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Abstract

We investigate climate change impacts on productivity and production risk on U. S. Pacific Northwest winter wheat farms. Using farm-level data from the Census of Agriculture, we use a partial-moment-based approach to estimate climate and irrigation influences on winter wheat yield and farm net return distributions. Mean precipitation, growing degree-days, and freezing degree-days are shown to have highly distinct seasonal effects on the first three moments of the farm-level yield and net return distributions. Irrigation substantially increases the certainty equivalent of irrigated farms by shifting the winter wheat yield distribution outwards, and by increasing mean net returns but also decreasing the skewness of the net return distribution and thus reducing downside risk. By the mid-21st century, climate-change projections from 20 global climate models downscaled to the study region reveal a range of possible positive and negative effects on the winter wheat yield and net return distributions.

***Key Words*:** Climate Change, Winter Wheat, Production Risk, Partial Moments

***JEL Classification*:** C5, D8, Q1

A variety of conclusions have recently been drawn about climate change's impacts on U.S. crop yields, net returns, and farmland values (Adams 1989; Mendelson and Rosenberg 1994; Deschenes and Greenstone 2007, 2012; Lobell, Cahill, and Field 2007; Schlenker and Roberts 2009; Ortiz-Bobea and Just 2013; Burke and Emerick 2016). Yet little attention has been paid to climate change's impacts on weather-related production risk (Tack, Harri and Coble 2012; Huang, Wang and Wang 2015). For this purpose we use a partial-moment-based approach (Antle 2010) to estimate climate's effects on the mean, variance, and asymmetry or skewness of winter wheat yield and farm net return distributions in the U. S. Pacific Northwest (PNW).[1]

Moment-based approaches have been used in a variety of production-risk studies, including mean-variance (Cooper 2010; Schoengold, Ding and Headlee 2015), mean-variance-skewness (Antle 1983; Antle and Goodger 1984; Di Falco and Chavas 2006; Huang, Wang and Wang 2015), mean-variance-skewness-kurtosis (Koundouri, Nauges and Tzouvelekas 2006), and partial moments (Antle 2010). Most early studies of agricultural production risk examined production risk in an expected utility framework (e.g., Anderson, Dillon and Hardaker 1977). Just and Pope (1978) observed that the conventional method of estimating the production function in logarithmic form imposed a restriction on the relationship between the output mean and variance and proposed a heteroscedastic additive error model to relax this restriction. Antle (1983) showed Just and Pope's proposed functional form imposed restrictions on the output distribution's second and higher-order moments and domenstrated how to estimate a system of moment functions without cross-moment restrictions. In terms of modelling behavior, the

[1] Describing changes in a distribution's shape in terms of asymmetry is complicated by whether the distribution is negatively or positively skewed. Throughout this paper we equate skewness with the algebraic value of the third central moment. Thus, an increase in skewness (value of the third central moment) means a reduction in asymmetry if the distribution is negatively skewed, or an increase in asymmetry if the distribution is positively skewed.

expected utility framework is known to impose restrictions found systematically violated in experimental studies (Kahneman and Tversky 1979; Machina 1989; Conlisk 1996; Starmer 2000), in part due to the way that decision makers respond differently to downside and upside deviations from an expected or reference value. To represent this behavior, downside risk has been used in the literature (Antle 1987) and quantified using the third central moment. Alternatively, the risk-value model was developed as a generalization of expected utility that uses partial moments to characterize decision makers' differential responses to downside and upside deviations (Jia, Dyer and Butler 2001; Delquie and Cillo 2006). Antle (2010) demonstrated that partial moments provide a more flexible representation of asymmetric distributions than do full moments, and showed how partial moment functions can be estimated and used to analyze production risk behavior with a risk-value model.

We contribute to this literature in four ways. First, we show how the full moment and partial moment models can be used to characterize the effects of climate on production risk. Second, we use farm-level panel data that can detect the farm-level, intra-seasonal interactions between management and yield and net return outcomes. Using farm-level data avoids the biases in aggregated data caused by averaging out farm-level variation (Fezzi and Bateman 2015), and is thus more appropriate for analysis of production risk. Third, we utilize seasonal data (spanning the winter wheat growing season of fall to early summer) to represent climate impacts, rather than annual average or growing-season average measures of climate that may mask the within-growing-season effects on crop growth that have been demonstrated in agronomic research. Lastly, we use both moment-based (expected utility and risk-value) decision models as well as visualization of outcome distributions to interpret impacts of climate change. Visualization of

changes in outcome distributions provides a way to interpret climate impacts without imposing assumptions on farmers' risk attitudes.

Our results show that climate measures, including mean total precipitation, growing degree-days and freezing degree-days, have differing effects at different stages of the growing season on the mean and high-order moments of winter wheat yield and farm net return distributions. These within-growing-season effects generally differ on the yield and net return distributions, as predicted by economic theory, because net returns embody economic responses that are not reflected in crop yields. Irrigation is shown to substantially boost irrigated farms' income certainty equivalents by shifting winter wheat yield distributions outward and boosting mean net returns but also by reducing net return skewness and hence downside risk. Climate change projections – particularly mean precipitation and temperature –from twenty global climate models downscaled to the study region suggest a range of positive and negative effects on the winter wheat yield and farm net return distributions by the mid-21st century.

Conceptual Framework

We define a climate as a stochastic process generating a weather distribution at a specified place and period, so that weather is a particular realization of this underlying distribution. Weather, that is, represents a short-term atmospheric phenomenon including variables as temperature, precipitation and their interaction. We use fall temperature as an example to evaluate the asymmetric impacts of climate change and adaptation on farm-level output distribution. In Figure 1, the right horizontal axis represents average temperature in fall, w, generated from a climate, $\chi(w|\theta)$, where θ is a vector of climate parameters that are expressed as the fall temperature distribution. A projected warmer climate due to climate change will shift the fall temperature distribution to the right, increase the frequency of medium and high temperatures,

and reduce the low-temperature frequency. Changes in low, medium, and high temperatures could have different impacts on crop production; a climate change impact assessment needs to take into account these differing temperature impacts.

In the example of Figure 1, farmers use a single-output production technology, $y = f(x, w, e)$, where y is output, x represents management, and e is other biophysical conditions. In Figure 1 the positive vertical axis represents output per unit, its upper bound $\bar{y}$ being maximum output per unit, the genetically determined production frontier that we assume here to be fixed. Since the realization of fall average temperature is uncertain at the beginning of the growing season, farmers face an *ex-ante* output distribution conditional on climate as well as management and biophysical conditions. The left horizontal axis expresses the probability density of the *ex-ante* output distribution, denoted by $\phi(y|x, \theta, e)$. This output distribution can be represented by its mean and high-order moments, which together describe its location and shape.

Suppose first that farmers make no effort to adapt to climate changes. What would climate's output-distribution impacts look like? In Figure 1, a projected warmer climate shifts the output distribution from $\phi(y|x, \theta, e)$ to $\phi(y|x, \theta', e)$ by way of its effects on fall average temperature, and as represented in the parameter shift from θ to θ'. In this example, a warmer climate negatively affects the output distribution by shifting it to the left, reducing the mean and shifting the higher-order moments. However, note that a warmer climate could have differing effects on yield and net returns at different crop growth stages, as we find in our analysis of winter wheat presented below.

Farmers however can reduce climate change losses with the appropriate adaptation. They can adjust input use and management practices in the short term, for example by adjusting planting date, irrigation water use, seed variety, and crop insurance coverage. They can additionally alter

their long-term investments, for example by changing farmland use or irrigation technology. As shown in Figure 1, these adaptation strategies can shift the management level from x to x', pushing the production function rightward from $f(x, w, e)$ to $f(x', w, e)$ and shifting the output distribution to the right from $\phi(y|x, e, \theta')$ to $\phi(y|x', e, \theta')$, so that this output distribution assumes a higher mean and/or lower variance and skewness.

Notice that a warmer climate in Figure 1 has an asymmetric effect on the output distribution's lower and upper tails. Specifically, rising temperature in the absence of adaptation shifts the density from the upper to the lower tail. Probability mass becomes concentrated at lower outputs and the output distribution becomes right-skewed, with its greater risk of low yields or a crop failure. Symmetric measures of production risk, like the variance, cannot represent such asymmetric effects. We need a flexible model of asymmetric distributions to characterize the differential effects of climate change on the lower and upper tails of the output distribution.

Economic Model

In this section we use the expected utility model and a risk-value model to show how climate change can affect the welfare of a risk-averse farmer, taking into account the farmer's decisions on input use. We assume farmers can optimally adjust input use (including variable input and capital service) to adapt to climate change. We show, with both full and partial probability moments, how farmer welfare can be influenced by climate change's asymmetric effects on the output distribution.

Model Setup

We consider a farm in which production is a single-period process on a single output. Along the process timeline, input use is selected, weather occurs, and output is realized. The production function is defined as

(1) $y \equiv f(x, w, e)$,

where y is output per unit, x is a vector of input uses, w is a vector of weather variables, e is a vector of soil conditions and farmer characteristics. We assume that: (i) the production function is strictly concave and twice differentiable in input use; (ii) weather w follows distribution $w \sim \chi(w|\theta)$, where θ is a vector of climate parameters on an individual farm; and (iii) farmers are risk averse as discussed below.

We define partial moments of the output distribution in absolute terms. In particular, the lower jth partial moment is defined as $\eta_j \equiv \eta_j(x, \theta, e, a) \equiv \int_0^a |y - a|^j \phi(y|x, \theta, e)\Phi(x, \theta, e, a)^{-1} dy$, $j \in \mathbb{N}, j \geq 2$ and the upper jth partial moment as $\varphi_j \equiv \varphi_j(x, \theta, e, a) \equiv \int_a^{\bar{y}} |y - a|^j \phi(y|x, \theta, e)[1 - \Phi(x, \theta, e, a)]^{-1} dy$, where a is a reference level, $\bar{y}$ a genetic yield potential, $\phi(y|x, \theta, e)$ the output density function, $\Phi(x, \theta, e, a)$ the probability that output is below the reference level, and $\Phi(x, \theta, e, a) = \int_0^a \phi(y|x, \theta, e) dy$. In the present study expected output is employed as the reference level, so that the central moments can be expressed as functions of the partial moments by way of

(2) $\mu_j \equiv \mu_j(x, \theta, e) = (-1)^j \eta_j \Phi(x, \theta, e, a) + \varphi_j[1 - \Phi(x, \theta, e, a)]$,

where μ_j is the jth central moment of the output distribution.

