0.020)	(0.019)	(0.062)	(0.067)	
Population density	0.010**	0.001**	0.013***	0.016***	0.648***
	(0.005)	(0.005)	(0.003)	(0.004)	
Population density squared	-1.23e-05	-1.23e-05	-1.95e-05***	-2.46e-05***	-0.274***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.078	0.075	0.093*	0.117**	0.251**
	(0.093)	(0.092)	(0.055)	(0.055)	
Max. growing tmp.	-0.099	-0.097	-0.116***	-0.140***	-0.295***
	(0.080)	(0.078)	(0.037)	(0.040)	
Squared sowing tmp. deviation	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.070***
	(0.0001)	(0.0001)	(0.000)	(0.000)	
Squared growing tmp. deviation	-0.001*	-0.001*	-0.001***	-0.001**	-0.051**
	(0.0005)	(0.0005)	(0.0001)	(0.0003)	
Mean growing rainfall	0.003***	0.002***	0.002***	0.001***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	
Sowing rainfall anomaly	0.025	0.038	0.083*	0.047	0.003
	(0.068)	(0.064)	(0.048)	(0.073)	
Growing rainfall anomaly	-0.110***	-0.126***	-0.200***	-0.179***	-0.010***
	(0.039)	(0.040)	(0.031)	(0.050)	
Linea trend	0.039***	0.042***	0.043***	0.038***	0.402***
	(0.003)	(0.004)	(0.001)	(0.002)	
Quadratic trend	-2.4e-04***	-2.7e-04***	-1.6e-04***	-1.1e-04***	-0.063***
	(0.0001)	(0.0001)	(0.000)	(0.000)	
Observations	1488	1488	1330	1330	1330
Underidentification test (Kleibergen-Paap rk Wald statistic)			427.85	280.82	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			36.801	24.154	

Overidentification test (*p*-value of Hansen J statistic)			0.526	0.383

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize, planting and growing season rainfall anomalies, and growing season mean temperature. All IVs are lagged once.

Price variables

Controlling for climate change and applying instrument variables for possible endogeneity of prices, the results indicate that agricultural production is indeed responsive to both own and competing crop prices. These supply elasticities are mostly larger than previous aggregate estimates (Haile *et al.*, 2016; Roberts & Schlenker, 2009; Subervie, 2008), which can be explained by potential omission of climatic variables in previous studies. Cross-price production responses are stronger than own price responses in the case of wheat and rice. While own crop price volatility, on the other hand, has negligible effect on soybean and rice production, it has detrimental impact on production of maize and wheat. In fact, the positive response of wheat production to a one standard deviation change in own prices could be offset by an equivalent change in wheat price fluctuations. Input price—as proxied by fertilizer index—negatively affects production of maize and soybeans but not that of wheat and rice.

Table 4. Determinants of global wheat production (dependent variable: log (mean production))

	FE	**FE'**	**FEIV**	**FEIV'**	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.042	0.058**	0.206*	0.190**	0.077**
	(0.030)	(0.029)	(0.110)	(0.085)	
Cross-price index		-0.090		-0.809***	-0.276***
		(0.062)		(0.280)	
Own price volatility	-0.377***	-0.338***	0.288	-2.125***	-0.088***
	(0.094)	(0.092)	(0.435)	(0.586)	
Fertilizer price index	0.046	0.087**	-0.480***	0.281	0.115
	(0.029)	(0.037)	(0.111)	(0.247)	
Population density	0.008***	0.008***	0.008***	0.010***	0.947***
	(0.002)	(0.002)	(0.003)	(0.002)	
Population density squared	-4.65e-06***	-4.63e-06***	-6.88e-06	-1.09e-05***	-0.367***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.030	0.025	-0.011	-0.034	-0.231
	(0.034)	(0.034)	(0.023)	(0.032)	
Mean growing tmp. squared	-0.004**	-0.003**	-0.001	-0.001	-0.201
	(0.002)	(0.002)	(0.001)	(0.001)	
Squared sowing tmp. deviation	-0.0002*	-0.0002*	0.0002*	-0.00004	-0.006
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Squared growing tmp. deviation	-0.0001	-0.0001	-0.0002***	-0.0002***	-0.069***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	
Mean growing rainfall	0.001	0.001	0.002	-0.001	-0.011
	(0.002)	(0.002)	(0.001)	(0.001)	
Sowing rainfall anomaly	-0.115	-0.128	-0.0415	-0.197***	-0.008***
	(0.075)	(0.078)	(0.066)	(0.073)	
Growing rainfall anomaly	-0.209**	-0.212**	-0.297***	-0.269***	-0.013***
	(0.094)	(0.091)	(0.051)	(0.040)	
Linear trend	0.044***	0.0422**	0.021***	0.010	0.143

