Climate Variation and Corn Price Volatility:

A Partial Equilibrium Model

A Thesis

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by

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APPROVAL FORM

The undersigned, appointed by the Dean of the Graduate School, have examined the thesis entitled

CLIMATE VARIATION AND CORN PRICE VOLATILITY:

A PARTIAL EQUILIBRIUM MODEL

presented by Nicholas Andrew Pirotte,

a candidate for the degree of Master of Science,

and hereby certify that, in their opinion, it is worthy of acceptance.

Professor Wyatt Thompson, PhD.

Professor Patrick Westhoff, PhD.

Professor Felix Fritschi, PhD.

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ABSTRACT

Projected future climate changes in the US Corn Belt provides motivation to study how these changes will affect the volatility of crop prices. Recent publications focused on how these changes in climate and climate variability affect the volatility of crop prices and yields, but we are aware of no research that focuses on how the changing of climate variability alone will affect the volatility of yields and area, as well as the market consequences. Considering these indicators, past publications do not account for the timing and intensity of weather variables when estimating the price impacts of climate driven changes to yields and area. This study builds on the previous literature to estimate how the timing of specific weather variables, important to corn yields and area, will affect the volatility of corn prices. The study finds that, under future climate scenarios, corn price volatility could increase, causing a potential change in producer receipts and a potential increase in government costs.

I. INTRODUCTION

Climate change has been a relevant topic for years now, and its implications are being predicted, and revealed, more and more as time goes on. Research that focuses on the relationship between the climate and agriculture is fairly common due the obvious interaction between the two disciplines, but there are still many uncertainties – even at the regional level. This study focuses on how climate variability will impact agriculture, because it has been studied much less than climate change. Studies such as Schlenker and Roberts (2009) and Miao et al. (2015), have looked at how US crop yields and area will be impacted by changes to the averages of climate variables, but they do not go into much detail about how changes in climate variability will affect these same agricultural variables. The economic effects that will result from climate driven changes in agriculture are difficult to determine because there is a large number of variables that must be considered in these estimates. More specifically, the agricultural economic effects of climate change and variability must consider the social sciences behind crop area, consumption, stocks, and trade in addition to the physical science behind climatology and plant physiology. Diffenbaugh et al. (2012) and Thompson et al. (2016) have estimated how future climate scenarios will increase crop price volatility, but the goal of these studies is not to measure how a shock to the timing of weather events will affect price volatility. This paper attempts to use a blend of previous literature and economic theory to estimate how changes in future climate variability, specifically precipitation, will transfer to corn price volatility.

Diffenbaugh et al. (2012) and Thompson et al. (2016) estimated how average changes in weather variables will increase corn price volatility. However, these studies do not specifically align the timing of weather variables with agronomic theory. Instead, Diffenbaugh et al. (2012) uses a growing season average as a precipitation estimate, and Thompson et al. (2016) relies on statistics to select the time period of its yield determining weather variables. Their methods serve as the starting point for this study.

As explained above, the question in this paper is how a change in the variability of weather during vulnerable growing stages will affect the volatility of the corn market. Relying on previous literature, corn physiology, and statistics, the study uses July precipitation as the single yield altering climate variable. The study also incorporates how changes in climate variation will impact corn area, because precipitation is a key factor in determining when a producer can work their land. The climate variable used to estimate corn area is May precipitation.

This study develops and uses a partial equilibrium (PE) model to estimate how short-term US corn prices, farm revenue, area, yields, stocks, and trade will change under different precipitation scenarios. To do so, we perform a series of shocks to the standard deviations, but not the averages, of the climate variables to provide evidence to whether or not previous studies may have over or under estimated price volatility in future climate scenarios. Understanding the climate driven price volatility of the future market will help grain producers, grain consumers, and policy makers to better prepare for the increased price risk. We are not aware of any other study that focuses on the impacts of climate change on crop yields, area planted, and market volatility.

