The Effect of Climate Change, CO₂ Fertilization, and Crop Production Technology on Crop Yields and Its Economic Implications on Market Outcomes and Welfare Distribution

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Introduction

Recent studies including those by the Intergovernmental Panel on Climate Change (IPCC) (2001, 2007) indicate that greenhouse gas (GHG) emissions and resultant atmospheric concentrations have lead to changes in the world's climate conditions including temperature and precipitation. The implications of climate change and atmospheric GHG concentrations for crop yields, and economic welfare has stimulated many studies.

A wide variety of findings have arisen regarding the effect of climate change on crop yields. Many studies find that climate change alters mean crop yields (e.g. Reilly et al. 2002; Schlenker and Roberts 2009; Huang and Khanna 2010), while Greenstone and Deschenes (2007) find a statistically insignificant relationship between climate change and crop yields. A few studies have addressed the contribution of climate change to yield variability (Chen, McCarl, and Schimmelpfennig, 2004; Isik and Devadoss, 2006; McCarl, Villavicencio, and Wu, 2008).

For the aspect of crop production technology, most studies employing econometric models with historical data of crop yield reveal that crop production technology generally helps improve future crop yield (see for example, Chen, McCarl, and Schimmelpfennig, 2004; McCarl, Villavicencio, and Wu, 2008; Huang and Khanna 2010). They usually utilize time trend as a proxy for crop production technology. However this may generate incorrect estimates of the real effect of technological change on crop yield since atmospheric CO_2, a potential key driver of potential yield impacts[1], is typically omitted. Furthermore unraveling time and CO_2 effects is difficult because of the almost perfect collinearity between time and atmospheric CO_2 plus the small variation of atmospheric CO_2 concentration across locations. Therefore, the time trend variable may implicitly capture both the effect of CO_2 fertilization and technological progress. This paper is the first study that attempts to resolve this difficulty by merging historical data with

the recent unique dataset of the response of crop yield to elevated CO_2 obtained from the free air carbon dioxide enrichment (FACE) experiments[2].

Moreover, a few papers play attention to the impact of the crop yield's change induced by the climate change on the market outcomes and welfare implications of economic units. Greenstone and Deschenes (2007) reveal that climate change will increase annual profits of US agriculture by $1.3 billion in 2002 dollars or 4 percent in the long run (2070-2099) with virtually no effect on yields among the most important crops (i.e., corn for grain and soybeans).

The extent to which mean and variation of crop yields change in the future in response to change in climate alters producer risk analysis and the need for risk sharing instruments. Moreover, the estimates of the climate effect on crop technological change can provide guideline for future agricultural research planning and it can be used to evaluate the returns to agricultural research. Also, the accuracy of projections of crop yield affects future food security and the potential for agriculture to contribute food and fiber, energy feedstocks and potential climate change mitigation contributions. All of these depend critically on both climate change influences and the magnitude of the CO_2 fertilization effect. Finally, welfare implications of economic units across US regions depend on the change in crop yield both statically and dynamically and the above mentioned drivers are important for policy makers in designing the farm programs, disaster relief legislation, research investments and climate related adaptation/mitigations policy/investment.

This paper reports on a simultaneous analysis of the impact of climate variables, crop production technology, and atmospheric CO2 on mean yield and yield's standard deviation of five major crops including corn, sorghum, soybeans, winter wheat and cotton, in the US merging state-specific, historical data for 1950-2009 with the dataset from the FACE experiments.

In addition the analysis investigates the implication of climate change on crop yield and its variability by using our estimated coefficients together with future climate change projections by standard global circulation models (GCMs) as reported in IPCC (2007). Finally, we explore the market outcomes and welfare implications of economic units given climate-induced shifts in yields across US regions.

Literature Review

Concerns about the potentially harmful impacts of climate change on agricultural production, especially crop yields, have led to several empirical studies with mixed findings. A majority of these studies have focused on the effect of temperature and precipitation on crop yields (Lobell and Asner 2003; Chen, McCarl, and Schimmelpfennig 2004; Greenstone and Deschenes 2007; McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009; Huang and Khanna 2010).

Regarding to the effect of temperature, Greenstone and Deschenes (2007) develop an approach adopt from Hedonic model and find that yields of corn and soybeans are negatively correlated to growing degree days. Schlenker and Roberts (2009) find similar results and find a non-linear effect of temperature on yields of corn, soybeans, and cotton. A similar result is illustrated by Huang and Khanna (2010). Using growing season temperature and employing the Just and Pope (1978, 1979) stochastic production function, Chen, McCarl, and Schimmelpfennig (2004) examine state-level panel data and find that yields of corn, cotton, sorghum, and winter wheat are adversely affected by growing season temperature. Unlike other studies, McCarl, Villavicencio, and Wu (2008) incorporating the interaction term of temperature and US regions in their model to capture the heterogeneity of temperature across US regions, they reveal that the effect of temperature on crop yields depends on location.

Regarding to the effect of precipitation, using yearly precipitation, Chen, McCarl, and Schimmelpfennig (2004) find that precipitation enhances yields of corn, cotton, soybeans, winter wheat, and sorghum, while it has a negative impact on wheat as also found in McCarl, Villavicencio, and Wu (2008) and Isik and Devadoss (2006). An inverted-U shape relationship between corn and soybean yield and precipitation is found in Schlenker and Roberts (2009). Similar results for corn, soybeans, and wheat are found in Huang and Khanna (2010), who employ monthly precipitation.

While a majority of climate impact studies relies on changes in means of climate variables, a few studies consider climate variability and extreme events. Using standard deviation as a measure of variation in temperature, McCarl, Villavicencio, and Wu (2008) find that increased variation has a negative impact on yields of all crops. Similar results were found for corn and soybeans by Huang and Khanna (2010). Variability measures reflecting precipitation intensity and Drought Severity were employed in McCarl, Villavicencio, and Wu (2008). They find that the increase in precipitation intensity decreases all crop yields, while an increase in their drought measure decreases cotton yield, but increases yields of corn, soybeans, sorghum, and winter wheat.

Our study will build of these incorporating variables of yearly precipitation intensity, number of days that maximum temperature exceeds 32 degree Celsius, and the drought index. Moreover, we also control for the effect of the El Niño-Southern Oscillation[3] (ENSO). Furthermore we construct an alternative index of yearly precipitation intensity based on the IPCC (2007) in particular the percent of annual total precipitation due to events exceeding the 1961-1990 95th percentiles.

For a temperature extreme measure unlike McCarl, Villavicencio, and Wu (2008) and Huang and Khanna (2010) who used the standard deviation of temperature, we utilize the number of days

that maximum temperature exceeds 32°C based on Mearns et al., (1984) depicting that days with abnormally high temperatures can harm crop growth and yield, which may not be captured by the mean and standard deviation of temperature. We use 32°C as a threshold based on evidence in Thompson (1975); Mearns et al. (1984); and Schlenker and Roberts (2009).

Several studies estimate the relationship between climate and yield variability. McCarl, Villavicencio, and Wu (2008) find that increase in yearly total precipitation reduces the variability of sorghum and soybean yields, while Chen, McCarl, and Schimmelpfennig (2004) find opposite result. Chen, McCarl, and Schimmelpfennig (2004) also conclude that temperature increases the yield variation for corn, soybeans, and winter wheat, while it reduces the yield variation for cotton and sorghum. McCarl, Villavicencio, and Wu (2008) also find that there is no statistically significant relationship between the drought index and crop yields. Precipitation intensity increases the variability of sorghum yield.

It is worth noting that empirical studies show mixed results regarding the effect of crop acreage on yield. Kaufmann and Snell (1997) and Huang and Khanna (2010) find that an increase in acreage decreases corn and wheat yield, respectively, while Chen, McCarl, and Schimmelpfennig (2004) and McCarl, Villavicencio, and Wu (2008) find that an increase in crop acreage increases corn, soybean, wheat, and sorghum yield but decreases cotton yield. Schlenker, Hanemann, and Fisher (2005) find that irrigated and dry land counties cannot be pooled in a single regression equation. The evidence suggests that the economic effects of climate change on agriculture need to be assessed differently in dry land and irrigated areas.

The periods of growing season in each crop are often assumed to be fixed by a majority of crop yield studies. For example, McCarl, Villavicencio, and Wu (2008), and Chen, McCarl, and Schimmelpfennig (2004) define the growing season period of corn, soybeans, sorghum, and

cotton between April to November and winter wheat between November to March in all states. Greenstone and Deschenes (2007) use the period of April 1-September 30 to quantify growing season degree-days of corn and soybeans. Unlike these studies, this study uses a state specific growing season definition for each crop based on USDA crop progress data. The data show that growing seasons for a crop vary across states.

As a result of technical change in crop production technology such as the development of new varieties and management practices, crop yields increase over time. Such technical change generally improves future crop yields, offsetting possible negative impacts of climate change (see for example, McCarl, Villavicencio, and Wu, 2008; Huang and Khanna 2010). These studies usually utilize a linear or quadratic time trend as a proxy for developments in crop production technology. This method may lead to incorrect estimates of the real effect of crop yields if other factors are correlated with time including CO_2 as previously stated in the introduction section.

