Adaptive Behavior of U.S. Farms to Climate and Risk

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Abstract

We analyze the effects of climate conditions and crop insurance on farm-level land allocation decisions among corn, soybeans, winter wheat, and hay in 10 Midwest states. Based on ARMS data, we estimate farmers' land allocation equations that control for market conditions, climate and soil variables, and insurance. A multivariate sample selection model is used for estimation. We find that: 1) beneficial heat has positive effects on corn and soybean acreage but negative effects on winter wheat acreage, 2) excessive heat has negative effects on corn and winter wheat acreage but have positive effects on soybean acreage, 3) an increase in precipitation by 1% increases corn acreage by 0.6% but decrease soybean and winter wheat acreage by 1.0% and 1.6%, 4) soybean acreage is more sensitive to summer drought, and 5) crop insurance alters farmers land allocation.

Keywords: Cropping pattern, climate change, crop insurance, ARMS.
JEL Codes: Q54, Q18, Q15, Q12.

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1 Introduction and Background

Recent climate models predict that climate change over the next few decades will have negative effects on Midwest agriculture. Increasingly hot and dry summers, increased spring precipitation, and more frequent extreme weather events could reduce crop yields and lower agricultural net returns (Pryor et al., 2014). Midwest agriculture is an important component of U.S. agriculture. Farmland accounts for more than two-thirds of land in the Midwest and constitutes 27% of U.S. cropland. The region also produces roughly 64% of U.S. corn and soybeans. Thus, projected climate change in the Midwest raises concerns not only about regional agricultural output but may also have important national and international impacts in many sectors.

Econometric analyses that do not consider adaptive behavior tend to overestimate the damage of climate change (Mendelsohn, Nordhaus and Shaw, 1994). Since agricultural production depends on local climate conditions, farmers generally respond to the harmful effects of weather and, in the long run, climate change. The government provides indirect and short-run adaptation options for farmers through agricultural policies, such as income support programs, as well as long-run options through public research and development (Malcolm et al., 2012).

An important farm-level adaptation option is to reallocate existing cropland between crops. The regional distribution of agricultural production will depend on these farm-level cropland allocations. Changes in cropland allocations also affect environmental conditions. For example, intensification of row cropping may alter precipitation patterns (Pielke et al., 2007; Anderson et al., 2013). Nitrogen-intensive crops may contribute to leaching and runoff that degrade water quality and contribute to adverse environmental outcomes. Analyzing cropland allocation also makes it possible to understand farmers' responses to government policies and unintended policy effects. For example, crop insurance may induce farmers to grow higher value, riskier crops that are less well-suited for their land and operations (Wu, 1999).

Corn and soybeans have been the dominant crops in Midwestern agricultural land use for the past several decades. The cropland allocated to corn has increased in recent years, while cropland allocated to soybeans has gradually trended downward. However, after 2012 the share of soybean acreage has increased relative to corn. This is largely due to changes in the relative output price of soybeans to corn. Cropland allocated to wheat and hay has been gradually decreasing throughout this time period.

However, aggregate land use change trends mask farmers' cropland allocation decisions. Farmers respond to local market and environmental conditions in different ways, i.e., farmers have crucial underlying heterogeneity. Natural resource endowments can differ among neighboring fields on the same farm. Thus, capturing heterogeneity within and between farms is useful in understanding more aggregate responses to weather and climate.

This study analyzes farm-level land allocation among corn, soybeans, winter wheat, and hay in the Midwest in response to regional weather and climate conditions. Since crop insurance has become an important agricultural policy tool (Goodwin, Vandeveer and Deal, 2004; Babcock, 2011; Walter et al., 2012) and is an adaptation options, this study identifies insurance effects on land allocation decisions. We seek to answer two research questions. First, how do weather and climate conditions influence farmers' land allocation at planting time? Second, how does government-subsidized crop insurance alter farmers' land allocation decisions? To help answer these, we specify equations for farmers' land allocation decisions and then estimate by using farm-level data in 10 Midwest states. To control for correlation between crop selection and cropland allocation, we use the two-step procedure. The remainder of the article is organized as follows. The next section reviews relevant literature. Section 3 illustrates basic assumptions of our model and describes how we estimate the acreage allocation equations. Section 4 explains how we construct farm data, county-level climate and soil data, and state-level price data. Section 5 explains the results. Section 6 discusses our conclusions and the limitations of our study. Section 7 appends summary statics of data and our estimation results.

2 Literature Review

Our paper is based on three research streams: land use change, climate change, and sample selections. First, research on land use change shows the effects of government policies, especially income support programs, on land allocations and unintended policy effects on environmental conditions (Wu, 1999; Young, Vandeveer and Schnepf, 2001; Goodwin, Vandeveer and Deal, 2004; Walter et al, 2013).[3] Wu (1999) analyzes the effects of corn crop insurance on farmers' land allocation and derives policy implications related to groundwater quality. He finds that corn crop insurance increases corn acreage, but its influence diminishes as farm size increases. Goodwin, Vandeveer and Deal (2004) perform a comprehensive analysis, including cropping pattern and insurance participation, and find modest effects of crop insurance on cropland allocation.

Climate variables and their interpretations in this study are based on recent climate change studies. To capture climate effects on crop yield, we use agronomic weather variables, such as growing degree days and extreme heat degree days similar to Schlenker and Roberts (2009), Ortiz-Bobea and Just (2012), and Roberts, Schlenker and Eyer (2013).

Our approach uses farm data from the Agricultural Resource Management Survey (ARMS) of USDA. The data contain variables that are censored at zero, which are the result of individual farmers' decisions (e.g., farmers' land use). The sample selection model (Heckman, 1976) has been widely used to resolve the indecisive censoring problem in micro-level data. In this latent variable model, researchers observe their variables of interest only when selection equations are greater than predetermined values (or latent values).