We assume expected output price is independent of output and define net return as $\pi \equiv y - vx$, where v is a vector of input prices normalized by the expected output price. The goal of a risk-averse farmer is to maximize her value function

(3) $\max_x V(\pi; x, \theta, e, v)$.

The value function's functional form depends on the manner of the farmer's response to risk. In the next two subsections we present two decision models, based alternatively on expected utility and risk-value, to illustrate how climate change would affect producer welfare.

Expected Utility Model

In the expected utility approach, individual farmers are assumed to have a concave utility function depending on uncertain net return. The value function is specified as $V(\pi) = E[U(\pi)]$, where $E[\cdot]$ is an expectation operator. The expected utility function instead can be approximated with the first three central moments of the net return distribution, that is by $U(\mu_1 - vx, \mu_2, \mu_3)$, where $\mu_1$is mean output. To simplify, we treat *x* and θ as scalars. Define $U_j \equiv \frac{\partial^j U}{\partial \pi^j}$, so that the first-order condition of (3) is

(4) $\partial\mu_1/\partial x - v = -\frac{1}{2}\frac{U_2}{U_1}\partial\mu_2/\partial x - \frac{1}{6}\frac{U_3}{U_1}\partial\mu_3/\partial x.$

We can rewrite the first-order condition (4) in the elasticity form

(4') $\mu_1^* - vx/\mu_1 = R_2 s_2 \mu_2^* - R_3 s_3 \mu_3^*$,

where $\mu_j^* \equiv \frac{\partial ln\mu_j}{\partial lnx}$, $s_j \equiv \frac{\mu_j}{\mu_1(\mu_1 - vx)^{j-1}}$, and $R_j \equiv (-1)^{j-1}\frac{U_j}{U_1}(\mu_1 - vx)^{j-1}$, $j = 2,3$.

Expression R_2 is approximately one-half the Arrow-Pratt relative risk aversion coefficient, and R_3 is approximately one-sixth of the relative downside risk aversion coefficient (Antle 1987). They collectively represent the farmer's risk attitude, reflecting her willingness to trade off a change in expected net return for a change in symmetric production risk (represented by the variance) and in downside risk (represented by the third moment), interpreted now as parameters.

The optimal solution of equation (3) takes the form,

(5) $x^o = x^o(v, e, \theta)$,

$y^o = y^o(v, e, \theta)$.

Note that the expected utility function can be written in terms of the certainty equivalent (CE), namely that satisfying $E[U(\pi)] \equiv U(CE) \equiv U(E[\pi] - R) = U(\mu_1 - vx - R)$, where R is the risk premium. The first-order condition of (3) is

(6) $\partial\mu_1/\partial x - v = \partial R/\partial x$.

Combining equations (4) and (6), we derive x's marginal effect on the risk premium by way of

(7) $\frac{\partial R^o}{\partial x} = -\frac{1}{2}\frac{U_2}{U_1}\frac{\partial\mu_2}{\partial x} - \frac{1}{6}\frac{U_3}{U_1}\frac{\partial\mu_3}{\partial x}$.

The right-hand sides of equations (4') and (7) can be interpreted as the marginal risk effects of the relevant input use, which in turn can be decomposed into variance and skewness effects.

Note that (7) defines the *reduced-form* risk premium, which assumes input use is adjusted optimally according to equation (5) conditional on the climate variables. We emphasize here that input use, expected output, and risk premium, as shown in equations (4') and (7), depend on climate parameters θ rather than on weather realizations, so our empirical estimates in the next section will be in terms of climate rather than the more derivative weather variables.

The risk premium can be used to analyze climate change's production risk effects. Considering R_2 and R_3 as parameters and using (7), the effect of a climate parameter on a farmer's risk premium is

(8) $$\frac{\partial R^o}{\partial\theta} = -\frac{1}{2}\frac{U_2}{U_1}\left[\frac{\partial\mu_2}{\partial\theta} + \frac{\partial\mu_2}{\partial x}\frac{\partial x}{\partial\theta}\right] - \frac{1}{6}\frac{U_3}{U_1}\left[\frac{\partial\mu_3}{\partial\theta} + \frac{\partial\mu_3}{\partial x}\frac{\partial x}{\partial\theta}\right]$$

$$= \frac{\partial R^o}{\partial x}\frac{\partial x}{\partial\theta} - \left[\frac{1}{2}\frac{U_2}{U_1}\frac{\partial\mu_2}{\partial\theta} + \frac{1}{6}\frac{U_3}{U_1}\frac{\partial\mu_3}{\partial\theta}\right].$$

Equation (8) shows that climate change influences the risk premium by way of its direct effects on the output distribution's high-order moments as well as by way of its indirect effects, namely on optimal input decisions (5) and the corresponding high-order effects of those decisions.

Risk-Value Model

In the risk-value model, individual farmers' value functions depend on a reference value interpreted here as expected net return, and on the negative and positive deviations from this reference value, a negative value assigned to deviations below and a positive value to those above this expected net return. Thus, the risk-value model provides a natural way to relate farmer decisions to the outcome distribution's partial moments, which represent these asymmetric effects.

To illustrate, let the risk-value model's value function depend on the second-order partial moments of the net return distribution; that is, $V(\pi) = U(\mu_1 - vx, \eta_2, \varphi_2)$. Define $U_{2\eta} = \frac{\partial U}{\partial \eta_2}$, $U_{2\varphi} = \frac{\partial U}{\partial \varphi_2}$, allowing us to express the first-order condition for maximizing value function (3) as

(9) $$\partial\mu_1/\partial x - v \;=\; -\frac{U_{2\eta}}{U_1}\partial\eta_2/\partial x - \frac{U_{2\varphi}}{U_1}\partial\varphi_2/\partial x.$$

We then can rewrite first-order condition (9) in the elasticity form

(9') $$\mu_1^* - vx/\mu_1 \;=\; s_2\left(R_{2\eta}\eta_2^* - R_{2\varphi}\,\varphi_2^*\right),$$

where $\eta_2^* \equiv \frac{\partial ln\eta_2}{\partial lnx}$, $\varphi_2^* \equiv \frac{\partial ln\varphi_2}{\partial lnx}$, $R_{2\eta} \equiv -\frac{U_{2\eta}}{U_1}\frac{\eta_2}{\mu_2}(\mu_1 - vx)$, and $R_{2\varphi} \equiv \frac{U_{2\varphi}}{U_1}\frac{\varphi_2}{\mu_2}(\mu_1 - vx)$.

Terms $R_{2\eta}$ and $R_{2\varphi}$ represent the farmer's risk attitude in the respectively negative and positive deviations from the expectation and can be interpreted as representing the psychological responses described as the disappointment and the elation in a risk-value model.

The optimal solution of equation (9) takes the form

(10) $$x^{oo} = x^{oo}(v, e, \theta),$$

$$y^{oo} = y^{oo}(v, e, \theta).$$

As in the expected utility model, we can derive *x*'s marginal effect on the risk premium by combining equations (6) and (9):

(11) $$\frac{\partial R^{oo}}{\partial x} = -\frac{U_{2\eta}}{U_1}\frac{\partial \eta_2}{\partial x} - \frac{U_{2\varphi}}{U_1}\frac{\partial \varphi_2}{\partial x},$$

then obtaining climate change's risk premium impact through

(12) $$\frac{\partial R^{oo}}{\partial \theta} = -\frac{U_{2\eta}}{U_1}\left[\frac{\partial \eta_2}{\partial \theta} + \frac{\partial \eta_2}{\partial x}\frac{\partial x}{\partial \theta}\right] - \frac{U_{2\varphi}}{U_1}\left[\frac{\partial \varphi_2}{\partial \theta} + \frac{\partial \varphi_2}{\partial x}\frac{\partial x}{\partial \theta}\right]$$

$$= \frac{\partial R^{oo}}{\partial x}\frac{\partial x}{\partial \theta} - \left[\frac{U_{2\eta}}{U_1}\frac{\partial \eta_2}{\partial \theta} + \frac{U_{2\varphi}}{U_1}\frac{\partial \varphi_2}{\partial \theta}\right].$$

Note that if input-use effects on the output distribution's full moments are symmetric, that is $\mu_2^* = \eta_2^* = \varphi_2^*$, $\mu_3^* = 0$, we can write $R_2 = R_{2\eta} - R_{2\varphi}$. Optimal input use determined from (9') then has the same risk implications as do those determined from (4'), so the risk-value and expected-utility models are equivalent (Antle 2010). If on the other hand the full-moment effects are asymmetric, the expected-utility and risk-value approaches draw generally conflicting pictures of the output risk and thus welfare implications of both an exogenous climate change and any input-use adjustments.

Econometric Strategy

We need an econometric strategy for estimating a covariate's mean and high-order effects on an agricultural system. To find one, we specify partial moments useful for determining asymmetric influences on farm outcome distributions. Consider first the output function

(13) $$y_{it} = \mu_1(m_{it}, \beta_{it}) + \varepsilon_{it}$$

in which y_{it} is output at farm i in year t, m_{it} a vector of site and farm characteristics (including both time-varying and -invariant covariates), β_{it} a vector of climate variables, ε_{it} an

idiosyncratic error term. The high-order central moments of the corresponding output distribution are

(14) $\varepsilon_{it}^{j} = \mu_j(m_{it}, \beta_{it}) + v_{it}, \quad j = 2, 3$

and the partial-moment functions specified as

(15) $|\varepsilon_{it}|^j = \eta_j(m_{it}, \beta_{it}) + v_{nit}$ if $\varepsilon_{it} < 0$

$|\varepsilon_{it}|^j = \varphi_j(m_{it}, \beta_{it}) + v_{pit}$ if $\varepsilon_{it} > 0$.

As Figure 1 illustrates we need a model flexible enough to quantify climate's and input use's asymmetric effects on this output distribution. Full moments, including those about zero and about the mean, as well as partial moments can be used to do so. But full moments cannot capture differential effects on the lower and upper tails as flexibly as partial moments can. Negative and positive partial moments involve twice as many parameters as the corresponding full moment does, providing a flexibility in the choice of subsets of parameters to represent the response of the lower and upper tails of the distribution to changes in exogenous variables. Thus, partial moments are likely to provide a better representation of asymmetric output distribution changes than full moments do. This comes at the cost of additional parameters, a minor cost if the observations are adequate. For comparative purpose we will use equations (14) and (15) to develop both a central- and a partial-moment approach to both of expected utility and a risk-value model of climate and irrigation effects.