This research attempts to remove the CO_2 effect from the technical change estimation by introducing a dataset on the response of crop yield to elevated CO_2 obtained from the FACE experiments (Long et al. 2006). Merging in the FACE dataset increases the variation of CO_2 concentration in the data and reduces the correlation between time and CO_2 concentration, which will allow estimation of these effects. Therefore, it allows us to differentiate the real effect of time – a proxy for technical change and the atmospheric CO_2 concentration as they influence crop yields.

Early studies related to the response of crop yield to atmospheric carbon dioxide (CO_2) were reviewed by IPCC (2007) (see for example, Parry et al. 2004). Their amassed evidence suggests that the crop yield reduction induced by climate change will be offset by the direct fertilization effect of rising CO_2 concentrations. However, almost all of information about crop responses to

elevated CO_2 from early studies is obtained from studies in controlled-environment chambers where released CO_2 may be retained and easily controlled, which has been argued to be an upwardly biased measure of the response of crop yields to elevated CO_2 (Long et al. 2006). Recent studies (see for example, Ottman et al. 2001; Ainsworth and Long 2005; Leakey 2009) are of the FACE type. Long et al. (2006) show that for each crop, the stimulation of yield observed in FACE experiments was well below (about half) that predicted from chambers. They reveal that, across FACE studies, that yields of C-3 crops soybean and wheat increase by about 14 and 13 percent, respectively at 550 part per million of CO_2 relative to ambient CO_2, while they find no significant relationship between yields of C-4 crops and CO_2.

Moreover, Leakey (2009) finds that unlike C-3 crops, for which there is a direct enhancement of photosynthesis by elevated CO_2, C-4 crops only benefit from elevated CO_2 in times and places of drought stress. Kimball (2006) analyzed data from the FACE studies and found an increase in yields of cotton, wheat, and sorghum at elevated CO_2 relative to ambient CO_2. Under ample water, the values range from 21-81 percent for cotton, 8-17 percent for wheat, and -11-1 percent for sorghum, while under lower water, values range from 50-51 percent for cotton, 5-12 percent for wheat, and 17-34 percent for sorghum. Amthor (2001) reviews fifty studies from both FACE and chamber studies and concludes that elevated CO_2 stimulates yield of water-stressed wheat, but usually does not fully compensate for water shortage.

Studies project the change in future crop yield induced by climate change using climate projections from global circulation models (GCMs). Huang and Khanna (2010) find that with 6°C increases in temperature, yields of corn, soybeans, and wheat are projected to decrease 45, 42, and 26 percent, respectively, in 2100. Using climate projections from Hadley GCM, in the medium term (2020-2049), Schlenker and Roberts (2009) find that yields are projected to

decrease about 20-30% for corn, 15-25% for soybeans and 20-25% for cotton. Using Hadley and Canadian GCMs, McCarl, Villavicencio, and Wu (2008) find that generally in 2030 yields of all crops except sorghum are increased regarding to the projected standard deviation of temperature. Similar to above mentioned studies, our study will project the change in future crop. This study will employs four of the most recent GCMs to reflect the uncertainty inherent in such projections.

Finally, climate change studies related to crop yield play less attention to the market outcome and welfare distribution issues. Greenstone and Deschenes (2007) estimate that climate change will increase annual profits of US agriculture by $1.3 billion in 2002 dollars or 4 percent in the long run (2070-2099). Our paper also quantifies the impact of the change in crop yields on the market outcomes and welfare aspects using the agricultural sector model (ASM), a price endogenous, spatial equilibrium mathematical programming of the agricultural sector in the US (Adams et al. 2008) as explained in the next section. ASM allows a farmer who is producing a given crop to switch crops in response to short-run variation in weather, which is the limitation in Deschenes and Greenstone (2007).

Model Specification and Methodology

Just and Pope Stochastic Production Function

In order to determine the effects of climate change, crop production technology, and CO_2 fertilization on both the average and variability of crop yields, a stochastic production function approach of the type suggested by Just and Pope (1978, 1979) is developed, which is similar to Chen, McCarl, and Schimmelpfennig (2004), Isik and Devadoss (2006), and McCarl, Villavicencio, and Wu (2008).

The basic concept of the Just and Pope stochastic production function estimates the production function as a term that gives the relationship between independent variables and the mean output level and a second that gives the relationship between independent variables and the variability of output. The Just-Pope production function can be estimated from panel data relating annual yield to exogenous variables producing estimates of the impacts of the exogenous variables on levels and the variance of yield. The form of production function is shown in equation (1).

(1) $$y = f(X, \beta) + \mu = f(X, \beta) + h(X, \alpha)\varepsilon$$

where: y is crop yield; $f(\cdot)$ is the mean function relating X to average yield with β as the associated vector of estimated parameters; X is a vector of explanatory variables. μ is a heteroskedastic disturbance term with a mean of zero. In addition, $h(\cdot)$ is a function that accounts for independent variable-dependent heteroskedasticity, allowing yield variability as a function of observed covariates with α as the corresponding vector of estimated parameters. Under the assumption that the error term ε is distributed with mean zero and unitary variance, $h^2(\cdot)$ is the yield variance.

In this estimation, like in many other studies, we employ crop planted acreage, yearly growing season mean temperature, yearly total precipitation, time trend and its square. However, this study develops a richer specification. Not only, do we explicitly control for temperature and precipitation but we also include climate variation and extreme event, and CO_2 concentrations. We also add interaction terms between region temperature; precipitation and region; and interaction with ENSO events and regions. Furthermore, we add the dummy variable of the FACE experiments to distinguish the observational data and the FACE experimental data[4]. As found in Schlenker, Hanemann, and Fisher (2005), we include the percent of crop irrigated

acreage to total crop planted acreage and its interaction term with the crop planted acreage to distinguish the effect of dry land and irrigated land on crop yield[5]. Finally, we pool data from 1950 - 2009 and separate time invariant state-specific effects of the constructed panel.

In general, there are two methods that have been employed to estimate the function. Just and Pope (1978, 1979) present a three-step, Feasible Generalized Least squares (FGLS) method and others have used a Maximum Likelihood Estimation (MLE) approach. Saha, Havenner, and Talpaz (1997) illustrate that the MLE is more efficient than the three-step estimation for small samples in Monte Carlo experiments. Nevertheless, this study employs a three-step, FGLS estimation because we have a large number of observations. Moreover, the MLE approach depends heavily on the correct specification of the likelihood function (McCarl, Villavicencio, and Wu 2008). As a robustness check, we also estimated the production function using the MLE approach[6] and found that the estimates from the two approaches were close to each other.

The procedure to estimate the three-step FGLS estimation can be explained as follows. In the first step, we estimate the model

(2) $$y = f(X, \beta) + \mu$$

using ordinary least square (OLS) regression and then obtain residuals ($\hat{\mu}$). In the second step, we regress the logarithm of squared residuals on X.

(3) $$\ln(\hat{\mu}^2) = h(X, \alpha) + \varepsilon$$

Then, we obtain the predicted values of those residuals and convert these predicted values using antilogarithm. These values are consistent estimators of variances. In the final step, we estimate the original model by weighted least squares (WLS) using the squared root of the predicted variances as weights.

$$(4) \qquad y.h^{-1/2}(\mathrm{X},\hat{\alpha}) = f(\mathrm{X},\beta).h^{-1/2}(\mathrm{X},\hat{\alpha}) + \mu.h^{-1/2}(\mathrm{X},\hat{\alpha})$$

To investigate the implication of future climate change on crop yield and its variability, we employ our estimated coefficients from the three-step FGLS estimation together with future climate change projected by standard global circulation models (GCMs) used in the IPCC (2007), consisting of GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3[7]. We utilize the IPCC SRES scenario A1B, which is characterized by a high rate of growth in CO_2 emissions and most closely reproduces the actual emissions trajectories during the period since the SRES scenarios were completed (2000-2008) (van Vuuren and Riahi 2008). It is reasonable to focus on A1B scenario group versus those in the B1 and B2 scenario groups that have lower emissions projections since in recent years actual emissions have been above the A1B scenario projections. At the same time, there has been considerable interest and policy development to encourage non-fossil fuel energy, which is consistent with the A1B scenario vs. A1F1 or A2.

Economic Modeling of Climate-Induced Shifts in Crop Yields

To explore the market outcomes and welfare implications of climate-induced shifts in yields across the US, we plug in our projected percentage changes of mean crop yields into the ASM, in which crop allocation decisions are based on the relative returns associated with the climate scenarios modeled. ASM includes all states in the conterminous United States, broken into 63 subregions for agricultural production and 11 market regions. The model also links the US to the rest of the world (ROW) via international trade of major commodities such as corn, wheat, soybeans, rice, and sorghum across 37 foreign regions[8]. Moreover, it includes information on transportation costs to all regions, which affect equilibrium exports. The ASM have been used extensively in numerous agricultural policy applications, including a large number of climate change–related studies for the IPCC, Environmental Protection Agency (EPA), and others (see

more details in Adams et al. 2005). Overall, the model framework is summarized by the following equations.