In general, the error terms are correlated between selection equations and the equations

[3]We focus on studies about U.S. agriculture policies.

for the variables of interest. Addressing these correlations is critical for consistent estimation. Some studies allow general correlation among all equations (Yen and Lin, 2006; Barslund, 2011). However, this approach is computationally burdensome and convergence is sensitive to initial points (Barslund, 2011). Millimet and Tchernis (2009) and Kasteridis, Yen, and Fang (2011) use a Bayesian approach. Even though a Bayesian approach is more robust to initial values, this approach is also computationally burdensome. In contrast, we use a two-step procedure that assumes independence between selection equations (Catsiapis and Robinson, 1982; Shonkwiler and Yen, 1999; Sckokai and Moro, 2006; Lacroix and Thomas, 2011).

3 Empirical Specification and Estimation

We use a reduced-form approach because it credibly identifies parameters of exogenous variables (e.g., climate) with simple specifications.[4] Results are also much more straightforward to interpret (Timmins and Schlenker, 2010; Chetty, 2008). One disadvantage is the omitted variable problem: if exogenous variables are correlated with omitted variables, resulting estimates are biased. A careful model specification with reasonable assumptions is necessary to alleviate omitted variable bias.

We impose the following assumptions: 1) farmers consider profit risk as well as expected profits when they allocate land; 2) output prices and production are assumed to be independent at the farm level; 3) farmers consider possible loss of production caused by extreme weather events, as well as expected climate conditions during the growing season; 4) farmers expected output and variance of output are represented by a function of output and input prices, variances and covariances of output prices, unexpected weather events, agricultural policies, total land, and climate conditions; and 5) farmers choose insurance before planting

[4] Although the definition of reduced-form methods has changed over time, key features include only using exogenous variables and imposing fewer assumptions than structural models (Timmins and Schlenker, 2010).

crops, i.e., farmers make land use decisions given insurance availability.[5]

There is correlation between farmer's crop choice and subsequent land allocation because of unobserved heterogeneity. This is similar to the correlation between labor market participation and subsequently earned wages (Heckman, 1976). To account for correlation between crop selection and land allocation, we specify crop selection equations and then assume that land allocation for each crop is observable when the corresponding crop selection equation is greater than zero. Consider the problem of farmer i who plants crop j among four crops. Our approach can describe this problem as

$$\begin{aligned} l_{ij} &= \tau_{ij} \cdot l^*_{ij}, \ j = 1, ..., 4 \\ l_{ij} &= l^*_{ij} \ \ if \ \ \tau_{ij} > 0 \\ l_{ij} &= 0 \ \ if \ \ \tau_{ij} \leq 0, \end{aligned} \tag{1}$$

where τ_{ij} represents farmer i's crop selection about crop j, l_{ij} is the observed amount of land allocated to crop j, and l^*_{ij} represents farmer i's latent land allocation to crop j (Wooldridge, 2010). If we assume a linear function for crop selection and land allocation, the reduced form equation for farmer i's acreage allocation to crop j (l^*_{ij}) and the corresponding crop selection equation (τ_{ij}) are as follows.

$$\begin{aligned} & l^*_{ij} = \alpha_j + Z'_i\beta_j + \gamma_j L_i + X'_{i,c}\theta_{1j} + \upsilon_{ij} \\ & s.t. \ \sum_{j=1}^{4} \beta_j = \sum_{j=1}^{4} \alpha_j = \sum_{j=1}^{4} \theta_{1j} = 0, \ \sum_{j=1}^{4} \gamma_j = 1 \\ & \tau_{ij} = S'_i\xi_j + X'_{i,c}\theta_{2j} + u_{ij}, \end{aligned} \tag{2}$$

where $Z_i = (\mathbf{p}, \Omega_p, \Omega_y, X_{i,ins}, W_i)'$. Note that $\mathbf{p}$ is the vector of output and input prices, Ω_p is the vector containing variances and covariances of output prices, and Ω_y is a vector of county-

[5]Farmers have to choose their coverage and products prior to the "sales closing date" before planting. Land is then allocated and reported to their insurance company. For example, the sales closing date for Iowa farmers is March 15. Moreover, we assume that farmers can borrow money for farm operations regardless of their insurance status, e.g., no credit constraints due to insurance

level crop yield variances. We assume that county-level crop yield variance is independent of individual farmers' behavior and use it as a proxy for the effects of unexpected weather events on crop production. Further, $X_{i,ins}$ is a vector of crop insurance dummies, $X_{i,c}$ includes variables related to climate and soil quality, and W_i is farmers' initial wealth (to control for changes in farmers' risk attitudes, i.e., risk aversion).

Farmers' total land is L_i and is used to take into account returns to scale of land. The sum of land allocated to four crops equals total land, implying the constraints on the sum of parameters in Equation (2). The coefficients from the hay equations are derived from these constraints to keep total acreage fixed.

To control for the effects of farmers' characteristics on crop selection, we include climate and soil conditions and farmers' socioeconomic characteristics (S_i), i.e., age, education, off-farm income in the preceding year, and whether they have considered retirement recently.[6]

To reduce computational burden, we assume independence between the crop selection equations i.e., $u_{ij} \perp u_{ik}$ for $j \neq k$. We also allow correlation between u_{ij} and υ_{ik} for $j \neq k$ because of unobserved agronomic constraints such as crop rotations (Lacroix and Thomas, 2011). Lastly, we assume that (u_{ij}, υ_{ik}) for $j \neq k$ has a bivariate normal distribution and u_{ij} follows the standard normal distribution. Then farmer i's expected land allocation to crop j becomes

$$\begin{aligned} E(l_{ij}^*|X_{ij}) &= Pr(l_{ij}^* > 0|S_{ij}, X_{i,c}) \times E(l_{ij}^*|\tau_{ik} > 0, k = 1, ..., 4,\ X_{ij}) + Pr(l_{ij}^* < 0|S_i, X_{i,c}) \times 0 \\ &= \Phi(S_i\delta_j + X_{i,c}'\theta_{2j}) \times (X_{ij}'\psi_j + \sum_{k=1}^{h} \pi_{kj}\lambda_{ki}), \end{aligned} \tag{3}$$

where X_{ij} represents a vector of the explanatory variables in acreage allocation equations and ψ_j is the the corresponding vector of parameters. Note that $\Phi(.)$ and $\phi(.)$ are the cumulative density function (cdf) and probability density function (pdf) of the standard normal distribution. The probability that farmer i chooses crop j is $\Phi(S_i\delta_j + X_{i,c}'\theta_{2j})$. The

[6]One limitation of this model specification is excluding dynamic agronomic constraints such as crop rotation and pest management

selection correction term from the selection equation for crop k is λ_{ki}, the inverse mills' ratio. The term is calculated as $\phi(S_i\delta_j + X'_{i,c}\theta_{2j})/\Phi(S_i\delta_j + X'_{i,c}\theta_{2j})$. The covariance between u_{ij} and υ_{ik} is π_{kj}. We first estimate each crop selection equation by using a binary probit model, and calculate the predicted values of the sample correction terms. Then linear regression is applied to Equation (3) based on the predicted correction terms.