Mean-function specification is important to the properties of the equation (13) residuals and hence to the properties of the partial- and full-moment functions. Tack, Harri and Coble (2012) suggested avoiding this problem by approximating its density function with the second and higher-order moments about zero. However, there are several arguments against using such high-order moments. First, because misspecifying the mean contaminates the estimated distribution

whether or not high-order moments are biased. A good approximation to the mean function is important even if bias is absent. Second, because Taylor series models must be expanded about the point of approximation, they are valid only in the convergence radius, and zero is an unnatural point of approximation for yields or short-run net returns. Third, with output distributions bounded from below at zero, a risk-value model could never be expressed in terms of moments about zero.

Accordingly, to implement both full and partial moment estimation, we use a flexible functional form for the mean function, quadratic in such continuous variables as climate and irrigation and farmer socio-economic characteristics as well as soil conditions described below. [2] We use a linear model for third-central-moment functions, where the dependent variable is comprised of cubed residuals taking on positive and negative values. A constant-elasticity exponential form was specified for second-order full and absolute partial-moment functions, for which dependent variables are powers of positive absolute residuals. Like other studies in the climate change and agricultural literatures (Mendelsohn and Rosenberg 1994; Lobell, Cahill and Field, 2007; Schlenker and Roberts 2009; Olen, Wu and Langpap 2016), we rely on spatial and temporal variations in climate conditions to establish the relationship between historical climate and the mean and high-order moments of the output distribution by using pooled cross-sectional regressions.

Consistent estimates of the mean function in equation (13) generate the residuals that are used to consistently estimate the high-order central and partial moment functions in equations (14) and (15). The error terms in (14) and (15) are heteroscedastic and correlated across moments. To

[2] We also include interactions between irrigation and precipitation variables in estimating the mean and central and partial moment functions. To avoid multicollinearity, we exclude interactions among climate variables.

account for heteroscedasticity and the cross-equation correlations, we use the heteroscedastic-consistent seemingly unrelated regression approach to jointly estimate second- and third-order moment functions. As in Antle (2010), joint estimation of equation (15)'s lower and upper partial moment functions also allows testing for the distributional symmetry necessary for ascertaining the equality of the partial moment parameters.[3]

Although irrigation in the West is heavily subsidized and construction and operating costs rose substantially during the study period (Schlenker, Hanemann and Fisher 2005), selection bias for irrigation may be present. We control for such bias by including the distance from the given observation's zip-code center to the nearest river. Wheat and input prices are excluded because they vary little in Pacific Northwest in a given census year. State by year fixed-effects are instead included to capture crop and factor price effects.

Multiproduct Farms

We have so far simplified our discussion to a single crop in a single production period. But in the PNW region analyzed below, annual cropping systems in the higher rainfall areas typically involve a rotation of winter wheat, spring wheat, and summer crops over a three- or four-year period. Some crop farms also raise livestock. To generalize the single-product output distribution utilized thus far, we aggregate multiple outputs in value terms and then use farm-level net return to model climate's impact on multiproduct agricultural systems.[4] In this way, farmers make

[3] Econometric climate-change impact assessments exclude CO_2 effects (Adams 1989; Mendelson and Rosenberg 1994; Deschenes and Greenstone 2007; Lobell, Cahill and Field 2007; Schlenker and Roberts 2009; Ortiz-Bobea and Just 2013; Burke and Emerick 2016), and much uncertainty remains about the interactions between temperature, water, and nutrients. The present study focuses on climate-determined weather effects as abstracted from CO_2 effects.

[4] An alternative solution is to use a multi-output production function, which is limited by data availability (see the discussion in Antle and Capalbo 2001).

decisions about input use to maximize economic returns among multiple production activities. However, we need to bear in mind that this approach only allows adjustment within the type of system being used, e.g., cropping systems in the application below, not systematic adaptations such as changes in land use from cropland to pastureland and rangeland.

Data Sources and Summary Statistics

We use farm-level data from the 2002, 2007 and 2012 Census of Agriculture.5 Our economic variables include winter wheat yield, annual farm revenue and net return, irrigated winter wheat acreage shares and shares of farmland enrolled in the Conservation Reserve (CRP) and Wetland Reserve (WRP) Programs. Social variables include farm experience, land tenure, and off-farm employment. The study region is confined to the U.S. Pacific Northwest.

Panel A in Table 1 reports summary statistics for these census years. Farms with less than 50 cropland acres are regarded as non-commercial producers and excluded. The secular rise in winter wheat yield and in farm net return suggests the presence of year fixed-effects due to technology innovations. Not shown in Table 1 is that winter wheat yields are higher on irrigated than non-irrigated farms. The production share of large farms in our sample also was rising during this period, reflecting the ongoing consolidation of the grain farming industry.

We rely on the Gridded Soil Survey Geographic (gSSURGO) database to construct soil variables. The gSSURGO data are derived from the Soil Survey Geographic database, consisting of detailed soil geographic information in the National Cooperative Soil Survey. Zip-code level soil variables are generated by overlaying a zip code map onto the given gSSURGO polygon and

[5] A farm in the *Census* is any operation producing and selling at least $1,000 of product in a given census year.

taking acreage-weighted averages of the polygons in each zip-code area. Panel B of Table 1 summarizes the winter wheat soil variable statistics in the PNW.

Historical weather data are derived with Abatzoglou and Brown's (2012) Multiplicative Adaptive Constructed Analogs (MACA) method, which downscales such daily weather variables as precipitation and maximum and minimum temperature. MACA data provide daily 1979-2013 weather data with spatial resolution of 4-km for the entire coterminous United States. The MACA model and data are used here to develop daily precipitation and temperature measures for the farmland in each zip-code area. This is accomplished for each grid cell by overlaying a land use map on the MACA data, then taking the acreage-weighted average across that zip-code's farmland.

Daily precipitation and temperature data are used to calculate total precipitation, growing degree-days, and freezing degree-days for three crop growth stages: fall (September to November), winter (December to February), and spring (March to June). Growing degree-day and freezing degree-day variables are constructed as a step function of daily average temperature.[6] Seasonal growing and freezing degree-days variables are then calculated by summing the daily measures across each season. Precipitation and temperature normals (or climate) are constructed by taking the 22-year averages of seasonal total precipitation and growing and freezing degree-days. Extreme-high-temperature events are left out of this study for two reasons: (i) their spatial variation during the growing season is inadequate; and (ii) the 35℃

[6] Following Deschenes and Greenstone (2007), daily average temperature below 0℃ generates zero growing degree-day; a daily average temperature between 0℃ and 23℃ generates the number of growing degree-days above 0℃; a daily average temperature above 23℃ generates 23 growing degree-days. Similarly, a daily average temperature below 0℃ generates the number of freezing degree-days below 0℃ (in absolute values); a daily average temperature above 0℃ generates zero freezing degree-day.

threshold at which they damage winter wheat rarely occurs in the PNW. Panel C of Table 1 gives climate-variable summary statistics for winter wheat farms in the PNW.

Results and Discussion

We report marginal effects of climate and irrigation on the mean and high-order moments of winter wheat yield and farm net return distributioins in the elasticity form in Tables 2 and 3. Appendixes A1 and A2 report marginal effects of all covariates in the elasticity form. Lower third-partial-moments in Tables 2 and 3 are estimated in absolute terms, so that the elasticities show opposite effects on the third central moments of winter wheat yield and farm net return distributions.

The Mean Effects of Climate and Irrigation

Columns (1) in Tables 2 and 3 present elasticity estimates of mean winter wheat yield and farm net return functions. In Table 2, mean growing degree-days representing medium temperature has a negative yield effect in fall (-1.39) and a positive yield effect in spring (1.00), and the yield effect in winter is positive but statistically insignificant. By contrast, mean freezing degree-days representing extreme low temperature shows opposite mean effects: a positive yield effect in fall and a negative yield effect in winter and spring. This is intuitive because early emergence due to a warmer fall causes winter wheat susceptible to winterkill, while a warmer spring favors winter wheat growth. A warmer winter's effect on winter wheat yield is a combination of two contrary effects: a cold winter lowers the survival rate of winter wheat but kills wheat pests and diseases.

In Table 2, mean precipitation also shows distinct effects on winter wheat yield across seasons: a negative yield effect in fall and winter but a positive yield effect in spring, although the yield effect in fall and winter are statistically insignificant. This reflects the fact that a wetter

fall is bad for planting and seeding winter wheat; a wetter spring is beneficial for winter wheat growth, and a wetter winter's yield effect depends on temperature.

Table 3 shows that climate variables have different mean effects on farm net return compared to winter wheat yield. The seasonal effects of mean growing degree-days on farm net return are substantially larger than on winter wheat yield in terms of magnitude: a negative net return effect in fall (-2.66) and winter (-1.04), and a positive effect in spring (4.25). Mean precipitation also shows larger seasonal effects on farm net return than on winter wheat yield. Furthermore, mean freezing degree-days has shown opposite mean effects on farm net return and winter wheat yield: an increase in spring mean freezing degree-days has a negative yield effect but a positive net return effect.

Climate variables' differing effects on farm net return and winter wheat yield can be explained by two factors. First, wheat farms have more adaptive strategies to increase profitability than improving winter wheat yield, e.g., rotating winter wheat with spring wheat and other crops as well as raising livestock. These management practices can reduce negative effects or increase positive effects of climate change on farm net return. Second, climate's effect on farm net return embodies economic responses on crop price as well as crop yield. Crop price can mitigate climate change's yield effect on net return through a negative relationship between yield and crop price. [7]

[7] The prices of major field crops including wheat are determined by global markets, and thus wheat price in the PNW is fixed at the global level and less likely to be affected by climate change occurring within this region. However, summer crops and feed crops such as peas and hay are traded at the regional or local level, and thus their prices are more responsive to regional climate change and impose a larger impact on farm net return compared to wheat price.

The irrigation elasticity of the mean winter wheat yield in Table 3 is positive and statistically significant. In interpreting the irrigation effect, keep in mind that we estimate a reduced-form function for winter wheat production, so other input use is assumed to be optimally adjusted by equations (5) and (10) when irrigated winter wheat acreage increases. This implies that a rise in irrigated winter wheat acreage shifts the production function outwards by increasing input use like fertilizer. Irrigation also shows a positive effect on the mean farm net return, with a relatively larger effect (0.24) compared to the effect of irrigation on winter wheat yield (0.17). This may be because irrigated winter wheat farms can reduce fallow acreage or continuously grow crops in rotation. These positive mean yield and net return effects are consistent with positive price premiums associated with land values due to irrigation water use and irrigation water rights (Faux and Perry 1999; Buck, Auffhammer and Sunding 2014).