	(0.006)	(0.007)	(0.004)	(0.006)	
Quadratic trend	-4.88e-04***	-4.77e-04***	3.71e-05		
	(0.0001)	(0.0001)	(0.0001)		
Observations	1176	1176	1072	1072	1072
Underidentification test (Kleibergen-Paap rk Wald statistic)			79.680	49.820	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			9.332	15.190	
Overidentification test (*p*-value of Hansen J statistic)			0.339	0.211	

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize and wheat, planting and growing season rainfall anomalies, and growing season mean temperature (all IVs lagged once).

Climate and weather variables

Average growing period temperature does not seem to negatively influence production of crops. In fact, production of maize and rice actually increases with increasing mean temperature during the growing season. It is instead rising temperature values at the two extremes—minimum temperature in the case of rice and maximum temperature in the case of maize—that are detrimental for crop production. While rising (growing period) temperature does not have statistically significant effect on wheat production, its effect on soybean production turns to negative beyond a temperature value of 32.5 degrees. Besides these temperature extremes, variations in both sowing and growing period temperature have negative effects on crop production. McCarl *et al*. (2008) have found similar results on the yield effect of temperature variation. Precipitation also plays a key role in production of each crop, in particular for rice production. Higher mean rainfall (both at planting and growing seasons) in general improves agricultural production, whereas rainfall extremes—as measured by SPAI—negatively influences production of each crop. As expected for rice, in particular, the number of wet growing days and sowing season rainfall are positively associated with higher crop production. Unexpected seasonal precipitation extremes are however harmful for rice production as they are for the other crops.

Table 5. Determinants of global soybean production (dependent variable: log (mean production))

	FE	**FE’**	**FEIV**	**FEIV’**	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.185*	0.170**	0.877***	0.694***	0.243***
	(0.099)	(0.079)	(0.176)	(0.187)	
Cross-price index		0.072		0.061	0.017
		(0.131)		(0.113)	
Own price volatility	-0.347*	-0.377	-1.291**	0.582	0.021
	(0.205)	(0.247)	(0.562)	(0.971)	
Fertilizer price index	-0.052	-0.084	-0.492***	-0.605***	-0.201***
	(0.056)	(0.065)	(0.046)	(0.092)	
Population density	-0.0232***	-0.0232***	-0.0229***	-0.0244***	-1.146***
	(0.007)	(0.007)	(0.001)	(0.001)	
Population density squared	4.33e-05***	4.33e-05***	4.19e-05***	4.67e-05***	0.753***