Environmental conditions $(X_{i,c})$ affect crop selections directly (θ_{2j}), acreage equations directly (θ_{1j}), and acreage equations indirectly though sample correction terms. For one environmental regressor, $q_{i,c}$, in $X_{i,c}$, the marginal effect of it is calculated as

$$\begin{aligned}\frac{\partial E(l^*_{ij}|X_{ij})}{\partial q_{i,c}} &= \Phi(S_i\delta_j + X'_{i,c}\theta_{2j}) \times [\theta_{1j,q} - \sum_{k=1}^{4} \pi_{kj} \times \theta_{2k,q} \times (\lambda_{kj} \times (S_i\delta_k + X'_{i,c}\theta_{2k}) + \lambda^2_{kj})] \\ &+ \phi(S_i\delta_j + X'_{i,c}\theta_{2j}) \times \theta_{2j,q} \times (X'_{ij}\psi_j + \sum_{k=1}^{h} \pi_{kj}\lambda_{ki}),\end{aligned} \tag{4}$$

where $\theta_{1j,q}$ and $\theta_{2j,q}$ are scalar coefficients corresponding to $q_{i,c}$ in θ_{1j} and θ_{2j} for $j = 1, ...4$. Since the climate variable units are unintuitive, we calculate the average acreage response elasticities of explanatory variables. These elasticities are weighted averages of each acreage response elasticity across our sample (Arnade and Kelch, 2007).

To correct the standard errors from the two-step procedure and control for the sampling scheme of the ARMS data, we use probability-weighted bootstrapping with replacement (Goodwin and Mishra, 2005). Specifically, we construct 2,000 random bootstrap samples based on farm-level probability weights in ARMS data, and then estimate Equation (2), Equation (4) and average acreage response elasticities 2000 times.[7] The reported bootstrapped standard errors are the standard deviations from the bootstrap samples.

[7] This approach implicitly assumes that population is equal over our research period.

4 Data

This study constructs a farm-level data set based on the Agricultural Resource Management Survey (ARMS) Phase III. One major benefit is that constant-returns-to-scale production need not hold for farm-level data, in contrast to aggregate data. We select 11,230 farms by four criteria: 1) farms' largest sources of gross farm income is from grains, oilseeds, dry beans and dry peas,[8] 2) farms operating in 10 states of the Midwest during 2004 - 2011,[9] 3) farmers cultivate more than 50 acres (Goodwin and Mishra, 2005), and 4) crops covered by crop insurance should be identifiable.[10] We use information on land allocation, crop insurance status, and socioeconomic characteristics. Since the ARMS data only contain harvested land, we use harvested land as a proxy for planted land. Farm equity is used for farms' initial wealth (Sckokai and Moro, 2006). The crops considered are corn, soybeans, winter wheat and hay.[11]

Daily PRISM (Parameter-elevation Regression on Independent Slope model) data are used to calculate climate variables from Roberts, Schlenker and Eyer (2013): growing degree days (GDD), extreme heat degree days (HDD), vapor pressure deficit (VPD), and precipitation. Based on daily maximum and minimum temperatures in the PRISM data, we use Snyder's (1985) simple method to compute GDD and HDD during the growing season (see the Appendix). GDD and HDD measure the amount of exposure to beneficial heat and harmful heat, respectively. Precipitation is calculated as the sum of total precipitation dur-

[8] These farms correspond to Type 1 farms in the ARMS data.

[9] We choose Iowa, Illinois, Indiana, Kentucky, Michigan, Minnesota, Missouri, Ohio, Pennsylvania, and Wisconsin as our study area to control for irrigation status. Since some questions related to farmers' characteristics and government policies changed after 2003, we restrict the study period after 2004 to achieve consistency of data.

[10] Specifically, we include farms whose entire cropland is covered by crop insurance programs. We also include farms whose cropland are partly covered by crop insurance. For example, when one farm plants four crops, and the sum of acreage of any three crops is less than acreage covered by farm's crop insurance, then we assume that the remaining crop is also covered by crop insurance. Finally, when the sum of acreage of any combination of crops is the same as acreage covered by crop insurance, then we assume that farmers bought crop insurances for these crops. For example, if the sum of corn and wheat acreage is the same as acreage covered by insurance, we assume that corn and wheat are covered by crop insurance, even though there may be other other crops planted.

[11] Hay includes alfalfa and other hay.

ing the growing season. VPD is the difference between how much water the air can hold when it is saturated and how much water it currently holds. Since high VPD means higher water requirements and greater solar radiation, high VPD has a positive correlation with crop yield when soil moisture is adequate (Roberts, Schlenker and Eyer, 2013). High VPD has a negative correlation with crop yields when soil moisture is inadequate. High VPD with inadequate soil moisture also causes stress similar to drought. Since VPD may be the most harmful during the hottest month of the growing season, we calculate VPD during July and August (VPD_{JA}) and include them in our model. All climate variables are averaged over the 20 years prior to each farm operating year. Finally, growing seasons for corn, soybeans and winter wheat differ across states and crops (USDA, 2010).[12]

Soils data are based on the Soil Survey Geographic database (SSURGO). We include slope, saturated hydraulic conductivity (Ksat), available water capacity (AWC), K-factor, depth to water table, and percentage of organic matter as variables representing soil quality and land characteristics. Slope is the difference in elevation, expressed in percent terms. Ksat measures the permeability of soil, and AWC represents how much water soil can store. K-factor indicates the susceptibility of soil to water erosion. "Depth to water table" is the minimum depth above a wet soil layer. Organic matter is the amount of decomposed plant and animal residue in the soil. Since the ARMS phase III data only contain county-level location information, all climate and soil variables are aggregated to the county.