The High-order Moment Effects of Climate and Irrigation

Columns (2)-(7) in Tables 2 and 3 present the elasticity estimates of marginal effects on the high-order moments of winter wheat yield and farm net return distributions. The p-values are calculated for the symmetry test for the equality of the partial moment parameters. Symmetry restrictions are rejected for the second and third partial moments. This implies that input use and climate have asymmetric effects on the lower and upper tails of winter wheat yield and farm net return distributions. Furthermore, the R^2 statistics show that the partial moment functions fit the data better than the central moment functions.

In Table 2, climate variables show asymmetric effects on the winter wheat yield distribution. We use fall mean growing degree-days as an example. Mean growing degree-days in fall has a positive effect on the yield distribution's lower partial moments and a negative effect on the upper partial moments. An increase in fall mean growing degree-days expands the yield

distribution's lower tail and reduces the upper tail, resulting in a reduction in the yield distribution's skewness. By contrast, central moment parameters' estimates show an increase in the yield distribution's skewness due to a warmer fall. Mean precipitation and freezing degree-days also present differential effects on the yield distribution's lower and upper tails. These results suggest that partial moments are better at capturing asymmetric effects of climate change on the output distribution as Figure 1 illustrated.

Climate variables have distinct seasonal effects on the winter wheat yield distribution's high-order moments in Table 2. In contrast to fall mean growing degree-days, a rise in winter and spring mean growing degree-days reduces probability mass concentrated on the yield distribution' lower tail, expands the upper tail, and thus increases the distribution's skewness. Similarly, mean precipitation and freezing degree-days present different effects on the yield distribution across seasons.

Climate variables in general show different effects on the farm net return distribution's high-order moments as compared to the winter yield distribution in Tables 2 and 3. Again, we use fall mean growing degree-days as an example. Mean growing degree-days in fall increases the net return distribution's skewness but reduces the yield distribution's skewness. Moreover, the yield and net return distributions' skewness effects differ in size due to an increase in mean freezing degree-days, although the two outcome distributions both become less negatively skewed in fall, more negatively skewed in winter and more positively skewed in spring.

Irrigation also presents different high-order moment effects on the winter wheat yield and farm net return distributions in Tables 2 and 3. The two outcome distributions' variances are increasing in irrigation, but with a substaintial larger increase on the net return distribution. Also, irrigation has asymmetric effects on the two outcome distributions' lower and upper tails, but

with a larger reduction in the yield distribution's skewness. Thus, both the yield and net return distributions impose an increasing risk from irrigation due to rising variance and declining skewness.

Overall, Tables 2 and 3 show that climate variables have different seasonal effects on the winter wheat yield and farm net return distributions' high-order moments, and these effects in general differ for the two outcome distributions. Climate and irrigation also show asymmetric effects on the two outcome distributions' lower and upper tails. With asymmetric effects, we can't interpret a rise in variance as necessarily increasing risk. We need decision models and visualized distributions to evaluate climate's and irrigation's risk attributes by combining variance and skewness effects.

Risk Attributes of Climate and Irrigation

We use two approaches to evaluate climate and irrigation's risk attributes. We first use two decision models (expected utility and risk-value) to quantify climate and irrigation's marginal risk effects. We set the Arrow-Pratt relative risk aversion coefficient to 1 and the downside risk aversion coefficient to 2 in the expected utility model, and $R_{2\eta} = 1$, $R_{2\varphi} = 0.5$ in the risk-value model as in Antle (2010).

Table 4 presents climate's and irrigation's marginal risk effects in the elasticity form under the two decision models. Climate variables' risk attributes vary across seasons and are consistent in most cases under the risk-value model, except for fall and winter mean growing degree-days. Mean precipitation is risk-increasing in fall but risk-decreasing in winter and spring; freezing degree-days is risk-increasing in winter but risk-decreasing in fall and spring. Fall and winter mean growing degree-days' risk implications depend on the outcome distribution used. This

reflects the farm net return distribution including economic responses from other crops and livestock as well as output prices and production costs excluded from winter wheat yield, as we discussed above on climate's mean effects on winter wheat yield and farm net return.

Table 4 also shows that climate variables' risk implications may depend on the decision model used. We use spring mean growing degree-days as an example. Spring mean growing degree-days is risk-decreasing under the risk-value model but risk-increasing under the expected utility model. Since the choice of a suitable decision model is based on farmers' risk behavior, it is of value to use visualized distributions to evaluate climate and input use's risk implications without imposing any abitrary assumptions on farmers' risk behavior as we discussed below.

Both the expected utility and risk-value models show that irrigation is risk-increasing according to winter wheat yield and farm net return distributions in Table 4. It is important to keep in mind that irrigation has a large positive mean effect on winter wheat yield and farm net return, so that irrigation's net effect on the certainty equivalent (mean effect minus risk premium) is positive. This implies that irrigated farms switch into irrigated agriculture because of increased productivity and profitability, rather than mitigating production risk (Koundouri, Nauges and Tzouvelekas 2006).

Next, we visualize changes in winter wheat yield and farm net return distributions due to climate change and irrigation. We use the Pearson system to simulate the ex-ante distributions of winter wheat yield and farm net return (Johnson, Kotz and Balakrishnan 1994). The Pearson system includes a variety of distributions in the exponential family and requires the first four moments to simulate a distribution. We estimate and compute the first three moments based on partial moment parameters in Tables 2 and 3 using equation (2) and set the kurtosis parameters at the sample mean.

Figure 2 presents irrigation's effects on winter wheat yield and farm net return distributions for irrigated farms. Irrigation shifts the yield distribution to the production frontier, and this mean-increasing effect dominates the variance and skewness effects. By contrast, irrigation substantially increases the net return distribution's variance with a large mass concentrated on the upper tail. These results suggest a larger risk-increasing effect of irrigation on the net return distribution than on the yield distribution, which is consistent with findings using the two risk behavior models in Table 4. Also, these results are consistent with the conventional wisdom of production risk—higher returns associated with higher risk.

We use mean growing degree-days as an example to visualize climate change's effects on winter wheat yield and farm net return distributions as it shows the strongest effects among climate variables in Tables 2 and 3. In Figure 3, we simulate the seasonal effects of an increase of 150 growing degree-days for rainfed farms. A warmer fall or spring shows a mean-shifting effect on the yield distribution with almost no risk effect, while a warmer winter increases the production risk on yield due to increased variance and skewness. Regarding the farm net return distribution, a warmer winter or spring substantially increases the production risk from increased variance, while a warmer fall reduces the production risk. These results suggest that a warmer climate has distinct seasonal effects, and these effects generally differ on the winter wheat yield and farm net return distributions.

Future Climate Impacts

Our prediction relies on future climate projections from 20 global climate models in the fifth Coupled Model Intercomparison Project (CMIP5) under Representative Concentration Pathway (RCP) 4.5, representing a medium greenhouse gas emission scenario with moderate climate

policy. Daily climate model output is downscaled for both historical (1950-2012) and future (2015-2050) periods with the MACA method (Abatzoglou and Brown 2012).

Most climate projections suggest the PNW will experience warmer and wetter growing seasons from September to June by 2050 compared to 2012 (Figure 4). Mean growing degree-days on average has a large increase in fall, but mean freezing degree-days shows a large increase in winter (Figure 5). A substantial uncertainty exists in projecting future climate using 20 global climate models.

Figure 6 presents projected future climate change's impacts on winter wheat yield and farm net return distributions.[8] On average, the winter wheat yield and farm net return distributions become positively skewed with small increases in variances but almost no change in means. This implies that winter wheat farms on average will experience a small negative effect due to climate change. However, there is a substantial uncertainty in projected winter wheat yield and farm net return distributions under climate change with a wide range of positive and negative effects on production risk.[9]

Conclusions

We developed a conceptual framework to describe the relationships between climate change and adaptation with the location and shape of the output distribution. A partial-moment-based approach was used in this study to evaluate asymmetric risk effects of climate change and

[8] 17 global climate model projections are used for simulating farm net return distributions, and the other three projections are excluded because they produce extreme climates and generate irregular farm net return distributions.

[9] Our projections exclude CO_2 effects. Results from Antle et al. (2017) show that climate change, in combination with CO_2 effects, will increase average winter wheat yields and farm net returns by 24% for the PNW dryland wheat-based systems by 2050 under RCP 4.5.

irrigation on the winter wheat yield and farm net return distributions for PNW winter wheat farms. Expected utility and risk-value models as well as distribution visualizations were used to examine climate and irrigation's risk implications.

We find that climate measures, including mean precipitation, growing degree-days and freezing degree-days, have distinct seasonal effects on winter wheat yield and farm net return distributions' mean and high-order moments. Our simulations show that irrigation substantially increases irrigated farms' certainty equivalent by shifting the yield distribution to the production frontier and boosting mean net returns but also reducing net return skewness and hence downside risk. We project that, by the mid-21st century, PNW winter wheat farms on average will experience a small negative effect on the winter wheat yield and farm net return distributions due to increased production risk from rising variance and skewness. Simulated future climate change impacts on the two outcome distributions are uncertain due to climate modelling uncertainty, resulting in a wide range of positive and negative effects.

This study improves scientific understanding of climate change impacts on agricultural systems, in particular on production risk (Adams 1989; Mendelson and Rosenberg 1994; Deschenes and Greenstone 2007, 2012; Lobell, Cahill, and Field 2007; Schlenker and Roberts 2009; Ortiz-Bobea and Just 2013; Burke and Emerick 2016). Our analysis complements Tack, Harri and Coble (2012) and provides new insights by estimating climate's asymmetric production risk effects at farm level. Our results show that with good data it is possible for econometric models to represent seasonal effects (Tack, Barkley and Nalley 2015); process-based models (integrated assessment models) represent weather effects on a daily basis and hence capture seasonal effects. An advantage of econometric models is that they are better at representing risk, because process-based models so far exclude pests and diseases and other

management aspects that would affect risk on crop production. A topic for future work would be to compare the two approaches in modelling climate change impact on production risk.

Several policy implications can be drawn from this paper. First, our results can help inform and design climate adaptation policies. With climate's asymmetric effects on crop yield and farm net return distributions, agricultural investments in climate adapation should reduce economic losses and production risk (or increase economic gains) from climate change. It is necessary to consider production risk effects when evaluating potential climate adaptation policies and technologies. Second, our results show climate's effects on crop yield and net return distributions depending on crop growth stages within the growing season. Farmers' optimal climate adaptation strategies should reflect differences among crop growth stages. Third, climate's risk implications on farmers' certainty equivalent depend on the decision model used and hence risk behavior assumptions. Policy-makers need to understand farmers' risk behavior to evaluate climate change and adaptation's production risk effects. Our visualized distribution is a desirable tool for farmers making their management decisions without imposing any assumptions on their risk behavior.