(5) $Max \quad -\sum_{j,k} \mathbf{g}_{jk} \mathbf{X}_{jk} - \sum_{k,r} \int \boldsymbol{\alpha}(\mathbf{R}_{rk}) \mathbf{dR}_{rk} + \sum_{i} \int \boldsymbol{\varphi}(\mathbf{Q}_i) \mathbf{dQ}_i$

$+ \sum_{i,f} \int \boldsymbol{\gamma}(\mathbf{FQD}_{if}) \mathbf{dFQD}_{if} - \sum_{i,f} \int \boldsymbol{\beta}(\mathbf{FQS}_{if}) \mathbf{dFQS}_{if} - \sum_{i,k,f} \mathbf{USFTC}_{ikf} * \mathbf{USFTRD}_{ikf}$

$- \sum_{i,f,f1} \mathbf{FFTC}_{iff1} * \mathbf{FFTRD}_{iff_1} - \sum_{i,k,k1} \mathbf{USTC}_{ikk1} * \mathbf{USTRD}_{ikk1}$

s.t

(6) $\sum_{j} \mathbf{y}_{ijk} * (\mathbf{1} + \mathbf{dyield}_{ik}) * \mathbf{X}_{jk} - \sum_{k} \mathbf{USFTRD}_{ifk} - \sum_{k1} \mathbf{USTRD}_{ik1k} + \sum_{k} \mathbf{USFTRD}_{ikf}$

$\sum_{k1} \mathbf{USTRD}_{ikk1} \le \mathbf{0}, \forall i, k$

(7) $\sum_{j} \mathbf{a}_{rjk} * \mathbf{X}_{jk} \le \mathbf{R}_{rk}, \forall r, k$

(8) $\mathbf{Q}_i - \sum_{i,j,k} \mathbf{y}_{ijk} * (\mathbf{1} + \mathbf{dyield}_{ik}) * \mathbf{X}_{jk} + \sum_{k,i} (\mathbf{USFTRD}_{ikf} - \mathbf{USFTRD}_{ifk}) \le \mathbf{0}, \forall i$

(9) $\mathbf{FQD}_{ik} + \sum_{k} \mathbf{USFTRD}_{ifk} + \sum_{f1} \mathbf{FFTRD}_{iff1}$

$- \mathbf{FQS}_{if} - \sum_{k} \mathbf{USFTRD}_{ikf} - \sum_{f1} \mathbf{FFTRD}_{iff1} \le \mathbf{0}, \forall i, f$

where

i indexes commodities; $f, f1$ index the rest of the world (ROW)'s regions;

j indexes production processes; $k, k1$ index US regions; r indexes resources;

$\mathbf{g}_{jk}$ is the cost of the jth production process per acre in US region k;

$\mathbf{X}_{jk}$ is the acrage of the jth production process in US region k;

$\boldsymbol{\alpha}(\mathbf{R}_{rk})$ is the inverse US factor supply function for resource r in region k;

$\mathbf{R}_{rk}$ is the resource supply for US region k of resource r;

$\boldsymbol{\varphi}(\mathbf{Q}_i)$ is the inverse US demand function for commodity i;

$\mathbf{Q}_i$ is the US domestic consumption of the ith commodity;

$\boldsymbol{\gamma}(\mathbf{FQD}_{if})$ is the inverse excess demand function for commodity i in importing ROW region f;

$\mathbf{FQD}_{if}$ is the excess demand quantity for commodity i in importing ROW region f;

$\boldsymbol{\beta}(\mathbf{FQS}_{if})$ is the inverse excess supply function for commodity i in exporting ROW region f;

$\mathbf{FQS}_{if}$ is the excess supply quantity for commodity i in exporting ROW region f;

$\mathbf{USFTC}_{ikf}$ is the transportation cost from US region k to ROW region f for commodity i;

$\mathbf{USFTRD}_{ikf}$ is the trade between US region k and ROW region f for commodity i;

$\mathbf{FFTC}_{iff1}$ is the transportation cost between ROW region f and $f1$ for commodity i;

$\mathbf{FFTRD}_{iff_1}$ is the trade between ROW region f and $f1$ for commodity i;

$\mathbf{USTC}_{ikk1}$ is the transportation cost between US region k and $k1$ for commodity i;

$\mathbf{USTRD}_{ikk1}$ is the quantity shipped between US region k and $k1$ for commodity i;

$\mathbf{y}_{ijk}$ is per acre yield for commodity i using jth production process of US region k;

$\mathbf{dyield}_{ik}$ is the crop yield percentage change due to the change in climate, atmospheric CO_2, and
  crop production technology;

$\mathbf{a}_{rjk}$ is the amount of resource r used in the jth production process of US region k;

$\mathbf{R}_{rk}$ is the amount of resource r available in US region k;

Equation 5 is the objective function mixing the price endogenous and spatial equilibrium models. The first line of equation 5 represents the area under the demand curves for commodity i subtracted by the area under the regional US factor supply curves for perfectly elastic production costs associated with production process j and quantity dependent prices for factor r summed across all k regions. The next three lines include terms typically used in the spatial equilibrium model. The first two terms of the second line gives the area under the ROW excess demand curves minus the area under the excess supply curves for commodity i in ROW region f. The last term of the second line and terms in the third line provide the summation of the transportation costs between the US and the ROW regions, among ROW regions, and among the US regions involved with trade, respectively. Equation 6 represents the regional balance constraint for goods depicted with a spatial equilibrium trade model in the US. Equation 7 is usual resource constraint for US region k. Equation 8 provides the national balance constraint for commodities in the US. Equation 9 is the balance constraint for traded goods in the ROW region f.

Data

Observational Data

The state-level dataset we use contains annual crop yields, planted acreage, and percent of irrigated acreage of corn, soybeans, sorghum, cotton, and winter wheat across the US from 1950 – 2009. The data were drawn from the website of USDA-National Agricultural Statistics Service (USDA-NASS)[9]. We encounter missing observations over the relevant time period for each crop, and of course not all states grow all of the crops. State-level climate data, total precipitation, seasonal growing season temperature, seasonal Palmer Drought Severity Index (PDSI) used in this study are obtained from the website of National Oceanic and Atmospheric Administration (NOAA).[10] We also construct variables, on state-yearly precipitation intensity, number of days

in each state that maximum temperature exceeds 32°C, and the crop-growing-season ENSO

phases by state using data from thousands of climate stations across US provided from the

website of NOAA[11]. Our state-yearly precipitation intensity can be calculated as follow.

$$(10) \qquad PrecipIntensity_{tr} = \frac{\sum_{i \in S} totalprecip_{itr}}{\sum_{i} totalprecip_{itr}} * 100$$

where

i indexes days, t indexes period (year), r indexes states of the US

S is the set containing days that have total precipitation exceeding the 1961-1990 95th percentiles

$PrecipIntensity_{tr}$ is the percent of total precipitation due to events exceeding the 1961-1990 95th

percentiles in year t at state r

$totalprecip_{itr}$ is the total precipitation of ith day in year t at state r

The observation data of the atmospheric CO_2 concentration collected from Mauna Loa (Hawaii)

are also provided by NOAA (http://www.esrl.noaa.gov/gmd/ccgg/trends/). We also encounter

missing observations of climate data in some states. Nevertheless, when missing observations

were present in a given state, we used the available data instead of deleting that state from the

estimation which would cause an unbalanced panel.

Free-Air CO$_2$ Enrichment (FACE) Experimental Data

The FACE experimental data is merged with the observational data to allow us to do an

estimation of the effect of CO_2 fertilization on crop yields. For our study, Arizona and Illinois are

only two states in US that have FACE experiment datasets we can use. In Arizona, the

experiment is done only on cotton, wheat, and sorghum, while in Illinois the experiment is done

on only corn and soybeans[12]. Cotton was planted in 1989, 1990, and 1991. Wheat was planted in 1993, 1994, 1996, and 1997. Sorghum was planted in 1998 and 1999. Corn was planted in 2004 and 2008. Lastly, soybeans were planted from 2002-2007. Each crop is planted under ambient CO_2 and elevated CO_2 environment in the field.

Empirical Results

A Major Difficulty of the Historical Agricultural Yield Studies and a Solution
Except the PDSI variable, other variables are studied in their logarithm form[13]. We calculate the correlation matrix among variables. We find that before including the FACE experimental data, there is no concern about the high correlation among explanatory variables in our observational data, except the very high correlation coefficients (about 0.99) between time trend and the CO_2 concentration in each studied crop. However once the FACE experimental data are included, the correlation drops substantially as shown in table1 except for corn, where we have only a few FACE observations. We show later that the results appear to be the best we can obtain as when we reduce the scope of our estimation to the US Central region only and thus decrease the correlation coefficients of time and CO_2 concentration that our estimates are very similar.

In table 1, we also separately summarize CO_2 concentration statistics in the observational data and the data set augmented with the FACE experimental data. Another important finding is that the standard deviation of the CO_2 in the FACE experimental data is about four times higher than that in the observational data, which supports our argument that incorporating the FACE experimental data could increase the variation of the CO_2 concentration, and might allow us to estimate both the effect of CO_2 fertilization and the effect of time as a proxy for crop technological progress.

Table 1. CO_2 concentration statistics and correlation coefficients between time trend and the CO_2 concentration before and after incorporating the FACE experimental data

		Soybeans	Cotton	Wheat	Corn	Sorghum
Before including the FACE data		0.9883	0.9906	0.9889	0.9880	0.9885
After including the FACE data		0.7574	0.5910	0.7285	0.9046	0.6827
Observational Data	Obs	1422	724	1869	1928	814
	Mean	347.22	348.37	348.87	346.25	347.52
	Std. Dev.	22.24	21.60	21.48	22.56	21.86
	Min	310.70	311.90	310.70	310.70	310.70
	Max	387.35	387.35	387.35	387.35	387.35
The FACE experimental Data	Obs	48	40	50	15	32
	Mean	464.48	458.00	456.40	458.00	464.50
	Std. Dev.	86.80	93.35	90.84	89.26	98.18
	Min	373.17	350.00	370.00	370.00	363.00
	Max	552.00	550.00	550.00	550.00	566.00

Note: the unit of CO_2 concentration is part per million (ppm).