For expected output prices, state-level futures prices are constructed by adjusting regional differences in farm-gate prices (Barr et al., 2011).[13] For example, the expected prices of corn (p_c^e) are calculated as follows.

$$p_c^e = \bar{F}_c^f - B_c, \quad B_c = \bar{F}_c^d - \bar{p}_c^r,$$

[12]Since USDA (2010) has no information about hay planting dates and harvesting dates, we use the growing season of corn for hay.

[13]Chicago Board of Trade (CBOT) futures prices are used for corn and soybeans, and the Kansas City Board of Trade futures prices are used for winter wheat.

where $\bar{F}_c^f$ is the average of daily February closing prices of December corn futures contracts. B_c is called the "basis", and used to delete systematic differences between farm-gate prices and futures prices. $\bar{F}_c^d$ is the average of daily December closing prices of December corn futures contracts, and $\bar{p}_c^r$ is the state-level farm received price. For futures prices of soybeans and winter wheat, we use daily February closing prices of November soybean futures contracts and daily February closing prices of July winter wheat futures contracts, respectively. Since there is no future market for hay, previous market prices are used as expected prices. To control for price support programs, we use the higher price between futures prices and national loan rates, i.e., max{future prices, national roan rates}, (Wu et al., 2004). We only include nitrogen prices as input prices, and multi-regional anhydrous ammonia prices are used as nitrogen prices. For Pennsylvania, we use prices of Urea for fertilizer with 44 $\sim$ 46% nitrogen content.

The expected covariance between output prices and variance of output prices are calculated as:

$$Var(p_{i,t}) = \sum_{j=1}^{3} \omega_j [p_{i,t-j} - E_{t-j-1}(p_{i,t-j})]^2$$

$$Cov(p_{i,t}, p_{k,t}) = \sum_{j=1}^{3} \omega_j [p_{i,t-j} - E_{t-j-1}(p_{i,t-j})][p_{k,t-j} - E_{t-j-1}(p_{k,t-j})]$$

where the weights ω_j are 0.5, 0.33, and 0.17, respectively (Chavas and Holt, 1990; Sckokai and Moro, 2006; Wu et al., 2004). $p_{i,t-j}$ is the state-level farm-received prices of crop i in year $t-j$ and E_{t-j-1} is farmers' expectation of harvest output prices at planting time in year $t-j$. All price variables are normalized by the planting year price index for the other inputs.[14] We regress county-level crop yields on a time trend and a constant, and its

[14]We construct the price index for the other inputs as $I = \sum_j w^j I_{PPI}^j$, where w^j is the relative weight of the jth input and I_{PPI}^j is the USDA-published price paid index of the jth input. Since the USDA-published relative weights of each inputs are based on farms' expense, including nitrogen cost, we adjust these weights by excluding nitrogen weights. Unfortunately, USDA does not publish nitrogen weights of crop farms. Instead, we use nitrogen weights of all farms. The other inputs include several production items, financial fees and family living expense (USDA, 2011).

residuals are used to calculate the county-level variance of each crop yield (Chavas and Holt, 1990; Wu et al., 2004).[15] Table 1 and Table 2 in the Appendix show the summary statics of the data used in the analysis.

5 Preliminary Results

The results show that climate conditions have significant and diverse effects on farmers acreage allocation and crop selections.[16] The results related to farmers' crop selections are in Table 3. First, HDD have negative effects on corn selections, but precipitation affects corn selection positively. These results are intuitive because corn is water-intensive and sensitive to drought. Second, GDD have positive but small effects on soybean selections. Third, precipitation affects winter wheat selection positively, but VPD during the growing season influence winter wheat selection negatively. These results would reflect the fact that high soil humidity at planting time prevents farmers from converting winter wheat to corn. Lastly, GDD have negative effects on hay selection, but HDD has positive effects. Since we use the same growing season for corn and hay, we may interpret these results as good climate conditions for corn, such as adequate GDD and fewer HDD, have negative effects on hay selections. Since summer drought has negative effects on hay production, the negative sign of VPD_{JA} on hay selection equation is understandable.

Table 5 shows the effects of climate conditions on farmers' acreage adjustment among four crops, given farmers' crop selections. Since the second step results do not account for climate effects on crop selection, the direction of some estimates are less-intuitive. First, GDD have positive effects on soybeans but negative effects on winter wheat. GDD also

[15]For counties having fewer than eight yield observations, we we use state-level yield to avoid reducing observations (Carriquiry, Babcock, and Hart, 2005)

[16]Table 3 gives the estimation results of crop selection equation and Table 4 and 5 present results of estimating the land acreage equations.

negatively affect corn acreage, even though the size of influence is small.[17] Second, HDD (excessive heat) have negative effects on soybean and winter wheat acreage. Third, VPD have positive effects on soybean and winter wheat. These results reflect that soybeans and winter wheat are grown in the drier areas than corn. However, during the summer, the positive effects of VPD on soybean acreage become negative. Lastly, estimates related to precipitation are consistent with the results of crop selection equations: precipitation has positive effects on corn acreage but negative effects on soybeans and winter wheat.