	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	-0.821	-0.825	-0.151	0.228	0.574
	(0.753)	(0.752)	(0.245)	(0.310)	
Mean growing tmp. squared	0.018	0.019	0.001	-0.007***	-0.751***
	(0.018)	(0.018)	(0.006)	(0.001)	
Squared sowing tmp. deviation	0.0002	0.0002	-0.0005**	-0.0005**	-0.040**
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	
Squared growing tmp. deviation	0.001***	0.001***	0.001**	0.001**	0.057**
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	
Mean growing rainfall	0.005*	0.005*	0.003	0.003	0.135
	(0.003)	(0.003)	(0.002)	(0.002)	
Sowing rainfall anomaly	-0.342	-0.329	-0.345**	-0.384**	-0.018**
	(0.226)	(0.207)	(0.151)	(0.153)	
Growing rainfall anomaly	0.150	0.151	0.133	0.0509	0.002
	(0.211)	(0.210)	(0.112)	(0.128)	
Linear trend	0.058***	0.059***	0.064***	0.054***	0.666***
	(0.008)	(0.008)	(0.007)	(0.008)	
Quadratic trend	-0.0001	-0.0001	0.0001	0.0002**	0.147**
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	
Observations	1363	1363	1259	1259	1259
Underidentification test (Kleibergen-Paap rk Wald statistic)			741.72	2811.30	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			69.96	265.16	
Overidentification test (*p*-value of Hansen J statistic)			0.188	0.3354	

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize, planting and growing season rainfall anomalies, and growing season mean temperature (all IVs lagged once).

Population density

The results on population density are quite interesting, with both the mean and quadratic terms being statistically significant in all cases. The effect of more (or cheaper) labor is statistically significant and positive on the production of wheat, maize, and rice. However, the effect of higher population density on production of these crops—through its effect on expansion or urbanization and land degradation— starts gaining more importance after a certain threshold. In particular, the effect of population density on crop production is non-linear, switching from positive to negative just above 650 people/km^2 for maize and rice and at slightly higher value for wheat (above 900). To put this into perspective, population density in countries such as Mauritius is just below the former threshold, whereas Bangladesh (1222) and Malta (1336) are already weigh above these turning points. In contrast to the effects on productions of wheat, maize, and rice, the effect of population density on soybean production is negative until a population density of just above 500 people/km^2—which is approximately the current population density of the Netherlands. Soybean production is largely mechanized in several producer countries, and hence soybean production is capital intensive but labor saving. Everything else remaining unchanged, cheaper labor may induce switching labor input to production of other (labor-intensive) crops (such as horticulture) from soybean production.

Table 6. Determinants of global rice production (dependent variable: log (mean production))

	FE	**FE'**	**FEIV**	**FEIV'**	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.013	0.034	0.620***	1.011***	0.423***
	(0.035)	(0.043)	(0.200)	(0.384)	
Cross-price index		-0.084		-2.064***	-0.496***
		(0.063)		(0.683)	
Own price volatility	0.309***	0.269***	-0.084	-2.915	-0.109
	(0.095)	(0.081)	(1.027)	(2.117)	(2.117)
Fertilizer price index	-0.059	-0.030	-0.614***	0.385	0.123
	(0.050)	(0.038)	(0.154)	(0.294)	
Population density	0.002	0.002	0.009***	0.008***	0.663***
	(0.001)	(0.001)	(0.002)	(0.002)	
Population density squared	-7.93e-07	-7.68e-07	-1.14e-05***	-1.16e-05***	-0.396***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.007	0.019	0.213***	0.270***	0.981***
	(0.074)	(0.077)	(0.069)	(0.100)	
Min growing. tmp.	-0.109	-0.123	-0.271***	-0.397***	-1.580***
	(0.097)	(0.105)	(0.060)	(0.135)	
Squared sowing tmp. deviation	0.0001	0.0001	-0.0004***	0.0004	0.136
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
Squared growing tmp. deviation	-0.0004	-0.0004	-0.0001	0.00003	0.004
	(0.0003)	(0.0003)	(0.0003)	(0.0006)	
Mean growing rainfall	0.0004	0.0004	0.001	0.004***	0.162***
	(0.0004)	(0.0004)	(0.001)	(0.001)	
Sowing rainfall anomaly	-0.056*	-0.055*	0.031	-0.338***	-0.018***
	(0.034)	(0.033)	(0.086)	(0.119)	
Growing rainfall anomaly	-0.039*	-0.037*	-0.202	-0.068	-0.004
	(0.024)	(0.022)	(0.137)	(0.352)	
Linear trend	0.021***	0.021***	0.029***	0.015*	0.185*
	(0.004)	(0.004)	(0.007)	(0.009)	
Observations	1405	1405	1247	1247	1247
Underidentification test (Kleibergen-Paap rk Wald statistic)			192.210	18.890	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			20.236	9.890	
Overidentification test (*p*-value of Hansen J statistic)			0.312	0.442	