Determinants of Crop Yields

As stated in the previous section, all variables other than the PDSI variable are studied in their logarithm form to reduce the heterogeneity of the variance and to provide a convenient economic interpretation (elasticities). We use the PDSI in a non log fashion since it ranges from -10 to +10. In addition to variables that we described in the literature review section, we include the variable of interaction between CO_2 and PDSI in our specification due to the fact that rising CO_2 indirectly increases the efficiency of water use of crops via reduction in stomatal conductance with crops expected to benefit from elevated CO_2 in times and places of drought stress (Long et al. 2006; Leakey 2009).

We estimate the model using the three-step FGLS estimation procedure. To capture the unobserved effects that are invariant overtime, we include state dummies as typically done in fixed effects model (see for example McCarl, Villavicencio, and Wu 2008). We also check the

correctness of our model specification using link test[14] provided in STATA. We find that the square term of the predicted values of the mean and variance of yield are statistically insignificant for each crop even at the 10 percent level, implying that our model specifications passed the link test, and hence are well specified.

The estimated coefficients of the mean yield regression from the three-step FGLS estimation are provided in table 2[15]. They are from the second-stage weighted least square (WLS) with predicted standard deviations as weights. To save space, estimated coefficients of individual state dummies are not reported here.

The coefficients of the dummy variable of the FACE experiments reveals that mean crop yields of soybeans, winter wheat, and sorghum from the FACE experimental data are higher than that from the observational data and vice versa for corn. The planted acreage of all crops except corn is positively correlated with the mean crop yield with statistically significance at the 1 percent level indicating that yield of these crops is likely to obtain the economies of scale for the expansion of crop planted acreage. In that regard our results are similar to Chen, McCarl, and Schimmelpfennig (2004) and McCarl, Villavicencio, and Wu (2008) for soybeans, wheat, and sorghum, but for cotton and corn.

For CO_2 concentration effect on crop yields, we find that average yields of the C-3 crops soybeans, cotton, and winter wheat are positively correlated with the CO_2 concentration with statistical significance at 1 percent level, while yields of corn and sorghum are not as expected. However, yields of corn and sorghum are negatively correlated to the interaction between CO_2 concentration and PDSI (again results are consistent with drought yield stimulation of CO_2 as in Ainsworth and Long 2005, Long et al. 2006, Leakey 2009). That is, yields of C-3 crops, soybeans, cotton, and wheat, are directly

Table 2. Estimated coefficients from mean crop yield regressions

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Acreage	0.028***	0.0129***	0.012***	-0.007	0.052***
	(0.0039)	(0.0058)	(0.0040)	(0.0054)	(0.0051)
CO2	0.309***	1.310***	0.241***	0.181	0.116
	(0.0820)	(0.1740)	(0.0431)	(0.1350)	(0.1682)
CO2 X PDSI	-0.078***	0.155***	0.0454***	-0.042**	-0.075***
	(0.0143)	(0.03104)	(0.0053)	(0.0168)	(0.0272)
Time Trend	0.011***	-0.0019	0.018***	0.040***	0.037***
	(0.0006)	(0.0015)	(0.0006)	(0.0007)	(0.0012)
Trend^2	-0.00002***	0.00014***	-0.00007***	-0.00014***	-0.00015***
	(8.94E-06)	(0.00002)	(7.89E-06)	(8.94E-06)	(0.000016)
Temperature	1.189***	0.755	0.055	1.348***	1.177***
	(0.1565)	(0.8707)	(0.1240)	(0.1632)	(0.4227)
Days_temp>32C	-0.028***	-0.075***	0.000	-0.017***	-0.072***
	(0.0019)	(0.0094)	(0.0016)	(0.0015)	(0.0059)
PDSI	0.474***	-0.900***	-0.269***	0.253***	0.450***
	(0.0841)	(0.1824)	(0.0317)	(0.0987)	(0.1596)
Precipitation	-0.006	-0.256**	-0.194***	-0.0157	-0.240***
	(0.0304)	(0.1084)	(0.0275)	(0.0334)	(0.0636)
Precip Intensity	-0.006*	-0.022***	-0.012***	-0.003	0.000
	(0.0035)	(0.0078)	(0.0032)	(0.0032)	(0.0055)
Temp X D2_NE	-1.311***		0.718***	-2.484***	-9.272***
	(0.2974)		(0.1873)	(0.3263)	(2.2730)
Temp X D3_NP	0.456	5.962***	-0.666***	-0.254	1.278***
	(0.3094)	(2.0887)	(0.2466)	(0.2773)	(0.4942)
Temp X D4_SE	-2.435***	1.610*	-1.317***	-3.841***	-1.776***
	(0.3130)	(0.9222)	(0.2350)	(0.3417)	(0.5282)
Temp X D5_SP	-3.512***	0.83	-2.427***	-1.799***	-1.919***
	(0.4209)	(0.9555)	(0.3579)	(0.6512)	(0.5363)
Temp X D6_MT		-0.470	-0.730***	-0.025	-4.030***
		(1.1538)	(0.1875)	(0.2579)	(0.6797)
Temp X D7_PA			0.192	-1.609***	
			(0.3151)	(0.2576)	
Precip X D2_NE	0.0597		-0.0214	-0.043	-0.254
	(0.0378)		(0.0391)	(0.0522)	(0.2202)
Precip X D3_NP	0.258***	-0.148	0.458***	0.325***	0.856***
	(0.0404)	(0.2572)	(0.0537)	(0.0434)	(0.0669)
Precip X D4_SE	0.217***	0.224**	0.074**	0.211***	0.303***
	(0.0384)	(0.1066)	(0.0381)	(0.0463)	(0.0710)
Precip X D5_SP	0.045	0.265**	-0.122***	0.320***	0.310***
	(0.0451)	(0.1065)	(0.0458)	(0.0659)	(0.0660)

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Precip X D6_MT		0.122	0.507***	0.052	0.570***
		(0.1135)	(0.0325)	(0.0381)	(0.0897)
Precip X D7_PA			0.294***	-0.056	
			(0.0444)	(0.0344)	
D2_NE X LaNina	0.025***		0.028***	-0.001	-0.430**
	(0.0149)		(0.0010)	(0.0142)	(0.1793)
D2_NE X Neutral	0.031**		0.003	0.048***	-0.041
	(0.0134)		(0.0089)	(0.0135)	(0.0817)
D3_NP X LaNina	-0.064***	-0.192**	0.018	-0.029**	0.019
	(0.0152)	(0.0872)	(0.0212)	(0.0121)	(0.0211)
D3_NP X Neutral	0.007	-0.063	-0.062***	-0.022*	-0.003
	(0.0152)	(0.0702)	(0.0185)	(0.0131)	(0.0220)
D4_SE X LaNina	-0.016*	-0.081***	0.001	-0.013	0.024*
	(0.0102)	(0.0165)	(0.01050)	(0.0110)	(0.0142)
D4_SE X Neutral	-0.008	-0.084***	0.001	-0.037***	-0.006
	(0.0100)	(0.0146)	(0.0088)	(0.0108)	(0.0131)
D5_SP X LaNina	-0.060***	-0.095***	-0.020	-0.011	-0.047***
	(0.0134)	(0.0172)	(0.0154)	(0.0216)	(0.0142)
D5_SP X Neutral	-0.014	-0.084***	-0.006	-0.028	0.013
	(0.0144)	(0.01467)	(0.0129)	(0.0205)	(0.0113)
D6_MT X LaNina		0.013	0.033***	-0.042***	0.064
		(0.0327)	(0.0109)	(0.0117)	(0.0397)
D6_MT X Neutral		0.028	0.004	-0.036***	0.114***
		(0.0254)	(0.0097)	(0.0081)	(0.0369)
D7_PA X LaNina			0.005	-0.051***	
			(0.0180)	(0.0091)	
D7_PA X Neutral			0.021	-0.042***	
			(0.0182)	(0.0090)	
DummyFACE	0.684***	-0.006	0.170***	-0.258**	0.512***
	(0.0769)	(0.2058)	(0.0569)	(0.1115)	(0.1444)
Constant	5.410***	-11.041***	7.198***	11.923***	4.483**
	(-1.3004)	(1.7896)	(0.8889)	(1.5328)	(1.8528)

Note: 1) ***, **, * are significant at the 1, 5, and 10 percent level, respectively and standard errors are in parentheses.