To understand the overall effects of climate conditions, we examine the results of acreage response elasticities (see Table).[18] First, GDD have positive effects on corn and soybean acreage but negative effects on winter wheat acreage on average. When GDD increase by 1%, corn and soybean acreage increase by 0.6% and 1.4%, but winter wheat acreage decrease by 1.3%. Since corn and soybeans require more GDD to mature, farmers prefer to grow corn and soybeans when they expect adequate GDD. Second, when HDD increase by 1%, soybeans supplant corn and winter wheat. Specifically, soybean acreage increases by 0.14%, while corn and winter wheat acreage decrease by 0.16% and 0.18%. This is intuitive: soybeans are more heat tolerant relative to corn and winter wheat. Third, when precipitation increases by 1%, corn acreage increases by 0.6%, but soybean and winter wheat acreage decrease by 1.0% and 1.6%. Since corn requires more water than soybeans and winter wheat, other things being equal, farmers who expect adequate precipitation have an incentive to shift land from winter wheat and soybeans to corn. Fourth, farmers' acreage allocation between soybeans and winter wheat depends on humidity and plant-cooling stresses. An increase in VPD_{JA} by 1% decreases soybean acreage by 6.9%. This implies that a severe summer drought could decrease the proportion of soybean acreage substantially, even though soybeans are relatively

[17]Since winter wheat require less GDD to mature, the negative effect of GDD on winter wheat is understandable. However, the negative effects on corn acreage is counter-intuitive. These results may be due to the correlation between GDD and omitted harmful weather variables not addressed by HDD (Ortiz-Bobea, 2011). To resolve this problem, we may have to calculate climate variables based on specific crop development stages (Ortiz-Bobea, 2011).

[18]Since marginal effects of climate variables depend on estimated coefficients, covariance between the first and the second step equations, and individual explanatory variables, the sighs of the acreage response elasticities can differ from coefficient estimates in Table 5.

tolerant to heat. Increases in VPD and VPD_{JA} by 1% increase winter wheat acreage by 3.9% and 9.2%. Winter wheat is more tolerant to this source of stress because it requires relatively less water to mature and has a wide and deep root system. Winter wheat is also harvested before July, so large increase in VPD_{JA} relative to other crops provides greater incentive for farmers to increase their proportion of winter wheat acreage holding everything else constant.

The results of county-level yield variance are less-intuitive (See Table 7). Since we use county-level yield variance as a proxy for the effect of unexpected extreme weather events, we can expect that acreage responses to own yield variance are negative and acreage responses to the other crops' yield variance are positive. However, estimates of hay and wheat yield variances have sighs opposite expectations. Since hay and wheat are minor crops in our study area, their production risk may be less important to farmers in determining land allocation.[19] Because alfalfa is a perennial crop, land allocation to alfalfa would be less responsive to annual land use allocation. This means that it is necessary to adjust crop choice sets according to regional characteristics in our study area.

Insurance effects are also significant. Since crop insurance programs reduce the variation of farms' profit related to crop production, we can expect that farmers will shift land from crops not covered by crop insurance programs to crops covered by crop insurance programs. This could be due to adverse selection and moral hazard (Wu, 1999). The results show that corn, soybeans, and winter wheat acreage increase when farmers have corresponding each crop insurance.

[19] Table 2 shows that the average acreage of hay and winter wheat is only 10% of the acreage for corn or soybean. Also, only about 17% and 27% of farms allocate their land to wheat and hay, respectively. But the proportion of farms growing corn or soybeans is larger than 90%. Our data set use state-level hay and winter wheat yield data for many counties' yield variances. Thus it is possible that counties that mainly grow corn and soybeans have state-level hay and winter wheat yield variances, which is generally less than county-level yield variance.

6 Conclusion

Future climate change is expected to have negative effects on Midwest agriculture. Research on climate change has been limited farmers adaptation behaviors in measuring climate change effects. This study identifies Midwest farmers' responses to climate conditions by analyzing their cropland allocations. Specifically, this study asked two questions. First, how do climate conditions influence cropland allocation in the Midwest? Second, how do crop insurance programs alter farmers land use decisions? To answer these two questions, we use a reduced-form approach to construct acreage allocation equations based on risk-averse farms and apply it to farm-level information in the Midwest. Our findings are: 1) an increase in overall temperature has negative effects on winter wheat acreage and positive effects on corn and soybeans, 2) excessive heat and summer drought reduce corn and soybean acreage, and 3) crop insurance programs distort farmers land allocation.

The findings contribute broadly to our understanding of climate change and land allocation. First, they can be used to predict the direction of future land use in the Midwest based on projected changes in climate variables (Kunkel et al., 2013). Farmers in the northern Midwest may grow more corn since average temperatures and precipitation are predicted to increase, holding soil productivity fixed. Average temperatures in the southern Midwest are expected to remain constant. However, the frequency of very hot days (over 95 °F) is predicted to increase, while precipitation is predicted to decrease in the southwestern Midwest. Farmers in this region may increase soybean acreage.

The results reported in this paper are preliminary. Thus, we plan to extend the analyses. First, we now have data that we can control for farm-level spatial heterogeneity of climate and soil. Second, by constructing farm-level measures of extreme weather events, we can identify farmers' adaptive response to extreme weather events directly. Third, based on data containing historical land use information, we plan to consider the impact of agronomic constraints, such as crop rotations, on land use decisions. Fourth, we plant to test the empirical hypothesis that crop insurance effects on land allocation are independent of crop selection. The effects of corn crop insurance may differ between farmers growing only corn and farmers growing both corn and soybeans. Crop insurance effects may depend on the combination of crops grown in the region and covered by insurance. Lastly, these results will be used with structural or simulation models combined with climate forecasting models to forecast Midwest crop acreage allocations in response to climate change.

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7 Appendix

7.1 Climate Variables

To calculate GDD and HDD, we must consider 4 cases depending on the daily temperature distribution, upper and lower thresholds. Let the upper bound be $34°C$ and the lower bound be $8°C$ (Ritchie and NeSmith , 1991). "tmax" is a daily maximum temperature, "tmin" is a daily maximum temperature, "lower" is the lower threshold, "upper" is the upper threshold, M = (tmax + tmin)/2 and W = (tmax-tmin)/2.

- Case 1: tmin ≥lower, $GDD = M - lower$.