This study finds that increased climate volatility in the US Corn Belt could result in more volatile corn prices, which may expose the relevant market players to increased price risk. The results suggest that there could also be increased variability in corn yields, area harvested, stocks, net farm revenues, and trade, which all likely contribute to the increased price risk.

II. REVIEW OF LITERATURE

As previously noted, the agricultural implications of climate change have been widely studied, especially in recent years. The literature relevant to this study focuses on the effects of climate variability on crop yields and area harvested, and consequently, on the volatility of crop market prices and quantities. Previous publications have looked at how average changes in climate variables may affect the volatility of crop yields, area, and prices, but there is no known publication that has focused on how changing climate variation will affect the volatility of agricultural markets while taking yield, area, and market effects into account. Furthermore, the previous literature does not account for the agronomic implications of the timing of weather events. The combination of the publications reviewed below provide the starting point this study.

Climate Change

The literature generally relies on the future climate predictions developed by the International Panel on Climate Change (IPCC). The IPCC is a multidiscipline, multilateral research committee that estimates the future climate and its implications, and it releases a report approximately every seven years. In its most recent publication, Assessment Report 5 (AR5), the IPCC predicts four likely climate scenarios that are based on the relative concentration pathways (RCPs), of future greenhouse gas (GHG) concentrations. Each RCP depends on if and when the atmospheric GHG concentrations stop increasing. Under all four RCP scenarios in AR5, the global temperature is expected to increase, but the severity of the temperature increase is uncertain (Table 2.1).

The IPCC also goes into some regional detail of its future climate expectations. Relevant to this study, the IPCC compares Central North American temperature and precipitation data from 1986 to 2005 with their estimates for the period of 2016-2035 under the four RCP scenarios (Table 2.2). They estimate under RCP 4.5 that average temperatures in June, July and August (JJA) will increase between 0.3^{0} C and 2.3^{0} C during their prediction period (IPCC AR5, 2013). The IPCC found a less conclusive result for precipitation under the same scenario. They estimate that the percent change of precipitation across the region in April through September (AMJJAS) will range from a 7% decrease to a 9% increase. Furthermore, the percent change in precipitation at the 50th percentile of the model results is zero. To summarize, the IPCC's estimates suggest that in the Central United States average temperatures in JJA will increase, but their estimated changes in rainfall patterns suggest that precipitation in AMJJAS may become more uncertain.

The IPCC's precipitation projections suggest that the uncertainty of future precipitation might increase, but these specific projections do not explicitly suggest increased precipitation variability (IPCC AR5, 2015). The IPCC does, however, claim that heavy precipitation events in North America are likely to increase (IPCC AR5, 2015). Arritt (2016) goes further than these IPCC projections and suggests that future precipitation in the US Corn Belt may become more variable. The study projects a possible slight increase in summer precipitation over the region, but a much larger increase in the frequency of heavy precipitation events. This finding suggests that rainfall averages might not drastically change, but there might be large increases in the frequency heavy precipitation. This projected increase in heavy precipitation combined with the small change in average total precipitation suggests increased precipitation variability over the region. Furthermore, the study suggests that the variability of climate might be more important than the averages in the US Corn Belt.

Table 2.1: IPCC AR5: RCP Scenarios

RCP Scenario	GHG Concentration Scenario	World Temperature Increase
RCP2.6	Peak and Decline by 2100	1.5^0 C
RCP4.5	Stabilization at a lower level by 2100	2.5^0 C
RCP6.0	Stabilization at a higher level by 2100	3.0^0 C
RCP8.5	Rising emissions through 2100	4.9^0 C

Source: IPCC AR5 (2013)

Table 2.2: IPCC AR5: Temperature and Precipitation Estimates 2015-2036

Scenario	Period	Min	25th Percentile	50th Percentile	75th Percentile	Max
Temperature (^{0} C)						
RCP 2.6	JJA	0.4	0.7	1.2	1.4	2.2
RCP 4.5	JJA	0.3	0.8	1.1	1.4	2.3
RCP 6.0	JJA	0.4	0.6	0.9	1.2	1.8
RCP 8.5	JJA	0.5	1.1	1.2	1.4	2.3
Precipitation (% Change)						
RCP 2.6	AMJJAS	-8	-1	1	4	8
RCP 4.5	AMJJAS	-7	-2	0	3	9
RCP 6.0	AMJJAS	-6	0	2	3	9
RCP 8.5	AMJJAS	-9	-2	1	3	9