2) Regional interacted dummies: D1_C –Central- (IN, IL, IA, MI, MO, MN, OH, WI); D2_NE –Northeast- (CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT); D3_NP – North Plains- (KS, NE, ND, SD); D4 –Southeast- (AL, FL, GA, KY, NC, SC, TN, VA, WV); D5 -South Plains- (AR, LA, MS, OK, or TX); D6 –Mountains- (AZ, CO, ID, MT, NV, NM, UT, WY); D7 –Pacific- (CA, OR, WA).

and positively respond to the elevated CO_2 via photosynthesis process, while C-4 crops do not. However, C-4 crops indirectly benefit from elevated CO_2 in times and places of drought stress meaning that the higher the level of drought stress, the greater the yields of C-4 crops. Unlike other crops, cotton and wheat in our study do not likely benefits from drought stress condition. This result is similar to what is concluded in Amthor (2001), who finds that elevated CO_2 stimulates yield of water-stressed wheat, but usually did not fully compensate for water shortage.

Now we examine the results for the time as a proxy for technical change as it influences mean crop yields. The results indicate that for all crops the effect of crop technological progress to mean yields is non-linear with inverted-U shape in all crops exhibiting diminishing technical change over time, except for cotton where the mean yield increases at an increasing rate. To investigate the claim that ignoring the variable of CO_2 concentration in the model is likely to overestimate the real effect of time - crop production technology on crop yield, we consider two model specifications, specification with (our main model) and without (alternative model) the CO_2 concentration. We then compare the marginal effect of crop production technology on crops yield of these two specifications as shown in figure 1. Except for sorghum, the marginal effect of crop technological progress on other crop yields from the model without the CO_2 variable is greater than the model with CO_2 variable overtime. Cotton has the biggest difference of the marginal effect of crop production technology on its yield between these two specifications.

As a robustness check, we also compare our estimates of crop production technology with previous studies, which did not include the CO_2 variable in their model as shown in table 3. Comparing the partial derivative of crop yields with respect to time trend at year 2000 across all studies, in general the effect of crop technological progress from our model without CO_2 concentration is in the range of previous studies. However, its effect from our model with CO_2

variable is generally lower than that from previous studies and our model without CO_2. For example, in cotton, its yield increases 8.2 and 11.29 lbs/acre/year in the model with and without CO_2, respectively. In Chen et al. (2004) and McCarl et al. (2008), its yield increases 10.11 and 11.56 lbs/acre/year, respectively. We also calculate the rate of change of crop technological progress and find that, in all cases, the model with the CO_2 variable has the rate of change of crop yields lower than the model without CO_2 as shown in the last row of table 3. This indicates that ignoring CO_2 concentration is contributing to yield increases over time and ignoring its effects, is likely to overestimate the effect of crop production technological progress on crop yields.

Next we examine the effect of climate change on mean crop yields. Before we start, it is worth noting that the coefficient of variable "Temperature" represents the effect of temperature on crop yields for the base region (Central), while coefficients of its interaction terms reflect the difference between the effect of temperature over a given region and the Central region. Notice that in table 2, the interaction terms between temperature and dummy variables of US regions are not uniformly present in all models. This is because of some crops are not grown in some regions. The same is true for interactions involving "Precipitation". Finally, the coefficients of interaction terms between the ENSO phases (El Nino, La Nina, and Neutral) and the dummy variables of US regions reflect the difference between the effects of ENSO phases in a particular region from that in the Central region.

Next we consider the effect of variables related to temperature on crop yields.

- We find that mean temperature has positive effect over Central (C) and Northern Plains (NP) regions (Negative for winter wheat in NP and no significant effect for cotton and winter wheat in C). It has negative relative effect for other regions excepting a Positive effect for

winter wheat in Northeast (NE), cotton in Southeast (SE), and corn in the Mountain (MT) regions.

- For the effect of extreme high temperature, we find that a higher of hot days (number of days that maximum temperature exceeds 32°C) adversely affects yields of soybeans, cotton, and winter wheat, consistent with the notion that a short period of abnormally high temperatures can have a significant harmful effect on final yield.

- For the effect of total yearly precipitation on crop yields, unlike McCarl, Villavicencio, and Wu (2008), our study finds a statistically significant relationship between with crop yields and interaction of precipitation and US regions, implying that there is heterogeneity of a crop yield that is affected by precipitation across US regions. This might be because this study controls for ENSO events. We find that precipitation has negative effect over the wetter Central (C) and Northeast (NE) regions with no significant effect for soybeans and corn in both regions). It has positive relative effect for the drier NP region (Negative for cotton). We find mixed results in the remaining regions.

- Precipitation effects are also covered through the PDSI, and precipitation intensity variables. For the effect of drought stress, as represented by the PDSI, its effect directly increases yields of soybeans, corn, and sorghum , while it decreases cotton yield similar to McCarl, Villavicencio, and Wu (2008), but different for winter wheat. However, if we include its indirect effect because of the interaction between drought stress and the CO_2 concentration, we find that its effect on yields of soybeans, corn, and sorghum tends to decrease, while its effect on yields of cotton and wheat-winter tends to increase as CO_2 increases.
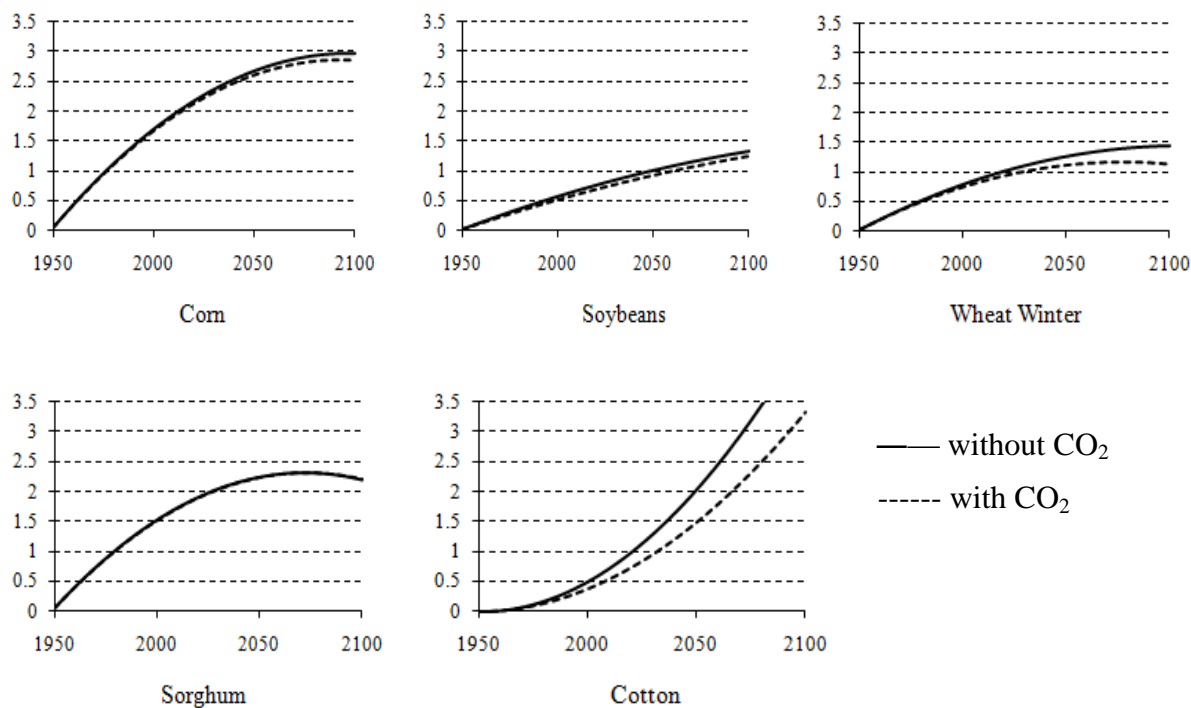
Figure 1. Marginal effect of crop production technology

Table 3. Comparison of estimates of crop production technology

	Corn		Soybeans		Wheat		Sorghum		Cotton	
	w CO$_2$	w/o CO$_2$	w CO$_2$	w/o CO$_2$	w CO$_2$	w/o CO$_2$	w CO$_2$	w/o CO$_2$	w CO$_2$	w/o CO$_2$
Huange and Khanna (2010) (1994-2007)	-	3.26	-	0.29	-	0.64	-	-	-	-
McCarl et al. (2008) (1960-2007)	-	1.89	-	0.39	-	0.67	-	0.40	-	11.56
Chen et al. (2004) (1973-1997)	-	3.30	-	0.35	-	0.63	-	0.11	-	10.11
our study (1950-2009)	2.49	2.55	0.29	0.33	0.62	0.63	0.32	0.35	8.20	11.29
% change/year	2.57	2.63	0.91	1.00	1.84	1.85	0.65	0.71	1.30	2.05

Note: 1) Unit of all crops is in bushels/acre/year, expect cotton, which has unit in lbs/acre/year.

2) w CO$_2$ and w/o CO$_2$ is the model with and without CO$_2$ variables, respectively.

3) The estimated results in the last row are the rate of technological change.

4) All estimates are calculated in year 2000.

- For precipitation intensity, we find it is harmful to soybeans, corn, and wheat, although its effect from our model is less than that from McCarl, Villavicencio, and Wu (2008).

- Finally, we examine the effect that ENSO events have on crop yields. We find that in general its effect is heterogeneous across regions and phase. We find that during the La Nina and Neutral phases, crop yields of soybeans, winter wheat, and corn in NE are slightly higher than that in Central region during the El Nino phase (base), but lower for sorghum. Crop yields in NP, SP, and PA are generally slightly lower than that in Central region during the El Nino phase, but higher for sorghum in SE during La Nina phase. Mixed results are discovered in MT region. Above results are consistent with what have been found in Wolter, Dole, and Smith (1999).