In interpreting findings from our econometric results it is important to keep in mind that factors such as CO_2 effects are excluded from this study. Also, the projections do not incorporate changes in biophysical, socio-economic conditions, technologies, and policies in the future world accompanied with climate change. Future research need to combine statistical approaches with process-based approaches to examine rising CO_2 level' effects on winter wheat production, and to design scenarios with consistent climate, biophysical, socio-economic conditions, technologies, and policies for projecting climate change's impacts in the future world. Moreover, irrigation in the historical period was subsidized by the government in the western US, and

irrigation water rights are regulated by the law, so that the percent of irrigated winter wheat acreage is fixed in the projections. Future research need to address this issue and explicitly model the decision making on irrigation in the context of climate change.

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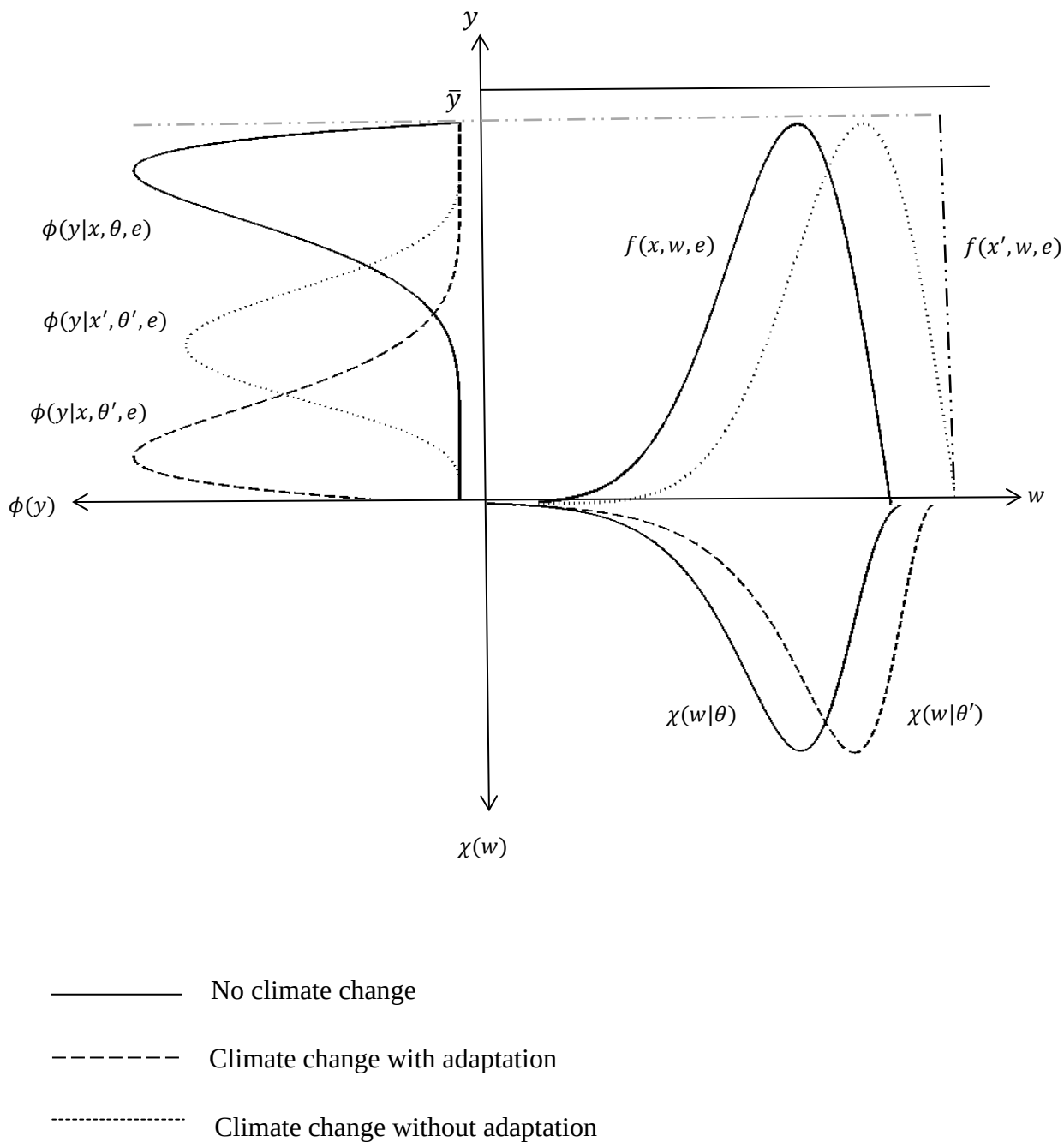


Figure 1: A conceptual framework of the impacts of climate change and adaptation on the output distribution

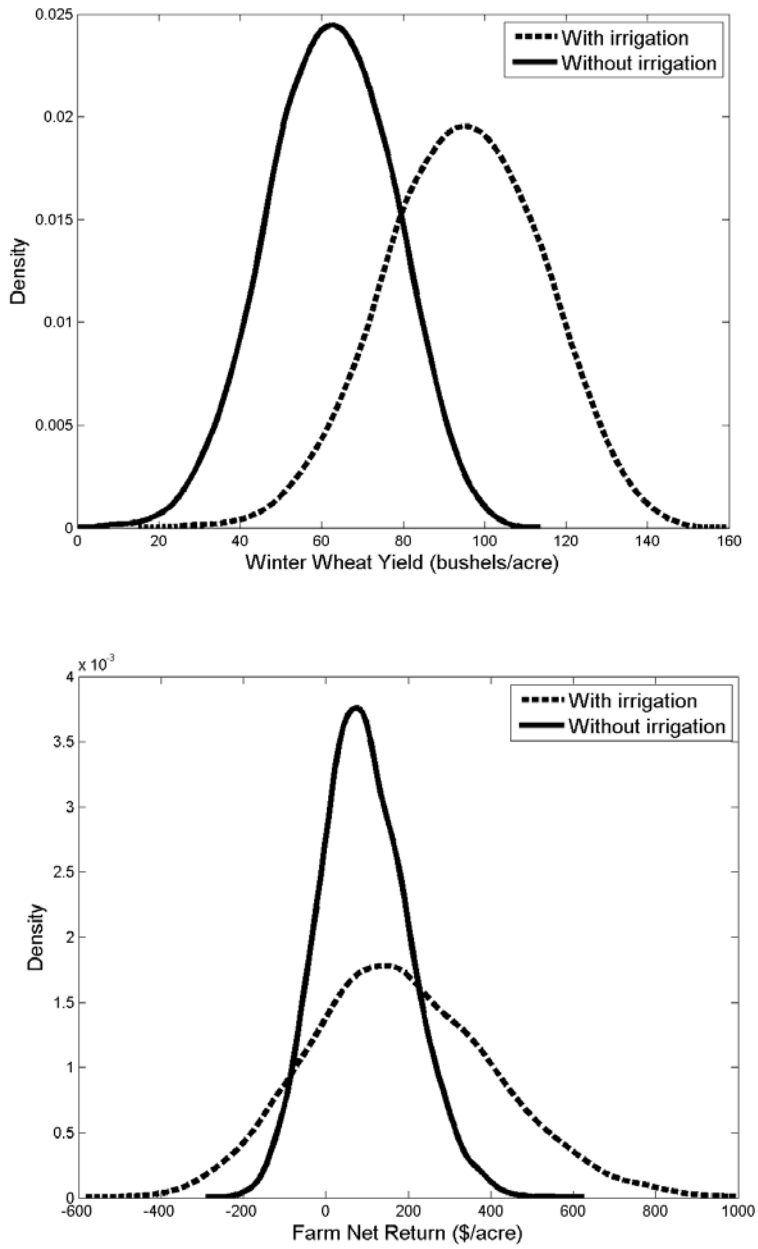
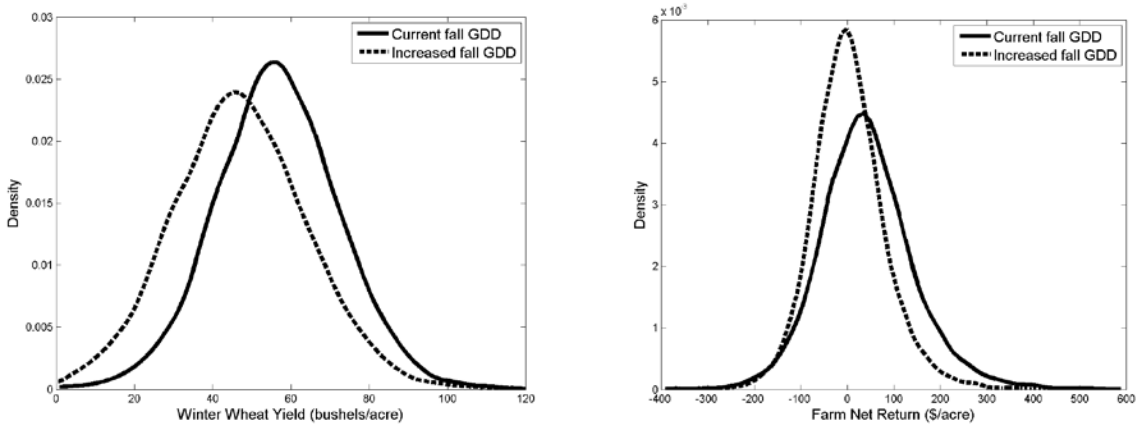
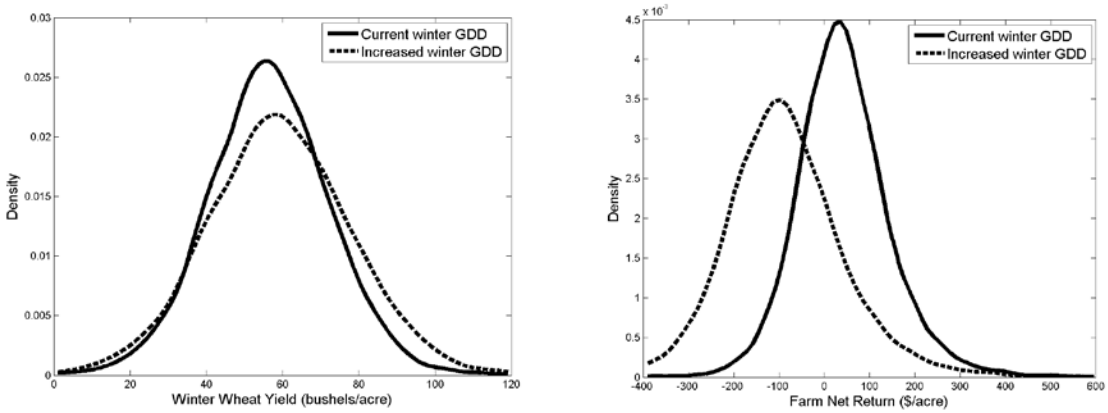