Notes: Asterisks *, **, and *** represent the 10%, 5%, and 1% levels of significance. Excluded instruments: Ending stocks maize, wheat and rice, stock variations of wheat; net import of wheat and rice, planting and growing season rainfall anomalies, and growing season mean temperature (all IVs lagged once).

Production variance

Table 7 reports results on the stochastic component of crop production—fluctuations in production. Not only do higher prices (in levels) provide incentive for farmers to producer more—that is, increase yield or acreage—they also increase the predictability of crop production. This is possible as higher crop prices induce agricultural investments in such as irrigation and disease-resistant seed varieties that in turn reduce production variance. Not surprisingly, crop price volatility has the opposite effect on production variance. We also find that higher fertilizer price has a positive effect on production variability, which is contrary to some of the findings in Just and Pope (1979). The effects on production variance of temperature and precipitation extremes are mostly positive but statistically significant for soybean and rice production (temperature) and for wheat production (precipitation). Production variability has a decreasing linear trend, thanks to more and improved early (weather and other risk) warning systems as well as other technological progress that reduces potential fluctuations in agricultural production.

Table 7. Determinants of variance of global crop production (dependent variable: log (production variance))

	Maize	Wheat	Soybeans	Rice
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)
Own crop price	-1.160***	0.197**	-1.317***	-0.859***
	(0.053)	(0.075)	(0.095)	(0.056)
Own price volatility	4.875***	0.978*	1.113*	-0.009
	(0.565)	(0.553)	(0.642)	(0.385)
Fertilizer price index	0.811***	0.114**	0.897***	0.856***
	(0.046)	(0.042)	(0.092)	(0.058)
Growing tmp. squared	0.002	0.001	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Growing tmp. variation	0.001**	0.0002	-0.004***	-0.0002
	(0.001)	(0.0003)	(0.001)	(0.001)
Growing rainfall shock	0.095	0.141**	0.0002	0.057
	(0.062)	(0.057)	(0.138)	(0.343)
Linear trend	-0.090***	-0.033***	-0.085***	-0.060***
	(0.005)	(0.006)	(0.007)	(0.004)
Intercept	-9.896***	-13.720***	-3.136***	-11.380***
	(1.114)	(1.853)	(0.892)	(1.125)
N	1330	1072	1259	1247

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance.

6. Conclusions

There is little doubt that the earth's climate is changing. Although agriculture is one of the drivers of this change, it also is one that is severely affected by the change. Climate-resilient agriculture is vital for achieving enhanced food security—which is a crucial component of the sustainable development goals (SDGs). This paper provides answers to questions that are prerequisite for policies that address agriculture and climate change. This paper not only evaluates the extent to which climate change affects global production of major staple crops, it also identifies specific climate and weather patterns that most harmfully affect crop production.

This study analyses the determinants of global average crop production for maize, wheat, rice, and soybeans over the period 1961–2013. We develop the reduced form empirical framework of this paper with the premise that average country crop production is influenced not only by climate factors but also by changes in economic variables. These effects include changes in farmers' crop management practices and land allocation decisions in response to input prices and expected output prices and price volatility. Additionally, as compared to previous studies, this study analyzes the impact on global crop production variance of price and weather extremes. We use IV panel data approach to control for potential endogeneity of input and output prices. It is worth to note here that our estimates are global average effects, that is, country variations (especially of temperature variables), are only subtly captured with the quadratic terms. It is well documented in the literature that the effect of climate change on production has large regional variations (Kang & Banga, 2013; Rosenzweig *et al.*, 2001). Our empirical results, however, yield estimates that can serve as parameters for projections that look for potential impact of climate change on food security with reasonable level of trade among countries.