Now, we turn attention to factors affecting the variability of crop yields. The estimated coefficients of the log crop yield variance regressions estimated in the first stage OLS are shown in table 4. The interpretation of a positive coefficient in this table implies that an increase in the associated variable leads to a higher yield variance and vice versa. Notice that for all crops, the joint significance test rejects the null hypothesis that the variability of crop yields are not determined by all explanatory variables in the model, implying that variance of all crop yields is non stationary similar to the results found in McCarl, Villavicencio, and Wu (2008) (cotton is different).

Notable findings are that

- Expansion of crop acreage decreases the variance of soybeans and corn yields.

- The increase in the CO_2 concentration reduces the variation of winter wheat and corn.

- There exist a U-shape relationship between crop production technology and the variance of corn yield where increases in time increase the variance of corn yield at an increasing rate.

- . The increase in temperature decreases the volatility of soybean yield in Central region, while it increases relative variability of yields of soybeans and winter wheat in NE and SE, respectively. It also decreases relative variability of yields of winter wheat and sorghum in NE and NP, respectively.

- A higher in the number of days that maximum temperature exceeds 32°C increases the variance of winter wheat.

- Considering the effect of precipitation on the variability of crop yields, we find that higher precipitation increases variability of winter wheat (decrease variability of corn yield) in the Central region, while it decreases the variation of winter wheat yield in NP, MT, and SE, and sorghum yield in NP. It also increases the volatility of corn yield in SP region.

- Precipitation intensity increases the variance of winter wheat.

- We find the heterogeneity of the variance of crop yields across regions due to the ENSO phases. For example, the variability of yields of winter wheat, corn and sorghum during the La Nina phase is higher than during the El Nino phase in SP.

Simulation of the Impacts of Climate Change on Future Crop Yields

To investigate the implication of future climate change on crop yield and its variability, we employ our estimated coefficients from table 2 and 4 with future climate change projections in each state of the US from GCMs as stated in the model specification and methodology section, while the projected PDSI and the probability of future ENSO phases obtained from Dai (2010) and Timmermann et al. (1999), respectively. According to Timmermann et al. (1999), the current probability of ENSO event occurrence (with present day concentrations of greenhouse gases) is 0.238 for the El Niño phase, 0.250 for the La Niña phase and 0.512 for the Neutral phase. They also project that probabilities for these three phases will change under increasing levels of GHGs

Table 4. Estimated coefficients from log crop yield variance regressions

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Acreage	-0.281**	-0.096	0.011	-0.522***	-0.093
	(0.1106)	(0.1085)	(0.1109)	(0.1150)	(0.1208)
CO_2	-1.813	-2.477	-2.831*	-5.350*	-1.010
	(1.7603)	(1.7379)	(1.5493)	(3.0889)	(1.7425)
CO_2 X PDSI	-0.063	0.137	0.190	-0.027	-0.039
	(0.4326)	(0.5526)	(0.2058)	(0.4230)	(0.5714)
Trend	-0.002	-0.015	-0.011	-0.0738***	-0.029
	(0.0191)	(0.029)	(0.0160)	(0.0148)	(0.0238)
Trend^2	0.00024	0.00023	0.000	0.0011***	0.00031
	(0.00026)	(0.0004)	(0.0002)	(0.0002)	(0.00035)
Temperature	-22.575***	-15.859	-0.880	-1.863	13.311
	(5.6790)	(15.8596)	(3.4657)	(5.0896)	(9.8555)
Days_temp>32C	0.225***	0.116	0.085*	0.054	0.278*
	(0 .0723)	(0.2043)	(0.0528)	(0.0512)	(0.1424)
PDSI	0.420	-0.835	-1.165	0.148	0.444
	(2.5444)	(3.2516)	(1.2162)	(2.4822)	(3.3514)
Precipitation	-1.542	-1.035	1.427*	-2.148**	-2.208
	(1.0738)	(2.0071)	(0.8226)	(0.9132)	(1.3849)
Precip Intensity	0 .152	0.084	0.149*	-0.042	0.200
	(0.1304)	(0.1501)	(0.0912)	(0.0883)	(0.1368)
Temp X D2_NE	34.053***		-12.067*	17.809	-6.738
	(10.2678)		(7.0394)	(8.5947)	(60.0009)
Temp X D3_NP	5.624	4.832	-5.863	-11.968	-34.597***
	(9.5418)	(26.1447)	(5.6480)	(8.1306)	(12.7683)
Temp X D4_SE	11.102	35.009	16.519**	12.471	-11.700
	(9.1176)	(17.6074)	(6.7243)	(9.5224)	(13.1818)
Temp X D5_SP	17.151	9.551	7.366	6.436	15.073
	(11.2194)	(18.1257)	(8.9693)	(10.8458)	(13.0952)
Temp X D6_MT		15.747	1.324	-9.327	-5.970
		(20.8440)	(5.2046)	(7.6126)	(11.5075)
Temp X D7_PA			-6.432	0.401	
			(8.7626)	(10.8799)	
Precip X D2_NE	-1.317		-1.962	0.748	-3.618
	(1.3693)		(1.3832)	(1.2742)	(5.2080)
Precip X D3_NP	-0.166	6.268	-2.322*	1.234	-3.821**
	(1.3038)	(3.6472)	(1.2359)	(1.2288)	(1.5858)
Precip X D4_SE	-1.652	0.292	-1.971*	0.439	0.143
	(1.1925)	(2.01535)	(1.1411)	(1.1690)	(1.6866)

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Precip X D5_SP	-1.648	1.607	0.171	2.387**	0.345
	(1.2628)	(2.0062)	(1.1956)	(1.1544)	(1.4553)
Precip X D6_MT		1.482	-2.979***	1.047	0.327
		(2.0745)	(0.9584)	(1.0735)	(1.5007)
Precip X D7_PA			-1.214	1.334	
			(1.2052)	(1.1619)	
D2_NE X LaNina	-0.662*		-0.029	0.193	1.219
	(0.3726)		(0.3897)	(0.3391)	(2.6136)
D2_NE X El Nino	-1.323***		-0.307	0.158	-1.512
	(0.3614)		(0.3699)	(0.3256)	(1.7593)
D3_NP X LaNina	-0.307	0.682	-0.130	0.271	-1.664***
	(0.4435)	(1.1928)	(0.4251)	(0.4179)	(0.4637)
D3_NP X Neutral	0.000	-0.013	-0.518	0.942**	-0.681
	(0.4178)	(0.9422)	(0.4012)	(0.3858)	(0.4396)
D4_SE X LaNina	-0.038	-0.737**	-0.054	0.029	0.161
	(0.2980)	(0.3439)	(0.2798)	(0.2855)	(0.3877)
D4_SE X Neutral	0.067	-0.463	-0.663**	0.085	0.155
	(0.2793)	(0.2953)	(0.2638)	(0.2759)	(0.3678)
D5_SP X LaNina	0.0567	-0.028	0.840**	0.536*	0.885***
	(0.3707)	(0.3964)	(0.3706)	(0.3318)	(0.3348)
D5_SP X Neutral	0.440	0.011	0.489	0.507	0.383
	(0.3565)	(0.3348)	(0.3470)	(0.3204)	(0.3112)
D6_MT X LaNina		0.622	-0.079	1.078***	-0.378
		(0.6531)	(0.2990)	(0.3187)	(0.6747)
D6_MT X Neutral		0.544	-0.142	0.595**	-0.413
		(0.5350)	(0.2768)	(0.2898)	(0.6273)
D7_PA X LaNina			-0.766	-0.222	
			(0.4820)	(0.4547)	
D7_PA X Neutral			-0.230	0.304	
			(0.4341)	(0.4071)	
DummyFACE	-2.744	0.142	1.444	-8.388***	1.452
	(2.1505)	(3.5337)	(1.5697)	(2.3200)	(2.0657)
Constant	68.131**	-67.504*	-51.114*	-7.442	1.037
	(-34.1210)	(38.6709)	(26.3072)	(40.2063)	(43.1475)
F(df1,df2)	F(56,1413)	F(42,737)	F(75,1842)	F(76,1866)	F(49,796)
Prob > F	3.65***	1.91***	2.52***	5.89***	3.23***

Note: 1) ***, **, * are significant at the 1, 5, and 10 percent level, respectively and standard errors are in parentheses.

2) Definitions of regional interacted dummies are provided in the note of table 2.

assumed under IPPC projections (IPPC, 1992). Under such a scenario, ENSO event frequency is forecasted to become 0.339, 0.310, and 0.351 for El Niño, La Niña and Neutral, respectively.

We simulate the projected percentage change of mean crop yield and its standard deviation in four scenarios. The first scenario is the base scenario in which all climate change and CO_2 variables are fixed at their average values during 1980–2009. The second scenario is the situation in which the CO_2 variable changes, but other climate variables are fixed at their mean level. The third scenario is the case in which all of the climate variables change, but the CO_2 variable is hold at its mean level. The second and third scenarios aim to measures the partial effect of the CO_2 fertilization and climate change, respectively. In the last scenario, both climate and CO_2 are changed, which is different from a majority of previous studies that often quantify only the partial effect of a single climate variable. This combined effect takes into account the fact that crop yields in the reality respond to the interaction among all climate variables including the atmospheric CO_2 concentration. We report the simulated percentage change of mean yields and their standard deviation of year 2050 averaged from our four GCMs as shown in table 5.