Figure 2: Simulated effects of irrigation on the distributions of winter wheat yield and farm net return for irrigated farms

(a) Fall



(b) Winter



(c) Spring

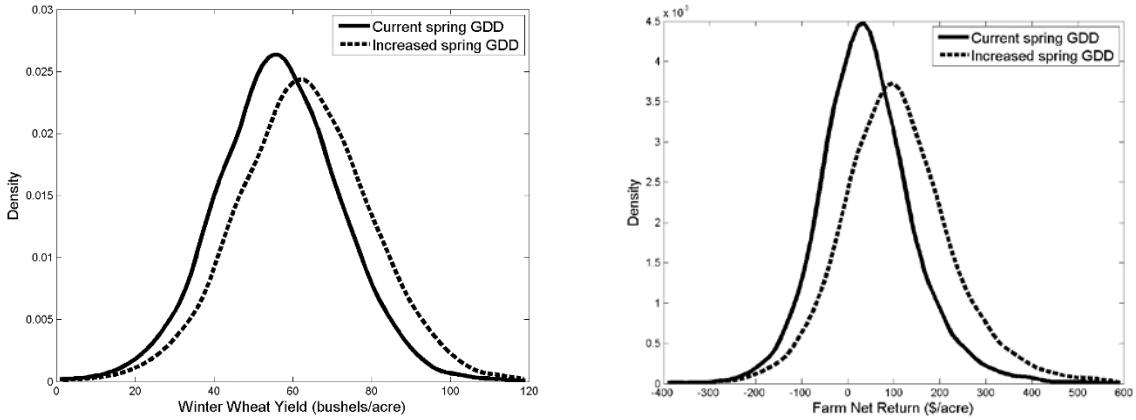


Figure 3: Simulated effects of seasonal mean growing degree-days on the distributions of winter wheat yield and farm net return for rainfed farms

Note: dashed lines indicate increases in the seasonal mean growing degree-days.

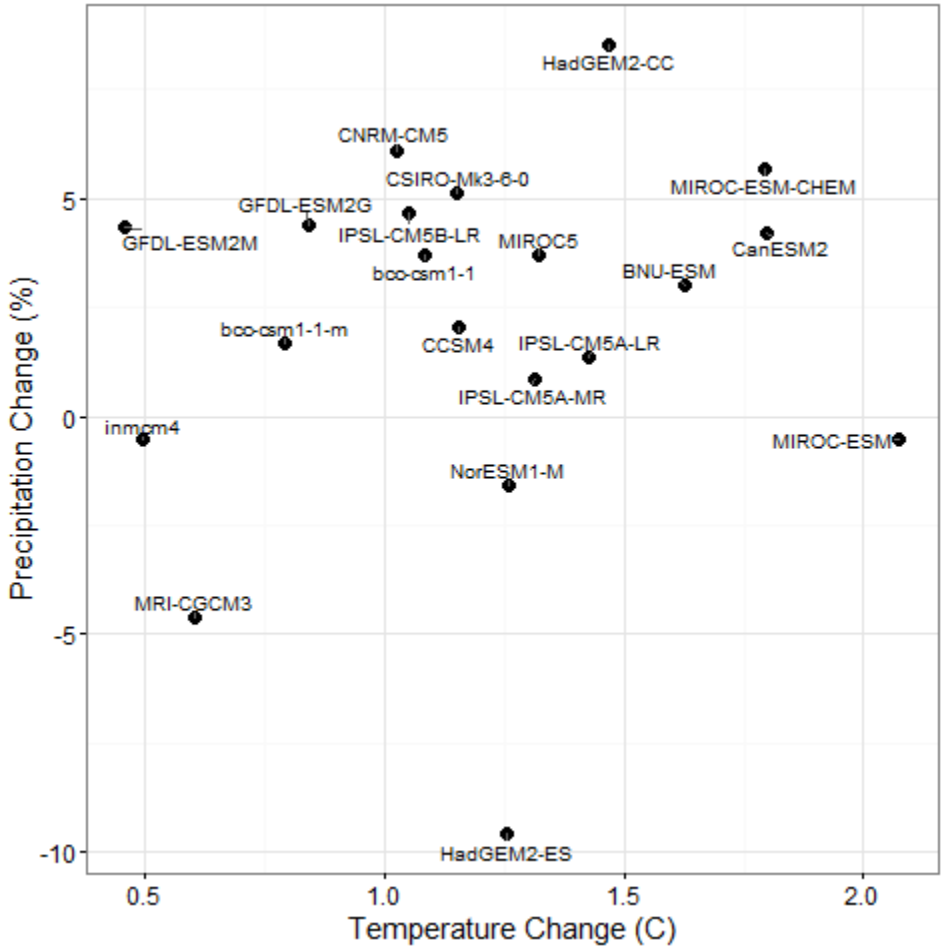


Figure 4: Projected changes in mean growing season total precipitation and average temperature by 2050 from 2012

Note: each dot represents a projection from a particular global climate model in the CMIP 5 under RCP 4.5.

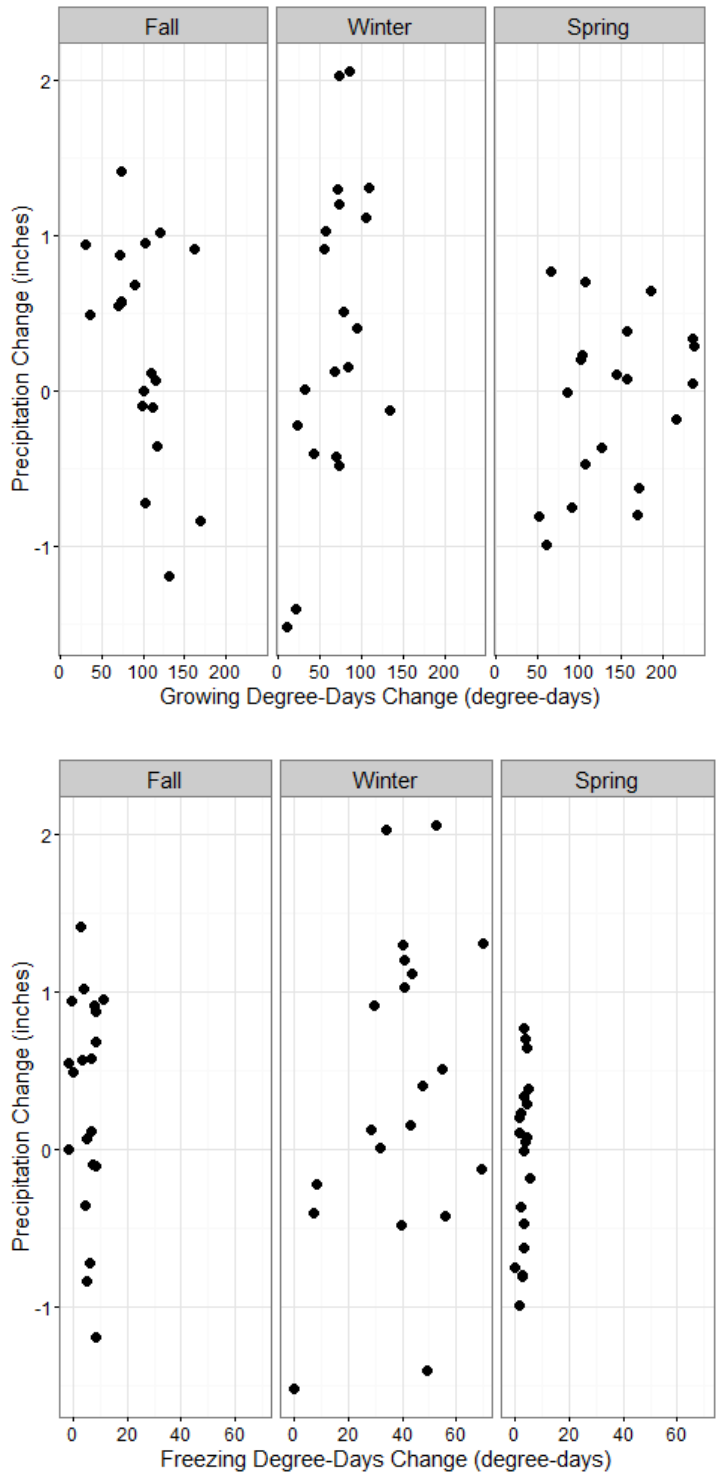


Figure 5: Projected changes in seasonal climate variables by 2050 from 2012

Note: each dot represents a projection from a particular global climate model in CMIP 5 under RCP 4.5.