We find stronger—than previous literature that do not control for climate change and price volatility—and statistically significant supply elasticities for all four crops with respect to own crop prices. These short-run supply elasticities range between 0.20 for wheat and to as high as unity for rice. With the exception of soybeans, we also find statistically significant and negative supply elasticities with respect to an index of competing crop prices. Our results furthermore underscore the relevance of output price volatility for the supply of the key global agricultural staple crops—especially on production of wheat and maize. Comparing the standardized effect sizes of own price and price volatility estimates for wheat and maize production, one can see that the effects are on par for wheat while the price volatility effect is only a fifth of the own price effect on maize production.

In agreement with previous studies, we also find that climate change has significant adverse effects on production of the world's key staple crops, through both yield and acreage effects. Our findings indicate that higher average temperature during growing seasons of these crops is not all bad—having a positive and statistical significant effect on productions of maize and rice. Instead, increasing temperature values at the two extremes—higher minimum temperature for rice and higher maximum temperature for maize—are detrimental to crop production. Similarly, higher average temperature becomes problematic for wheat and soybeans after a certain critical level, albeit being statistically insignificant for the former. More importantly, this study finds that weather extremes—both in terms of temperature and precipitation shocks— during the growing months have significant adverse impacts on the production of the abovementioned food crops. This paper also finds negative impacts of price and weather extremes on the stochastic component of crop production, that is, on the variance of global crop production. In other words, price and weather extremes do not only adversely affect average global food production, they also positively contribute to the year-to-year fluctuations of food availability.

Last but not list, we find that the linear time trend is statistically significant and positive in both the average production and the production variance estimates of all crops. This result is compelling as it shows that improvements in technology and agronomic practices have the capacity to both boost global food production as well as reduce annual fluctuations in food availability. Thus, combating climate change using both mitigation and adaptation technologies is crucial for global production and hence food security.

References

Baum, C. F., Schaffer, M. E., & Stillman, S. (2007). Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *Stata Journal, 7*(4), 465-506.

Binswanger, H. P., & Rosenzweig, M. R. (1986). Behavioural and material determinants of production relations in agriculture. *The Journal of Development Studies, 22*(3), 503-539.

CCSP. (2008). The effects of climate change on agriculture, land resources, water resources, and biodiversity in the United States. A Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research (pp. 362). Washington, DC, USA: U.S. Department of Agriculture.

FAO. (1996). Rome Declaration on World Food Security and World Food Summit Plan of Action (pp. 13–17). World Food Summit: Rome, Italy.

FAO. (2012). Agricultural Statistics, FAOSTAT. FAO (Food and Agricultural Organization of the United Nations). Rome, Italy.

FAO. (2016). Nutritive Factors. Economic and Social Development Department, FAO, Rome.

FAO, IFAD, & WFP. (2015). *The State of Food Insecurity in the World 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress*. Rome, Italy: Food and Agriculture Organization of the United Nations.

Haile, M. G., Kalkuhl, M., & von Braun, J. (2016). Worldwide Acreage and Yield Response to International Price Change and Volatility: A Dynamic Panel Data Analysis for Wheat, Rice, Corn, and Soybeans. *American Journal of Agricultural Economics, 98*(1), 172-190.

HLPE. (2012). Food security and climate change *A report by the High Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security*. Rome, Italy: FAO.

IPCC. (2001). *Contribution of Working Group I, II, and III to the Third Assessment Rreport of the Intergovernmental Panel on Climate Change*. Geneva, Swizerland: IPCC.

IPCC. (2007). *Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland, IPCC.

Jones, A. D., & Yosef, S. (2015). The implications of a changing climate on global nutrition security. In D. E. Sahn (Ed.), *The fight against hunger and malnutrition* (pp. 432-466). Oxford: Oxford Univeristy Press.

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of econometrics, 7*(1), 67-86.

Just, R. E., & Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, 276-284.