For the partial effect of CO_2 fertilization (Scenario1), we find that if atmospheric CO_2 continues to increase, yields of all crops are likely to be higher in the future in all regions. CO_2 concentration is likely to increases yields of C-3 crops (soybeans, cotton, and winter wheat) more than yields of C-4 crops (corn and sorghum). The most advantaged crop is cotton. Our results of corn and soybeans close to what are reviewed in Long et al. (2006). Moreover, a higher atmospheric CO_2 in the future decreases the standard deviation of yields of all crops in all regions.

Fixing the atmospheric CO_2 at its mean level and varying climate we find that climate change has a positive effect on yield on all crops in the NP and SE regions (excepting a Negative for

winter wheat in the SE), while it has negative effect on yield of all crops in the SP, CB, and D regions and a Positive effect for winter wheat in SP, corn in CB, cotton in D). We find mixed results in other remaining regions. For yield variability, the climate change increases the standard deviation of crop yields in D, MT, and SE (Decrease for cotton in D and MT, and corn in SE). We find mixed results in other remaining regions.

Under the situation that all climate and CO_2 variables are changed simultaneously, the effect of CO_2 fertilization generally outweighs the effect of climate change on mean crop yields in NP, LS, CB, SE, AP, and PA. On the other hand, yields of corn and sorghum will be decreased in SP and D. Moreover, in 2050, yield variability of all crops are projected to reduce in all regions, except sorghum and cotton in NP, sorghum and soybeans in SP and D, soybeans in LS, sorghum in CB and MT.

Implications of the Change in Crop Yields on Market Outcomes and Welfare Distribution

After incorporating our projected percentage changes of mean crop yields in the previous section into the ASM, market outcomes (including crop prices and their planted acreage) and the welfare distribution across regions are reported in table 6 and 7, respectively. Our first finding is that prices of all crops tend to decrease in 2050 compared to the base scenario, where there is no change in climate and atmospheric CO_2 as shown in table 6. This finding is consistent with results in the previous section, which reveals that yields of all crops are projected to increase in almost all US regions and this is possibly greater than the increase in the demand for crops. Next finding is that planted acreage of all crops in NP, except winter wheat, is projected to increase with the highest percentage change in corn and soybeans, respectively. This result is consistent to what is shown in scenario 3 of table 5 that yields of almost all crops increase the most in NP. On the other hand, planted acreage of all crops in SP, LS, D, SE, and MT is simulated to decrease

Table 5. Average percentage change of mean yields and their standard deviation in 2050

Region	% Change in mean yields					% Change in standard deviation of yields				
	Corn	Sorghum	Soybeans	Cotton	Wheat	Corn	Sorghum	Soybeans	Cotton	Wheat
Scenario 1: Change in CO_2 but no climate change										
NP	5.61	1.63	9.37	84.65	12.83	-67.80	-19.83	-32.76	-38.47	-42.57
SP	7.23	3.80	11.89	77.49	12.03	-67.62	-19.40	-32.20	-39.98	-43.44
LS	6.33		10.67		11.90	-67.70		-32.49		-43.54
CB	5.76	2.47	9.79	83.23	12.20	-62.88	-19.75	-27.21	-39.17	-43.27
D	7.56	4.63	13.14	76.68	11.09	-67.59	-19.24	-31.91	-40.14	-44.41
NE	7.07	1.78	13.17		11.41	-67.69	-18.34	-31.57		-44.20
SE	8.37	5.86	14.37	71.97	10.57	-67.51	-19.01	-31.62	-40.82	-44.93
AP	7.78	4.51	13.48	74.19	10.85	-67.55	-19.27	-31.82	-40.59	-44.70
PA	8.75				10.04	-67.47				-45.62
MT	7.09	2.89		52.79	10.89	-67.64	-19.14		-31.49	-44.42
Scenario 2: Climate change but no change in CO_2										
NP	13.08	39.91	10.06	13.82	1.58	-12.77	1723.52	34.15	92.42	-11.29
SP	-24.42	-10.28	-8.07	-1.09	21.72	-8.17	511.16	365.44	-22.30	-37.63
LS	-0.72		-4.56		8.60	75.60		71.47		-12.05
CB	0.57	-0.89	-0.15	-4.68	-2.72	-0.89	59.01	-22.51	-21.15	26.91
D	-18.05	-11.82	-17.30	4.02	-6.85	6.51	502.85	201.37	-23.44	5.85
NE	0.23	-15.35	5.05		-6.30	-17.69	4.86	-14.25		-1.48
SE	3.19	0.57	2.32	1.31	-6.71	-0.14	10.06	3.40	18.88	35.32
AP	3.49	-1.24	2.61	0.72	-4.86	-9.76	-3.98	-6.13	11.73	20.05
PA	1.59				-0.78	17.57				36.93
MT	-0.84	-21.38		24.96	-3.72	25.50	104.73		-33.82	65.37
Scenario 3: All changes										
NP	22.28	47.21	25.79	96.23	12.33	-71.68	1375.66	-8.30	14.86	-51.20
SP	-18.32	-5.52	4.93	70.64	34.55	-70.19	394.50	218.11	-53.97	-65.70
LS	7.24		8.88		20.01	-43.00		17.17		-51.67
CB	8.16	4.15	12.76	65.27	7.54	-63.03	28.46	-43.10	-53.19	-30.22
D	-11.43	-7.14	-5.52	79.34	2.91	-65.42	387.72	106.01	-54.67	-41.87
NE	8.36	-11.33	19.93		3.51	-73.32	-13.74	-41.19		-45.92
SE	11.57	6.02	16.97	74.50	3.01	-67.58	-10.98	-29.29	-29.63	-25.70
AP	11.81	3.94	17.14	74.11	5.15	-70.71	-22.43	-35.84	-33.77	-34.03
PA	9.85				9.71	-61.82				-24.71
MT	7.17	-17.33		86.37	6.36	-59.26	69.39		-55.22	-9.10

Note: 1) NP –North Plains- (KS, NE, ND, SD); SP –South Plains- (OK, TX); LS –Lake States-(MI, MN, WI); CB –Corn Belt-(IL, IN,IA, MO); D –Delta-(AR, LA, MS); NE –Northeast-(CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT); SE –Southeast- (AL, FL, GA, SC); AP –Appalachia- (KY, NC, TN, WV); PA –Pacific- (CA, OR, WA); MT –Mountain-(AZ, CO, ID, MT, NV, NM, UT, WY)

2) Numbers in table are averaged from 4 GCMs; GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3.

(increase for cotton in SP and MT, and corn in D and SE). Mixed results are found in remaining regions. Percentage of planted acreage of corn, sorghum, soybeans, cotton, and winter wheat is projected to increase the most in AP, CB, AP, MT, and PA, respective. Summing up across US regions, only planted acreage of soybeans is projected to increase in 2050.

Our last finding is related to the regional welfare distribution as shown in table 7. In all regions, consumer surplus (CS) is projected to increase slightly due to the CO_2 fertilization and climate change, while producer surplus (PS) changes are heterogeneous across US regions. Producer surplus in SP, D, and PA tend to increase, while it is projected to decrease in remaining regions. In total, it decreases about $ 4.72 billion. Summing up PS and CS, we find that total welfare is projected to drop only in NP and CB. Overall the total US welfare is increased about $ 2.27 billion compared to the base scenario.

Table 6. Average crop acreage and price change with/without change in climate and CO$_2$

Region	Crop acreage without change in climate and CO$_2$ (million acres)				
	Corn	Sorghum	Soybeans	Cotton	Wheat W
North Plains	12.054	4.906	9.095	0.000	4.123
South Plains	0.710	3.764	2.046	1.819	0.007
Lake States	7.043	0.000	7.543	0.000	0.359
Corn Belt	25.990	3.325	25.712	1.611	1.897
Delta States	0.426	0.433	5.794	2.241	0.000
Northeast	0.662	0.010	0.798	0.000	0.000
Southeast	0.850	0.222	1.934	0.470	0.000
Appalachia	1.287	0.613	2.517	7.838	0.000
Pacific	0.298	0.230	0.000	0.102	0.113
Mountains	0.633	0.579	0.000	0.123	2.907
Total	49.953	14.081	55.439	14.204	9.406

Region	Percentage change in acreage with change in climate and CO$_2$				
North Plains	9.59	2.20	14.01	—	-7.16
South Plains	-13.76	-0.52	-37.43	16.42	-62.15
Lake States	-19.25	—	-19.53	—	-53.27
Corn Belt	-7.98	29.17	-3.37	151.31	-45.82
Delta States	10.82	-52.47	-2.79	-13.40	—
Northeast	3.46	-15.84	1.83	—	—
Southeast	3.77	-77.40	-11.62	-64.58	—
Appalachia	169.51	-82.15	168.26	-96.15	—
Pacific	-14.29	-96.03	—	106.47	23.14
Mountains	-36.92	-47.32	—	533.08	-15.24
Total	-0.73	-2.42	3.66	-32.65	-18.87

Scenario	Major crop prices				
	Corn (US\$/bu)	Sorghum (US\$/bu)	Soybeans (US\$/bu)	Cotton (US\$/bale)	Wheat W (US\$/bu)
Without change in climate and CO$_2$	2.61	7.95	9.93	260.31	4.56
With change in climate and CO$_2$	2.42 (-7.16)	7.22 (-9.19)	9.34 (-5.89)	217.88 (-16.30)	3.82 (-16.15)

Note: 1) Numbers in parentheses represent the percentage change.
2) "—" means no data available.
3) Numbers in table are averaged from 4 GCMs; GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3.