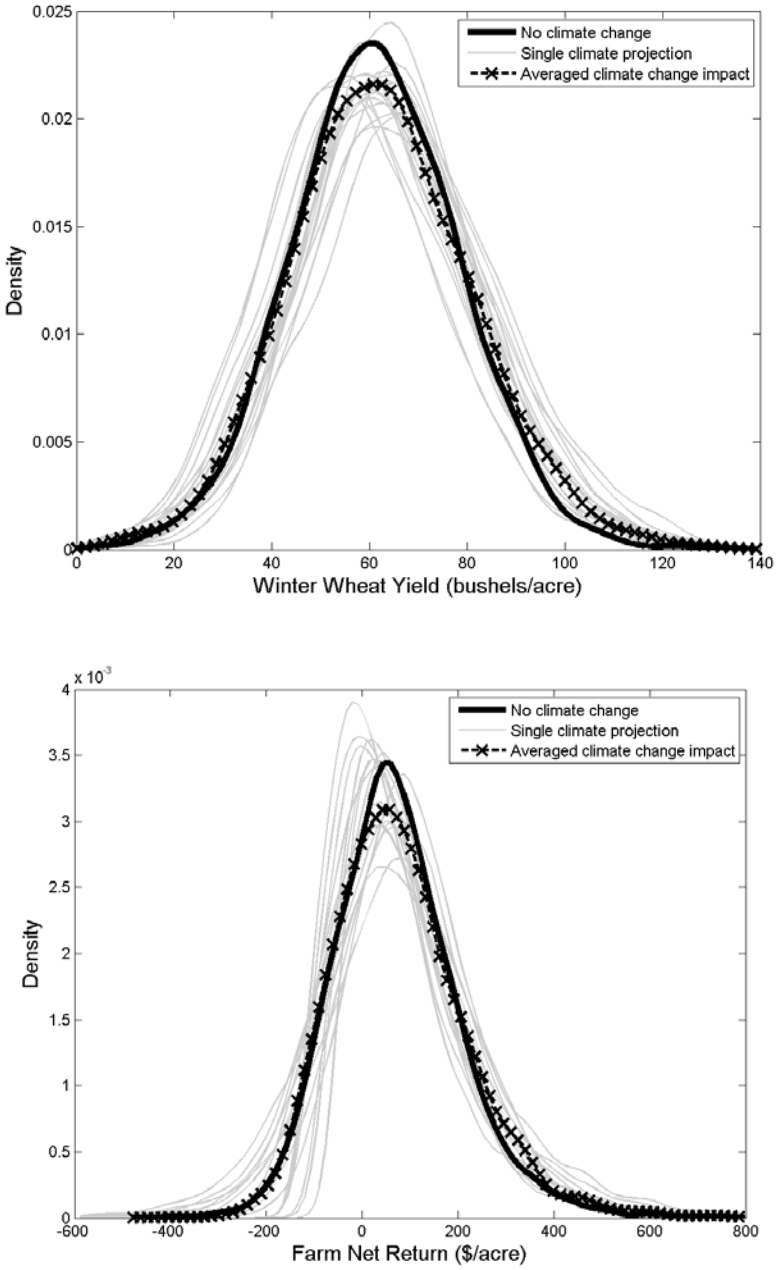


Figure 6: Impacts of climate change on the winter wheat yield and farm net return distributions for the U.S. Pacific Northwest wheat-based systems by 2050 under RCP 4.5

Note: each dashed grey line represents a predicted outcome distribution from a future climate projection.

Table 1: Summary Statistics of Winter Wheat Farms in the U.S. Pacific Northwest

Variables	2002		2007		2012		Definition
	Mean	Std.	Mean	Std.	Mean	Std.	
A. Economic and Social Variables							
Winter wheat yield	58.3	30.7	64.0	30.4	72.1	32.3	Winter wheat yield (bushel/acre)
Farm net return	77.9	174.6	83.9	173.9	103.4	199.9	Farming net return over farmland acreage ($/acre)
Large farm	0.6	0.5	0.8	0.4	0.9	0.3	Total annual farm revenue of over $250,000 (1 = yes, 0 = no)
CRP and WRP programs	0.1	0.2	0.1	0.2	0.1	0.1	Share of cropland under CRP and WRP programs
Experience	24.6	13.0	27.5	13.1	28.5	13.2	Farming experience (years)
Land tenure	0.8	0.4	0.8	0.4	0.8	0.4	Farm fully or partially owned by operator (1 = yes, 0 = no)
Farming occupation	1.0	0.2	0.9	0.2	1.0	0.2	Operator occupation (1 = farming, 0 = employed off-farm)
Irrigation	18.8	37.5	20.7	39.0	21.9	39.7	Percent of irrigated winter wheat acreage
Distance	33.2	22.1	33.7	22.1	32.6	22.1	Distance from zip-code center to the nearest river (km)
B. Soil variables							
Slope	15.5	8.0	15.4	8.0	15.2	8.2	Average land slope in percent
Sand content	26.4	12.0	26.4	12.0	26.6	11.8	Average percent of particles with 0.05-2 mm in diameters
Soil organic content	7.3	3.9	7.3	3.8	7.4	4.0	Average soil organic content in 1 meter depth (kg C/m^2)
Wetland index	2.0	4.7	1.9	4.6	2.3	5.5	Index of wetland percent
Soil loss tolerance factor	3.6	0.8	3.6	0.8	3.6	0.8	Soil loss tolerance factor (tons/acres/year)
C. Climate variables							
Fall Precipitation	4.1	1.9	3.7	1.8	3.8	2.2	22-year averaged total precipitation in fall (inch)
Winter Precipitation	5.2	3.0	5.0	2.7	5.5	3.6	22-year averaged total precipitation in winter (inch)
Spring Precipitation	5.6	2.3	5.4	2.2	5.7	2.5	22-year averaged total precipitation in spring (inch)
Fall GDD	8.9	1.0	8.9	1.0	9.1	1.0	22-year averaged growing degree-days in fall (100 degree-days)
Winter GDD	1.6	0.9	1.6	0.9	1.7	1.0	22-year averaged growing degree-days in winter (100 degree-days)
Spring GDD	13.5	1.5	13.6	1.5	13.3	1.6	22-year averaged growing degree-days in spring (100 degree-days)
Fall FDD	0.3	0.1	0.3	0.1	0.2	0.1	22-year averaged freezing degree-days in fall (100 degree-days)
Winter FDD	1.9	0.9	1.9	1.0	1.6	1.0	22-year averaged freezing degree-days in winter (100 degree-days)
Spring FDD	0.0	0.1	0.1	0.1	0.1	0.1	22-year averaged freezing degree-days in spring (100 degree-days)
Observations	5449		4542		4415		

Note: Farm net return is in 2012 dollars. The growing period for winter wheat is from September to June (inclusive) with three different seasons: fall (Sep-Oct-Nov), winter (Dec-Jan-Feb) and spring (Mar-Apr-May-Jun).

Table 2: Elasticity Estimates of the Mean and High-order Moment Functions for Winter Wheat Yield

	Mean		Variance		3rd central moment		Lower 2nd moment		Upper 2nd moment		Lower 3rd moment		Upper 3rd moment	
Variables	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
Fall precipitation	-0.10	-1.68	0.17	0.88	-13.00	-2.15	0.80	3.22	-0.49	-1.80	0.89	2.72	-0.47	-1.26
Winter precipitation	-0.05	-1.45	-0.10	-0.94	6.95	2.06	-0.25	-1.91	0.13	0.83	-0.27	-1.54	0.18	0.84
Spring precipitation	0.26	7.63	0.39	2.76	6.66	1.77	-0.35	-2.01	0.67	3.45	-0.43	-1.82	0.61	2.22
Fall GDD	-1.39	-6.39	1.35	1.29	5.23	0.25	4.23	3.60	-4.35	-3.13	6.06	3.52	-5.16	-2.49
Winter GDD	0.04	0.86	-0.08	-0.59	0.19	0.06	-0.07	-0.43	0.75	4.03	-0.04	-0.20	0.86	3.20
Spring GDD	1.00	6.75	0.74	1.16	10.45	0.78	-2.03	-2.71	3.79	4.61	-3.24	-2.95	4.96	4.13
Fall FDD	0.03	0.52	-0.23	-1.13	1.78	0.39	-0.17	-0.81	-0.37	-1.45	-0.36	-1.24	-0.27	-0.74
Winter FDD	-0.11	-1.84	-0.11	-0.69	-4.42	-1.17	0.22	1.14	-0.33	-1.60	0.51	1.84	-0.82	-2.78
Spring FDD	-0.05	-3.74	0.18	5.75	1.30	1.74	0.10	3.20	0.25	7.13	0.14	3.41	0.35	7.03
Irrigation	0.17	29.48	0.22	18.16	-0.71	-1.84	0.24	15.26	0.08	4.75	0.35	15.48	0.08	3.39
Intercept	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Socio-economic variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Soil variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
State by Year FE	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Asymmetry test (p-value)							(<0.001)				(<0.001)			
R-square	0.6443		0.0654		0.0051		0.0895		0.0712		0.1041		0.0765	
Sample mean	75		373		750		367		378		12034		12094	
Observations	14,406		14085		14085		6622		7463		6622		7463	

Note: The lower third partial moment is estimated as an absolute moment, so the elasticities show opposite effects on the third central moment. Socio-economic variables used in estimation include whether a farm is classified as a large farm, share of farmland enrolled in the CRP and WRP programs, years of farming experience, land tenure, and off-farm employment. Soil variables used in estimation include slope, sand content, soil organic content, wetland index, and soil loss tolerance factor.

Table 3: Elasticity Estimates of the Mean and High-order Moment Functions for Winter Wheat Farm Net Return

	Mean		Variance		3rd central moment		Lower 2nd moment		Upper 2nd moment		Lower 3rd moment		Upper 3rd moment	
Variables	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
Fall precipitation	-0.88	-3.00	0.99	4.51	-5.68	-2.72	0.67	2.81	0.55	1.94	0.77	2.26	0.40	1.06
Winter precipitation	0.52	2.90	-0.33	-2.52	4.41	3.71	-0.61	-4.28	0.14	0.91	-0.96	-4.59	0.40	2.01
Spring precipitation	0.65	3.98	-0.49	-2.57	2.28	1.74	-0.18	-0.89	-0.05	-0.23	0.02	0.07	0.10	0.34
Fall GDD	-2.66	-2.56	-4.34	-3.74	4.97	0.67	-8.11	-6.69	-1.26	-0.89	-10.80	-5.73	-2.26	-1.09
Winter GDD	-1.04	-5.06	0.29	1.96	-1.05	-0.92	1.15	7.61	-0.16	-0.86	1.74	7.91	-0.15	-0.58
Spring GDD	4.25	6.01	4.08	6.01	1.99	0.42	2.98	3.96	3.47	4.26	3.24	2.71	5.10	4.32
Fall FDD	-0.12	-0.50	-1.42	-6.78	2.36	1.49	-2.68	-10.98	-0.49	-1.93	-4.36	-11.69	-0.48	-1.33
Winter FDD	-1.22	-4.29	0.82	4.28	-2.26	-1.72	2.09	9.46	-0.01	-0.02	3.49	10.04	-0.11	-0.36
Spring FDD	0.15	2.28	0.18	3.96	0.06	0.22	0.09	1.76	0.18	3.99	0.13	1.57	0.22	3.60
Irrigation	0.21	7.24	0.43	24.08	0.11	0.84	0.53	23.77	0.41	21.38	0.71	15.16	0.51	16.83
Intercept	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Socio-economic variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Soil variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
State by Year FE	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Asymmetry test (p-value)							(<0.001)				(<0.001)			
R-square	0.1426		0.1996		0.0060		0.2051		0.2296		0.1367		0.1784	
Sample mean	151		40535		3497949		33713		47500		13926480		21287105	
Observations	14406		14096		14096		7121		6975		7121		6975	

Note: The lower third partial moment is estimated as an absolute moment, so the elasticities show opposite effects on the third central moment. Socio-economic variables used in estimation include whether a farm is classified as a large farm, share of farmland enrolled in the CRP and WRP programs, years of farming experience, land tenure, and off-farm employment. Soil variables used in estimation include slope, sand content, soil organic content, wetland index, and soil loss tolerance factor.