- Case 2: tmin < lower and tmax ≤ upper,
  $GDD = (M - lower)(\pi/2 - \theta) + Wcos(\theta)/\pi$,
  where $\theta = arcsin((lower - M)/W)$

- Case 3: tmin ≥ lower and tmax > upper,
  $GDD = M - lower - (M - upper)(\pi/2 - \tau) + Wcos(\tau)/\pi$,
  where $\tau = arcsin((upper - M)/W)$

- Case 4: tmin<lower and tmax>upper,
  $GDD = (M - lower)(\pi/2 - \theta) + Wcos(\theta)/\pi - (M - upper)(\pi/2 - \tau) + Wcos(\tau)/\pi$

HDD is only calculated at case 3 and case 4. HDD and VPD can be calculated by below equations.

$$HDD = ((M - upper)(\pi/2 - \tau) + Wcos(\tau))/\pi$$

$$VPD = 0.6107[exp((17.269tmax)/(237.3 + tmax)) - exp((17.269tmin)/(237.3 + tmin))]$$

7.2 Data and Estimation Results

Table 1: Summary Statistics - Environmental Conditions

Variables	Definition	Mean	Std.Dev	Min	Max
Soil					
Slope	slope (%)	2.58	2.14	0.08	16.19
Depth	Depth to water table (cm)	32.68	15.68	0.40	122.64
$Ksat$	Hydraulic conductivity (Ksat, m/s)	6.31	6.19	0.46	69.64
AWC	Available water capacity (AWC, in./in.)	0.12	0.06	0.01	0.22
K-factor	K factor	0.19	0.10	0.01	0.44
OM	Organic matter (%)	1.93	1.09	0.14	5.67
Climate					
GDD	GDD for corn	1801.95	156.56	1195.01	2250.58
	GDD for soy	1772.73	170.88	1243.26	2420.79
	GDD for Wheat	973.52	129.33	642.25	1500.65
HDD	HDD for corn	0.93	0.82	0.00	6.11
	HDD for soy	0.95	0.88	0.00	6.93
	HDD for Wheat	0.08	0.15	0.00	1.08
VPD	VPD for corn	278.56	16.40	204.67	338.50
	VPD for soy	267.20	17.58	192.74	352.17
	VPD for Wheat	242.97	33.47	154.25	334.59
Pre	Precipitation for corn	474.06	46.16	257.77	597.56
	Precipitation for soy	437.05	41.45	288.45	583.66
	Precipitation for Wheat	593.21	132.34	246.71	990.89
VPD_{JA}	VPD in July and August	316.82	22.48	218.66	414.14

Table 2: Summary Statistics - Market Variables

Variables	Definition	Mean	Std.Dev	Min	Max
	Harvested Acreage				
$Corn$	Corn grain (acre)	467.28	684.15	-	-
Soy	Soybean (acre)	389.94	520.84	-	-
$Wheat$	Wheat grain (acre)	26.97	148.04	-	-
Hay	alfalfa, other hay (acre)	14.38	58.22	-	-
$Land$	Sum of land for 4 crops	898.57	1124.43	-	-
	Expected Price				
$Pcorn$	Corn grain ($/bu)	3.99	1.35	1.98	6.50
$Psoy$	Soybean ($/bu)	8.81	3.11	5.00	14.44
$Pwheat$	Wheat ($/bu)	4.80	2.05	2.59	9.17
$Phay$	alfalfa, other hay ($/ton)	106.40	23.13	58.50	173.00
	Covariance of Prices				
$Var(corn)$	Corn and Corn	1.00	0.93	0.03	2.36
$Cov(corn, soy)$	Corn and Soybean	1.91	1.83	0.07	4.53
$Cov(corn, wheat)$	Corn and Wheat	0.67	0.86	-0.31	2.25
$Cov(corn, hay)$	Corn and hay	-2.61	6.92	-32.94	16.79
$Var(soy)$	Soybean and Soybean	5.44	3.47	0.80	10.58
$Cov(soy, wheat)$	Soybean and Wheat	1.64	1.94	-0.15	5.42
$Cov(soy, hay)$	Soybean and Hay	2.80	20.90	-40.13	58.54
$Var(wheat)$	Wheat and Wheat	0.90	0.96	0.02	3.04
$Cov(wheat, hay)$	Wheat and Hay	4.22	8.83	-20.03	26.22
$Var(hay)$	Hay and Hay	338.21	336.99	1.99	1387.69
	Variance of production				
Var_{corn}	Corn grain	372.87	126.06	82.53	1078.17
Var_{soy}	Soybean	31.47	12.09	2.24	86.03
Var_{wheat}	Wheat	84.60	36.67	9.22	226.59
Var_{hay}	Hay	0.22	0.11	0.02	0.73
	Farm Characteristics				
Age	Age	55.16	12.09	-	-
$Equity$	Equity ($1,000)	1946.4	3096.4	-	-
Off_farm	Previous year off-farm income ($1,000)	36.94	63.95	-	-
	Dummy variables				
$Retire$	Intention of retirement=1	0.06	0.24	-	-
$Edu1$	less than high school=1	0.04	0.21	-	-
$Edu2$	high school=1	0.46	0.50	-	-
$Edu3$	Some college=1	0.29	0.45	-	-
$Edu4$	4-year college graduate and beyond=1	0.20	0.40	-	-
I_c	Insurance for corn	0.66	0.47	-	-
I_s	Insurance for soybean	0.65	0.48	-	-
I_w	Insurance for wheat	0.10	0.30	-	-
I_h	Insurance for hay	0.15	0.36	-	-
$P_{Nitrogen}$	Nitrogen Price ($/pound)	0.37	0.10	0.23	0.55
$\#\ of\ obs$	11,230				

Note: Min and Max information related to ARMS data is omitted because of the confidential reason.