Table 7. Impact of change in crop yields due to change in climate and CO_2 on regional welfare in US\$ Billion

Region	Without change in climate and CO_2			With change in climate and CO_2		
	CS	PS	Total Welfare	CS	PS	Total Welfare
North Plains	41.47	7.78	49.25	41.62	6.12	47.74
				(0.38)	(-21.38)	(-3.06)
South Plains	157.86	3.61	161.47	158.46	3.75	162.20
				(0.38)	(3.82)	(0.46)
Lake States	139.82	4.82	144.65	140.35	4.30	144.65
				(0.38)	(-10.82)	(0.01)
Corn Belt	273.08	14.68	287.76	274.11	12.39	286.50
				(0.38)	(-15.62)	(-0.44)
Delta States	73.11	1.92	75.03	73.39	2.03	75.42
				(0.38)	(5.94)	(0.52)
Northeast	424.38	0.94	425.33	425.99	0.86	426.85
				(0.38)	(-8.70)	(0.36)
Southeast	176.68	1.16	177.85	177.35	1.12	178.47
				(0.38)	(-3.90)	(0.35)
Appalachia	176.74	1.79	178.52	177.41	1.47	178.87
				(0.38)	(-17.93)	(0.20)
Pacific	275.66	5.42	281.08	276.71	5.63	282.34
				(0.38)	(3.86)	(0.45)
Mountains	104.75	4.08	108.83	105.15	3.83	108.98
				(0.38)	(-6.19)	(0.13)
Total	1843.55	46.21	1889.76	1850.54	41.49	1892.03
				(0.38)	(-10.21)	(0.12)

Note: 1) Numbers in parentheses represent the percentage change. "CS" and "PS" are defined as

consumer's surplus and producer's surplus, respectively. Total welfare is the

summation of the consumer's and producer's surplus.

2) Numbers in table are averaged from 4 GCMs; GFDL-CM 2.0, GFDL-CM 2.1, MRI-

CGCM 2.3.2a, and CNRM-CM3.

Conclusions

This study estimates effects of climate variables, crop production technology, and atmospheric CO_2 on yields of five major crops including corn, sorghum, soybeans, winter wheat and cotton, in the US using both historical data and the unique dataset from the FACE experiments. We also investigate their impacts on future crop yields and their variability. Finally, we explore market outcomes and welfare implications of economic units across US regions.

We find that that yields of C-3 crops, soybeans, cotton, and wheat, positively respond to the elevated CO_2, while yields of C-4 crops, corn and sorghum do not. However, we find C-4 crops indirectly benefit from elevated CO_2 in times and places of drought stress. The effect of crop technological progress on mean yields is non-linear with inverted-U shape in all crops, except cotton. Our study also reveals that ignoring the atmospheric CO_2 in econometric model of crop yield studies is likely to overestimate the effect of crop production technology on crop yields.

For climate change impact, the average climate conditions and their variability are found to contribute in a statistically significant way to both average crop yields and their variability. If all climate and CO_2 variables are changed simultaneously in the future, the effect of CO_2 fertilization generally outweighs the effect of climate change on mean crop yields in many regions.

In terms of market outcomes and welfare distribution, prices of all crops tend to decrease in 2050. Planted acreage of all crops in NP, except winter wheat, is projected to increase, while it tends to decrease in SP, LS, D, SE, and MT for almost all crops. In all regions, consumer surplus (CS) is projected to increase, while producer surplus (PS) are heterogeneous across US regions, but in total it decreases about $ 4.72 billion. Overall the total US welfare is increased about $ 2.27 billion compared to the base scenario.

Several clear policy implications arise:

- Policy makers and risk modelers in crop insurance companies should consider the non stationary of crop yield distribution when developing their probabilistic models where climate plays a significant role.

- Policy makers dealing with agricultural research planning should play attention to the increase at decreasing rate of crop production technology by for example allocating research funding to improve productivity of these crops. Increasing the efficiency of funding spent on research projects should also be considered. Moreover, returns to agricultural research should be reevaluated by taking into account the effect of the CO_2 fertilization to make sure that the estimated returns will not be exaggerate their real values.

- Similar to Long et al. (2006), most models used to predict future crop yields should be aware of using the assumption of CO_2 fertilization from chamber studies since it may overestimate the real effect of CO_2 fertilization on crop yields.

- Farm programs and disaster relief registration should be designed to assist producers in regions where their welfare losses are founded.

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[1] It is known that carbon dioxide (CO_2) concentration directly affects plant photosynthesis and water use, thereby potentially affecting the growth and yield of crops.

[2] In the FACE experiments, air enriched with CO_2 is blown into the rings where crops are grown in the real field (not in the chamber). Then, a computer-control system uses the wind speed and CO_2 concentration information to adjust the CO_2 flow rates to maintain the desired CO_2 concentration. Finally, crop yield in the elevated CO_2 rings are compared to that in the control rings with non-elevated CO_2 (ambient) environment. Details of the FACE experiments are provided in Long et al. (2006).

[3] The El Niño–Southern Oscillation (ENSO), which refers to fluctuations in both sea-surface temperatures (SSTs) in the eastern equatorial Pacific and in sea-level pressures in the southern Pacific (Southern Oscillation Index, SOI), is one of the most important controlling factors in global interannual climate variability (Hastenrath, 1995; Phillips et al., 1999).

[4] It is equal to 1 if the data collected come from the FACE experiments, and equal to 0 if data come from the observational data.

[5] Because of the availability of the FACE experimental data, this study cannot separately run crop yield estimation classified by dry land and irrigated land.

[6] The log-likelihood function of equation (1) are $lnL = -\frac{1}{2}\left[n * \ln(2\pi) + \sum_{i=1}^{n} ln(h(X_i, \propto)^2) + \sum_{i=1}^{n} \frac{(y_i - f(X_i, \beta))^2}{h(X_i, \alpha)^2}\right]$ under the assumption that $y_i \sim N(f(X_i, \beta), h(X_i, \alpha)^2)$ and $\varepsilon_i \sim N(0, 1)$.

[7] The first two models are developed by the Geophysical Fluid Dynamics Laboratory (GFDL), USA. The third model is developed by the Meteorological Research Institute, Japan. The last model is developed by National Centre of Meteorological Research, France.

[8] ASM foreign regions include the European Economic Community, North Central Europe, Southwest Europe, Eastern Europe, Adriatic, Eastern Mediterranean, Former Soviet Union, North Africa, East Africa, West Africa, South Africa, Red Sea, Iran, India, Taiwan, Japan, South Korea, North Korea, China, Bangladesh, Indonesia, Myanmar, Pakistan, Philippines, Thailand, Vietnam, West Asia, Southeast Asia, Australia, Caribbean, Eastern Mexico, Eastern South America, Western South America, Argentina, Brazil, Canada, and Other.

[9] http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/index.asp

[10] www.esrl.noaa.gov/psd//data/timeseries/. The PDSI is a standardized measure of surface moisture conditions, ranging from about -10 to +10. It has become the semi-official drought index with negative values denoting dry condition and positive values indicating wet condition

[11] www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv=GSOD&countryabbv=US&georegion abbv=&resolution=40 for the time series of daily precipitation and temperature and www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml for ENSO information. We thank Dr. Chi-Chung Chen, professor in the Department of Applied Economics, National Chung-Hsing University, Taichung, Taiwan for his useful suggestion related to the selection of ENSO phases.

[12] We thank Dr.Bruce A. Kimball, from USDA Agricultural Research Service (USDA-ARS) in providing us the FACE experimental dataset of cotton, sorghum, and wheat. We also thank Dr.Donald R. Ort, Dr.Lisa Ainsworth, and Dr.Andrew Leakey from SOYFACE, University of Illinois at Urbana Champaign and USDA-ARS.

[13] For robustness, the observational data were tested for unit roots, although after we pool observational and the FACE experimental data together, our data does not fully have a panel data

structure. Using Fisher-type test (Choi 2001) and Levin-Lin-Chu (LLC) (Levin, Lin, and Chu 2002) test, all series except CO_2, which is I(1), are stationary in the level, I(0). However, after we apply the panel unit root tests to the residual of the model, the residual is stationary in the level, I(0), implying that our model might not be encountered with the problem of spurious regression (Granger 1981).

[14] If a regression equation is correctly specified, we should be able to find no additional independent variables that are significant except by chance. One kind of specification error is called a link error, implying that dependent variable needs a transformation or "link" function to properly relate to the independent variables (Tukey 1949; Pregibon 1980).

[15] Using the MLE approach with the same specification and likelihood function as shown in endnote 6, its estimated coefficients close to coefficients using the three-step FGLS estimation. Moreover, we perform our robustness check for corn due to small observations from the FACE experimental data by considering only the Central region to decrease the correlation coefficients of time trend and the atmospheric CO_2. Our estimated coefficients of the atmospheric CO_2 with and without scoping the region are very similar.