Source: IPCC AR5 (2013)

Corn Growth and Weather

Weather plays an important physiology role in the determining of corn yields. Corn has many growth stages (Table 2.3) and the timing of weather related stress is an important factor when determining how this stress will affect the resulting yields. Corn is especially vulnerable to hot and dry weather during the tasseling and silking growth stages. (Nielsen, 2016; Nielsen, 2016). The timing of when these two growth stages occur is inconsistent because they vary based on many things including planting date, variety, farming practices, and location. For this research, the beginning of these stages is assumed to be approximately 65 to 75 days, estimated from 1400 growing degree days, after corn is planted (Neild and Newman, 1990; Abendroth, Elmore, Boyer and Marlay, 2011). Even with this assumption, it is still difficult to estimate when exactly in the calendar year these growth stages will occur, because corn planting dates differ based on things such as farming practice, variety, and the region in which the corn is planted. Under the assumption that corn is typically planted in the Central US Corn Belt between April 15th and May 15th, the reproductive stage is calculated to begin between June 20th and July 30th (Neild and Newman, 1990). Unfortunately, the readily available climate data is based on monthly, not daily, data. The choice was made to use July weather variables because the above calculation suggests that July is more likely than June to encompass the previously stated vulnerable growth stages. It should be noted that the assumptions made above are limitations of this study.

Table 2.3: Corn Growth Stages

Growth Stage	Appearance	Growth Stage	Appearance
VE	Emergence	R1	Silking
V5	5th leaf	R2	Blister
V10	10th leaf	R4	Dough
V15	15th leaf	R5	Dent
VT	Tasseling	R6	Maturity

Source: Adapted from (Nafziger, 2009)

Yield models

Schlenker and Roberts (2009) and Miao et al. (2015) provide the most relevant corn yield models for this paper. Schlenker and Roberts (2009) studies the nonlinear relationship between temperature and US corn yields. The article uses the range in daily temperatures at the county level in the US to determine how temperatures affect crop yields. The authors find that every day during the growing season that the temperature is above 29^0 C, the resulting corn yield drops off sharply. They also determine that summer temperatures below 29^0 C have no impact or a very small positive impact on yields. The study estimates that, relative to a 24-hour day with a temperature of 29^0 C, each 24-hour period at 35^0 C results in an approximately 5% decrease in corn yields and each day at 40^0 C results in an approximately 7% drop off in corn yields.

Schlenker and Roberts (2009) also looks at how average total precipitation in June and July may offset high temperatures. They determine that increased precipitation during the periods of high temperatures may mitigate some of the impacts of the heat. They estimate that with increased precipitation, each 24-hour period with temperatures of 35^0 C will result in only an approximate 3% decrease in yields, and each 24-hour period with temperatures of 40^0 C will only result in an approximate 5% decrease of yields. The authors also look at how July temperatures affect corn yields relative to the rest of the growing season months because tasseling usually occurs in July. They find, with statistical significance, that July temperatures effect corn yields more than the other months of the growing season. They discount this finding by acknowledging only a small R^2 increase when an exogenous July temperature variable is introduced. Schlenker and Roberts (2009) provides a starting point for future research.