Table 3: Estimates of crop selection equations

	Corn	Soybean	Wheat	Hay
$Cons$	-2.602**	-0.591	0.597	0.300
	(1.088)	(1.146)	(0.541)	(0.730)
GDD	0.000	0.001**	-0.000	-0.001*
	(0.001)	(0.001)	(0.000)	(0.000)
HDD	-0.259***	-0.116	-0.411	0.118**
	(0.060)	(0.076)	(0.294)	(0.051)
VPD	0.002	-0.009	-0.0127***	0.005
	(0.006)	(0.012)	(0.001)	(0.004)
Pre	0.003***	-0.000	0.003***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
VPD_{JA}	0.007	0.001	-0.002	-0.006*
	(0.005)	(0.011)	(0.002)	(0.003)
OM	0.102	0.005	0.021	-0.143**
	(0.087)	(0.082)	(0.069)	(0.060)
$Slope$	-0.020	-0.087***	-0.072***	0.115***
	(0.020)	(0.017)	(0.017)	(0.014)
$Ksat$	-0.006	-0.024***	0.000	0.005
	(0.006)	(0.005)	(0.004)	(0.004)
AWC	7.664**	6.860**	-9.258***	-0.006
	(3.543)	(3.274)	(3.207)	(2.627)
K-factor	-3.780***	-2.698**	4.490***	-0.050
	(1.253)	(1.313)	(1.451)	(1.101)
$Depth$	-0.000	0.004*	0.003	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
$Edu1$	-0.180	-0.083	0.161	0.040
	(0.160)	(0.160)	(0.152)	(0.126)
$Edu2$	0.115	0.082	0.080	0.036
	(0.101)	(0.105)	(0.097)	(0.079)
$Edu3$	0.1219	0.165	-0.045	0.018
	(0.099)	(0.106)	(0.098)	(0.080)
Age	-0.009***	-0.003	0.004	0.005**
	(0.003)	(0.003)	(0.002)	(0.002)
$Retire$	-0.531***	-0.548***	-0.345***	-0.121
	(0.112)	(0.115)	(0.116)	(0.102)
Off farm	-0.001***	-0.001***	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year Dummies	Yes	Yes	Yes	Yes

Note: *** means significance at 1% level. ** means significance at 5% level. * means significance at 10% level. () means standard deviations of estimates.

Table 4: Estimates of acreage equations

	Corn	Soybean	Wheat	Hay
$Cons$	-20.448	50.192***	-2.336***	-27.408**
	(16.423)	(17.067)	(0.616)	(16.339)
t	6.117	-2.170	-266.312***	262.365***
	(8.883)	(8.096)	(23.621)	(20.821)
$Equity$	0.000***	-0.000***	-0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.014)
P_{corn}	22.744***	-18.266**	-28.106	23.628
	(7.987)	(7.514)	(22.220)	(20.851)
P_{soy}	-7.662*	-0.442	128.266***	-120.162***
	(5.577)	(5.620)	(15.883)	(15.129)
P_{wheat}	-20.344***	11.233**	114.176***	-105.066***
	(6.258)	(5.722)	(15.679)	(13.591)
P_{hay}	-0.604***	-0.072	-0.388	1.064**
	(0.168)	(0.172)	(0.605)	(0.571)
$Var_p(corn)$	-31.015	-318.225***	2051.914***	-1702.674***
	(61.077)	(50.757)	(195.654)	(178.688)
$Cov_p(corn, soy)$	51.932**	136.473***	-841.422***	653.017***
	(31.945)	(26.551)	(95.690)	(87.579)
$Cov_p(corn, wheat)$	-223.998***	62.059*	1535.077***	-1373.138***
	(51.497)	(44.481)	(134.563)	(119.347)
$Cov_p(corn, hay)$	-1.677***	-0.061	-0.258	1.996**
	(0.349)	(0.356)	(1.159)	(1.087)
$Var_p(soy)$	9.057	-6.045	-169.148***	166.135***
	(7.314)	(7.008)	(18.784)	(17.002)
$Cov_p(soy, wheat)$	22.171**	10.077	-237.461***	205.212***
	(10.336)	(9.113)	(26.612)	(25.001)
$Cov_p(soy, hay)$	0.287***	0.104	-0.663**	0.271
	(0.114)	(0.108)	(0.312)	(0.289)
$Var_p(wheat)$	68.087***	-16.957*	-427.135***	376.005***
	(12.902)	(11.992)	(46.034)	(39.787)
$Cov_p(wheat, hay)$	0.327**	0.261*	2.566***	-3.154***
	(0.169)	(0.171)	(0.355)	(0.331)
$Var_p(hay)$	0.009**	-0.007*	0.013	-0.016*
	(0.004)	(0.005)	(0.012)	(0.011)
$Nitrogen$	-325.697***	147.108***	-625.310***	803.899
	(50.903)	(45.007)	(177.345)	(158.108)
$\pi_{corn,j}$	248.144***	-173.307***	261.280***	-
	(38.147)	(15.298)	(35.417)	-
$\pi_{soy,j}$	-156.595***	280.162***	-360.715***	-
	(22.149)	(37.201)	(61.102)	-
$\pi_{wheat,j}$	43.162***	-6.413	141.078***	-
	(6.758)	(6.550)	(36.560)	-
$\pi_{hay,j}$	87.090***	-157.340***	330.849***	-
	(24.290)	(23.124)	(74.314)	-

Note: Standard deviations are from 2,000 bootstrap runs. *** means significance at 1% level. ** means significance at 5% level. * means significance at 10% level. () means standard deviations of estimates.

Table 5: Estimates of acreage equations (continue)

	Corn	Soybean	Wheat	Hay
GDD	-0.057***	0.238***	-0.593***	0.413***
	(0.024)	(0.026)	(0.068)	(0.066)
HDD	-2.666	-4.504*	-528.787***	535.956***
	(3.074)	(2.943)	(60.592)	(60.908)
VPD	0.545	1.360*	3.406***	-5.311***
	(1.148)	(0.983)	(0.701)	(1.376)
Pre	0.525***	-0.411***	-0.425***	0.311***
	(0.039)	(0.040)	(0.108)	(0.099)
VPD_{JA}	-0.761	-1.381*	-0.038	2.180**
	(0.986)	(0.848)	(0.612)	(1.253)
OM	-9.147***	16.911***	-19.696**	11.932
	(3.195)	(3.142)	(11.199)	(10.539)
$Slope$	9.531***	-19.824***	29.441***	-19.149
	(2.577)	(2.503)	(7.879)	(7.726)
$Ksat$	3.029***	-3.394***	4.451***	-4.086***
	(0.318)	(0.325)	(0.789)	(0.796)
AWC	23.407	-434.499***	-2282.242***	2693.334***
	(120.361)	(121.420)	(446.748)	(426.471)
K-factor	-45.058	263.830***	971.390***	-1190.162***
	(53.472)	(52.665)	(197.900)	(188.566)
$Depth$	-0.503***	0.754***	0.005	-0.255
	(0.123)	(0.133)	(0.362)	(0.363)
$Var_y(corn)$	-0.030***	-0.016**	0.020	0.027*
	(0.009)	(0.008)	(0.022)	(0.020)
$Var_y(soy)$	0.261***	-0.153**	-0.259	-0.367
	(0.078)	(0.079)	(0.312)	(0.293)
$Var_y(wheat)$	-0.073***	0.094***	0.239***	-0.260***
	(0.029)	(0.027)	(0.095)	(0.086)
$Var_Y(hay)$	88.200***	-38.932***	-148.412**	104.143***
	(8.558)	(8.453)	(25.624)	(23.313)
Ins_c	107.585***	-80.492***	-148.576***	121.483***
	(3.627)	(3.773)	(10.850)	(10.060)
Ins_s	-100.543***	99.915***	3.414	-2.785
	(3.674)	(3.292)	(7.803)	(7.190)
Ins_w	-90.379***	-15.665***	382.073***	-276.029***
	(3.555)	(2.989)	(9.937)	(7.886)
State dummies	Yes	Yes	Yes	Yes