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

Kang, M. S., & Banga, S. S. (2013). Global agriculture and climate change. *Journal of Crop Improvement, 27*(6), 667-692.

Lloyd, S. J., Sari Kovats, R., & Chalabi, Z. (2011). Climate change, crop yields, and undernutrition: development of a model to quantify the impact of climate scenarios on child undernutrition. *Environmental Health Perspectives, 119*(12), 1817.

Lobell, D. B., & Burke, M. B. (2008). Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environmental Research Letters, 3*(3), 034007.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011a). Climate trends and global crop production since 1980. *Science, 333*(6042), 616-620.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011b). Supporting online material for: Climate trends and global crop production since 1980. *Science, 333*, 616-620.

McCarl, B. A., Villavicencio, X., & Wu, X. (2008). Climate change and future analysis: is stationarity dying? *American Journal of Agricultural Economics, 90*(5), 1241-1247.

Miao, R., Khanna, M., & Huang, H. (2016). Responsiveness of Crop Yield and Acreage to Prices and Climate. *American Journal of Agricultural Economics, 98*(1), 191-211. doi: 10.1093/ajae/aav025

Miranda, M. J., & Helmberger, P. G. (1988). The effects of commodity price stabilization programs. *The American Economic Review, 78*(1), 46-58.

Moschini, G., & Hennessy, D. A. (2001). Uncertainty, risk aversion, and risk management for agricultural producers. *Handbook of Agricultural Economics, 1*(A), 88-153.

OECD. (2008). Rising Food Prices: Causes and Consequences. Organisation for Economic Co-operation and Development (OECD). Paris, France. .

Parry, M., Evans, A., Rosegrant, M. W., & Wheeler, T. (2009). *Climate change and hunger: responding to the challenge*. Rome, Italy: World Food Programme.

Roberts, M. J., & Schlenker, W. (2009). World supply and demand of food commodity calories. *American Journal of Agricultural Economics, 91*(5), 1235-1242.

Roberts, M. J., & Schlenker, W. (2013). Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate. *American Economic Review, 103*(6), 2265-2295.

Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P. R., & Chivian, E. (2001). Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global change & human health, 2*(2), 90-104.

Sacks, W. J., Deryng, D., Foley, J. A., & Ramankutty, N. (2010). Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography, 19*(5), 607-620.

Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. *The American Economic Review*, 65-73.

Shaw, L. H. (1964). The effect of weather on agricultural output: A look at methodology. *Journal of Farm Economics*, 218-230.

Sivakumar, M., Das, H., & Brunini, O. (2005). Impacts of present and future climate variability and change on agriculture and forestry in the arid and semi-arid tropics. *Climatic Change, 70*(1-2), 31-72.

Subervie, J. (2008). The variable response of agricultural supply to world price instability in developing countries. *Journal of Agricultural Economics, 59*(1), 72-92.

Thornton, P., & Cramer, L. (2012). *Impacts of climate change on the agricultural and aquatic systems and natural resources within the CGIAR's mandate. CCAFS Working Paper 23*. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security.

von Braun, J., & Tadesse, G. (2012). Food Security, Commodity Price Volatility and the Poor. In Masahiko Aoki, Timur Kuran & G. Roland (Eds.), *Institutions and Comparative Economic Development*: Palgrave Macmillan Publ. IAE Conference Volume 2012.

Endnotes

[1] Please refer to Haile *et al.* (2016)for further discussion of this concept.

[2] We apply calories per metric ton of 3340 for wheat, 3560 for maize, 3350 for soybeans and 3600 for rice (FAO, 2016). Estimations where equal weights were used also yield similar results.

[3] These threshold values are in degree Celsius 30 for wheat and 32 for each of the other three crops (Thornton & Cramer, 2012).

[4] The specific IVs included in each crop production equation and statistical test results are indicated in the tables that report respective results.

[5] Summary statistics of all remaining crop production datasets are available upon request.

[6] To keep tables 3–6 in a reasonable size, we only present estimations of key variables in these tables. A complete presentation of estimations can be available upon request.