Table 4: Elasticities of Risk Premium with Respect to Climate and Irrigation

VARIABLES	Expected Utility Model		Risk-value Model	
	mean	t-stat	mean	t-stat
A. Winter Wheat Yield Distribution				
Fall Precipitation	0.09	0.08	0.41	4.16
Winter Precipitation	-0.05	-0.08	-0.13	-2.35
Spring Precipitation	0.02	0.03	-0.28	-4.03
Fall GDD	0.16	0.04	2.75	5.59
Winter GDD	-0.01	-0.02	-0.20	-3.12
Spring GDD	0.05	0.02	-1.80	-5.94
Fall FDD	-0.04	-0.05	0.00	-0.03
Winter FDD	0.01	0.01	0.22	2.88
Spring FDD	0.02	0.13	-0.03	-2.14
Irrigation	0.03	0.48	0.08	12.79
B. Farm Net Return Distribution				
Fall Precipitation	4.48	3.67	0.96	0.51
Winter Precipitation	-2.92	-4.20	-5.05	-4.78
Spring Precipitation	-1.91	-2.44	-0.60	-0.40
Fall GDD	-8.31	-1.85	-31.80	-3.11
Winter GDD	0.96	1.43	7.12	5.56
Spring GDD	4.02	1.44	-9.18	-1.52
Fall FDD	-3.14	-3.35	-13.13	-7.01
Winter FDD	2.32	2.95	12.67	7.81
Spring FDD	0.20	1.23	-0.55	-1.52
Irrigation	0.48	6.26	0.32	1.76

Appendix A1: Elasticity Estimates of the Mean and High-order Moment Functions for Winter Wheat Yield

Variables	Mean		Variance		3rd central moment		Lower 2nd moment		Upper 2nd moment		Lower 3rd moment		Upper 3rd moment	
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
Fall precipitation	-0.10	-1.68	0.17	0.88	-13.00	-2.15	0.80	3.22	-0.49	-1.80	0.89	2.72	-0.47	-1.26
Winter precipitation	-0.05	-1.45	-0.10	-0.94	6.95	2.06	-0.25	-1.91	0.13	0.83	-0.27	-1.54	0.18	0.84
Spring precipitation	0.26	7.63	0.39	2.76	6.66	1.77	-0.35	-2.01	0.67	3.45	-0.43	-1.82	0.61	2.22
Fall GDD	-1.39	-6.39	1.35	1.29	5.23	0.25	4.23	3.60	-4.35	-3.13	6.06	3.52	-5.16	-2.49
Winter GDD	0.04	0.86	-0.08	-0.59	0.19	0.06	-0.07	-0.43	0.75	4.03	-0.04	-0.20	0.86	3.20
Spring GDD	1.00	6.75	0.74	1.16	10.45	0.78	-2.03	-2.71	3.79	4.61	-3.24	-2.95	4.96	4.13
Fall FDD	0.03	0.52	-0.23	-1.13	1.78	0.39	-0.17	-0.81	-0.37	-1.45	-0.36	-1.24	-0.27	-0.74
Winter FDD	-0.11	-1.84	-0.11	-0.69	-4.42	-1.17	0.22	1.14	-0.33	-1.60	0.51	1.84	-0.82	-2.78
Spring FDD	-0.05	-3.74	0.18	5.75	1.30	1.74	0.10	3.20	0.25	7.13	0.14	3.41	0.35	7.03
Irrigation	0.17	29.48	0.22	18.16	-0.71	-1.84	0.24	15.26	0.08	4.75	0.35	15.48	0.08	3.39
Distance	-0.06	-923.88	0.07	3.10	1.34	2.49	-0.06	-2.36	0.02	0.80	-0.10	-2.68	0.07	1.58
Large farm	0.06	17.47	-0.07	-3.40	0.59	1.42	0.00	-0.09	0.02	0.60	-0.01	-0.38	0.06	1.60
CRP and WRP programs	-0.01	-11.99	0.00	0.71	-0.32	-2.91	0.03	7.08	-0.04	-5.51	0.05	9.19	-0.07	-5.89
Experience	0.00	0.17	0.01	0.41	1.29	2.36	-0.15	-5.40	0.09	2.71	-0.25	-6.27	0.10	2.30
Land tenure	0.00	0.50	-0.01	-0.33	0.37	0.72	-0.11	-4.32	0.10	2.92	-0.19	-5.74	0.14	3.01
Farming occupation	0.01	0.78	-0.11	-2.53	-0.44	-0.39	-0.07	-1.31	-0.13	-2.24	-0.11	-1.72	-0.20	-2.52
Slope	0.00	-0.43	0.03	0.92	-0.54	-0.67	-0.09	-2.25	-0.01	-0.21	-0.19	-3.11	-0.09	-1.33
Sand content	-0.19	-15.34	0.02	0.66	0.46	0.57	-0.08	-1.98	-0.02	-0.54	-0.16	-2.92	-0.12	-1.90
Soil organic carbon	0.08	5.77	-0.04	-0.67	-0.85	-0.67	0.04	0.60	-0.45	-5.53	0.11	1.28	-0.69	-5.95
Wetland index	0.00	0.09	0.01	0.88	0.21	0.93	0.00	0.15	-0.01	-1.14	0.00	0.18	-0.02	-1.72
Soil loss tolerance factor	-0.01	-0.60	-0.30	-2.86	1.91	0.81	-0.48	-4.09	-0.09	-0.63	-0.81	-5.07	-0.14	-0.71
Intercept	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
State by Year FE	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Asymmetry test (p-value)							(<0.001)				(<0.001)			
R-square	0.6443		0.0654		0.0051		0.0895		0.0712		0.1041		0.0765	
Sample mean	75		373		750		367		378		12034		12094	
Observations	14,406		14085		14085		6622		7463		6622		7463	

Note: The lower third partial moment is estimated as an absolute moment, so the elasticities show opposite effects on the third central moment.

Appendix A2: Elasticity Estimates of the Mean and High-order Moment Functions for Winter Wheat Farm Net Return

Variables	Mean		Variance		3rd central moment		Lower 2nd moment		Upper 2nd moment		Lower 3rd moment		Upper 3rd moment	
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
Fall precipitation	-0.88	-3.00	0.99	4.51	-5.68	-2.72	0.67	2.81	0.55	1.94	0.77	2.26	0.40	1.06
Winter precipitation	0.52	2.90	-0.33	-2.52	4.41	3.71	-0.61	-4.28	0.14	0.91	-0.96	-4.59	0.40	2.01
Spring precipitation	0.65	3.98	-0.49	-2.57	2.28	1.74	-0.18	-0.89	-0.05	-0.23	0.02	0.07	0.10	0.34
Fall GDD	-2.66	-2.56	-4.34	-3.74	4.97	0.67	-8.11	-6.69	-1.26	-0.89	-10.80	-5.73	-2.26	-1.09
Winter GDD	-1.04	-5.06	0.29	1.96	-1.05	-0.92	1.15	7.61	-0.16	-0.86	1.74	7.91	-0.15	-0.58
Spring GDD	4.25	6.01	4.08	6.01	1.99	0.42	2.98	3.96	3.47	4.26	3.24	2.71	5.10	4.32
Fall FDD	-0.12	-0.50	-1.42	-6.78	2.36	1.49	-2.68	-10.98	-0.49	-1.93	-4.36	-11.69	-0.48	-1.33
Winter FDD	-1.22	-4.29	0.82	4.28	-2.26	-1.72	2.09	9.46	-0.01	-0.02	3.49	10.04	-0.11	-0.36
Spring FDD	0.15	2.28	0.18	3.96	0.06	0.22	0.09	1.76	0.18	3.99	0.13	1.57	0.22	3.60
Irrigation	0.21	7.24	0.43	24.08	0.11	0.84	0.53	23.77	0.41	21.38	0.71	15.16	0.51	16.83
Distance	-0.08	-27.51	-0.09	-3.16	0.08	0.42	-0.09	-2.87	0.07	2.18	-0.16	-3.37	0.10	2.19
Large farm	0.05	3.29	0.03	0.99	0.16	1.14	0.03	0.84	0.25	7.03	0.02	0.39	0.37	7.01
CRP and WRP programs	-0.07	-13.87	-0.16	-8.85	-0.12	-3.16	-0.09	-7.09	-0.22	-8.50	-0.11	-5.02	-0.27	-5.85
Experience	0.01	0.46	-0.05	-1.93	-0.10	-0.52	0.10	3.22	-0.25	-8.04	0.13	3.07	-0.38	-8.99
Land tenure	0.06	2.94	0.18	5.68	0.53	2.90	0.08	2.24	0.41	9.91	0.01	0.30	0.61	9.52
Farming occupation	0.01	0.26	-0.09	-1.97	-0.28	-0.72	0.12	2.14	-0.12	-2.31	0.37	4.03	-0.16	-2.42
Slope	-0.07	-1.71	-0.21	-4.84	-0.16	-0.57	-0.17	-3.32	-0.05	-1.07	-0.26	-3.27	-0.11	-1.59
Sand content	-0.27	-4.66	0.14	4.37	-0.20	-0.71	0.10	2.44	0.44	12.14	0.15	2.66	0.64	13.46
Soil organic carbon	-0.10	-1.39	0.22	3.12	-0.55	-1.25	0.33	4.64	-0.05	-0.58	0.37	3.30	-0.10	-0.75
Wetland index	0.02	1.05	-0.01	-1.90	-0.21	-2.71	0.00	0.20	-0.02	-1.82	0.01	0.55	-0.03	-2.03
Soil loss tolerance factor	0.23	2.11	-0.33	-2.94	0.11	0.14	0.04	0.34	-0.03	-0.26	0.15	0.79	-0.01	-0.06
Intercept	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
State by Year FE	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Asymmetry test (p-value)							(<0.001)				(<0.001)			
R-square	0.1426		0.1996		0.0060		0.2051		0.2296		0.1367		0.1784	
Sample mean	151		40535		3497949		33713		47500		13926480		21287105	
Observations	14406		14096		14096		7121		6975		7121		6975	

Note: The lower third partial moment is estimated as an absolute moment, so the elasticities show opposite effects on the third central moment.