Note: Standard deviations are from 2,000 bootstrap runs. *** means significance at 1% level. ** means significance at 5% level. * means significance at 10% level. () means standard deviations of estimates.

Table 6: Acreage response elasticities to environmental conditions

	corn	soy	wheat
GDD	0.604*	1.411**	-1.316**
	(0.452)	(0.040)	(0.696)
HDD	-0.160***	0.135***	-0.177***
	(0.037)	(0.039)	(0.036)
VPD	4.517	2.229	3.865**
	(3.625)	(3.223)	(2.074)
Pre	0.630**	-1.013***	-1.554***
	(0.328)	(0.315)	(0.630)
VPD_{JA}	0.151	-6.889**	5.654***
	(3.505)	(3.123)	(1.656)
OM	0.087**	-0.164***	0.351***
	(0.046)	(0.049)	(0.103)
$Slope$	0.027	0.030	-0.185***
	(0.030)	(0.030)	(0.073)
$Ksat$	0.120***	-0.176***	0.124***
	(0.018)	(0.019)	(0.032)
AWC	7.721***	-2.347	6.613**
	(2.169)	(2.162)	(2.985)
K-factor	1.021*	0.053	3.978***
	(0.623)	(0.586)	(0.863)
Depth	0.026	-0.052**	0.407***
	(0.033)	(0.033)	(0.088)

Note: Standard deviations are from 2,000 bootstrap runs. *** means significance at 1% level. ** means significance at 5% level. * means significance at 10% level. () means standard deviations of estimates.*** means significance at 1% level.

Table 7: Acreage response elasticities

	Corn	Soybean	Wheat	Hay
$Equity$	0.099***	-0.122***	-0.089**	0.298***
	(0.036)	(0.044)	(0.042)	(0.121)
P_{corn}	0.782**	-0.656*	-0.753	2.012
	(0.444)	(0.425)	(0.875)	(2.273)
P_{soy}	-0.574	-0.035	7.523***	-22.274***
	(0.667)	(0.687)	(1.366)	(3.517)
P_{wheat}	-0.818**	0.467	3.488***	-10.342***
	(0.410)	(0.376)	(0.674)	(1.648)
P_{hay}	-0.572**	-0.071	-0.318	2.498*
	(0.251)	(0.274)	(0.734)	(1.676)
$Var_p(corn)$	-0.301	-3.125***	17.364***	-40.209***
	(0.892)	(0.782)	(2.197)	(5.423)
$Cov_p(corn, soy)$	0.966	2.574***	-13.676***	29.493***
	(0.883)	(0.780)	(2.002)	(4.993)
$Cov_p(corn, wheat)$	-1.448***	0.397	8.936***	-21.203***
	(0.436)	(0.399)	(1.051)	(2.375)
$Cov_p(corn, hay)$	0.036***	0.001	0.001	-0.110*
	(0.013)	(0.010)	(0.019)	(0.072)
$Var_p(soy)$	0.507	-0.346	-8.167***	22.855***
	(0.597)	(0.608)	(1.257)	(2.850)
$Cov_p(soy, wheat)$	0.335*	0.151	-3.278***	7.518***
	(0.218)	(0.195)	(0.451)	(1.131)
$Cov_p(soy, hay)$	0.006	0.002	-0.033	0.014
	(0.005)	(0.005)	(0.039)	(0.015)
$Var_p(wheat)$	0.574***	-0.142	-3.252***	7.756***
	(0.163)	(0.155)	(0.444)	(1.036)
$Cov_p(wheat, hay)$	0.013*	0.010	0.137***	-0.308***
	(0.009)	(0.011)	(0.022)	(0.028)
$Var_p(hay)$	0.032*	-0.023	0.057	-0.134
	(0.023)	(0.026)	(0.056)	(0.101)
$Nitrogen$	-0.867***	0.406**	-1.363***	5.302***
	(0.208)	(0.189)	(0.552)	(1.327)
$Var_y(corn)$	-0.082**	-0.046*	0.043	0.180
	(0.036)	(0.033)	(0.072)	(0.179)
$Var_y(soy)$	0.062**	-0.037	0.045	-0.214
	(0.029)	(0.029)	(0.082)	(0.223)
$Var_y(wheat)$	-0.043**	0.059**	0.117**	-0.373***
	(0.026)	(0.025)	(0.064)	(0.156)
$Var_y(hay)$	0.607***	-0.294***	-0.868***	1.886***
	(0.100)	(0.102)	(0.229)	(0.551)
Ins_c	0.784***	-0.609***	-0.869***	2.199***
	(0.041)	(0.044)	(0.229)	(0.231)
Ins_s	-0.733***	0.756***	0.020	-0.050
	(0.042)	(0.039)	(0.068)	(0.165)
Ins_w	-0.659***	-0.118***	2.234***	-4.998***
	(0.040)	(0.035)	(0.091)	(0.195)

Note: Standard deviations are from 2,000 bootstrap runs. *** means significance at 1% level. ** means significance at 5% level. * means significance at 10% level. () means standard deviations of estimates.*** means significance at 1% level.