Miao et al. (2015) is another recent publication that estimates not only how climate variables affect corn yields, but also how they affect corn area in the US. The study uses data from agriculturally relevant, rain fed counties east of the 100th meridian between the months of March and August for the years 1977 to 2007. The corn yield model relies on the following variables: growing degree days (GDDs), GDDs squared, over-heat days, monthly average precipitation, monthly average precipitation squared, temperature deviation from the monthly mean, a time trend, and a time trend squared. It should be noted that the study uses three models, and the previously stated variables are used in model one with no additions. Models two and three use the same variables as model one, but they include a dummy variable to account for the Federal Agriculture Improvement and Reform Act of 1996 (FAIR Act). The FAIR Act was a major policy change that took place during the reference period of the study, and it is presumably included because it could have changed producer revenue expectations. Model three makes another addition to include a crop price term and fertilizer price term. Although Miao et al. (2015) argues in the favor of the model with the price effects, a version without the price effects is more comparable with the yield equation estimated in the present study. Therefore, model two is chosen to be reviewed because it is the most relevant to this study. The chosen model estimates that, of the time specific weather variables, July is the most influential on corn yields precipitation (Table 2.4). For completeness, the weather results from the model that includes the price terms are also shown, and these results also suggest that July is also the most important month for precipitation (Table 2.4). The findings of Miao et al. (2015) that demonstrate the importance of July weather, specifically precipitation, is an important take away of their research because their findings support the variables selected for the yield equation in this study.

Miao et al. (2015) also estimates how weather variables affect corn acreage in a similar manner. They find that there is a statistically significant, negative relationship between corn acreage and April precipitation. Their results show that precipitation in May in also has a negative relationship with corn acres, but this result is not statistically significant. The study also independently tests soybeans acreage with the same model, and finds that May precipitation has a statistically significant, positive effect on soybean acres. They suggest that this relationship indicates that May precipitation discourages corn planting, and instead results in more soybean acres. This is a reasonable finding because if a producer cannot get into his field during May, then they may decide to plant more soybeans instead of planting corn very late in the season.

Equilibrium Model

The two types of equilibrium models seen in the literature are partial equilibrium (PE) models and general equilibrium (GE) models. The difference between the two models is that a GE model includes all sectors of the economy, while the PE model represents explicitly only a specific portion of the economy. Both types of models are common in the literature. There is some variation in the PE models used in the literature, but the research that uses a GE model often uses the Global Trade Analysis Project (GTAP) model. While still useful, the general limitation of using a PE model is that it may over or under estimate economic impacts of a shock because it does not explicitly include all markets that the respective shock may have an important effect on. Nelson et al. (2014) provides a relevant example of this by comparing the results of climate impacts on agriculture between five accepted GE models and four accepted PE models. The results from the study suggests that the PE models might overestimates the climate impacts of agricultural yields, area, and price but might underestimates the impact on consumption. Understanding the possible limitations of using a PE is important when looking at past literature.

Diffenbaugh et al. (2012) is the first study focused on how climate driven yield changes in the US Corn Belt will affect US corn price volatility. The study uses a form of the GTAP model to estimate the price impact of climate change by shocking corn yield variability. The basis for the shock comes from a climate scenario that is estimated in the IPCCs Assessment Report 4 (2007), and their chosen scenario is most similar to the previously defined RCP 6.0 scenario. The resulting values from this climate scenario are then used in an adapted Schlenker and Roberts (2009) yield equation for the time period 2020 to 2040. The relevant climate variables used in the Schlenker and Roberts (2009) yield equation are growing degree days (GDD) between 10^0 C and 29^0 C, GDD over 29^0 C, and average precipitation over the growing period. Under the selected climate change scenario, the authors estimate less than a 6% increase in GDD between 10^0 C and 29^0 C, an increase between 100% and 160% of GDD over 29^0 C, and up to a 50% increase in growing season precipitation. The study then imposes these climate changes into their yield equation to find that yield variability might increase from a historical value of 22% to a future projection of 48%. For reference, the study uses the period 1980 to 2000 for its historical data and it uses the period 2020 to 2040 in its projections to calculate future yield variability. The authors then double the supply volatility and observe the effects that this shock has on corn price volatility in their adapted GTAP model. . More specifically, the study introduces this climate driven increase to the volatility of corn yields as a shock to the volatility of corn supply in the GTAP model. They then observe how this supply shock will affect price volatility. The model suggests that from 2020 to 2040 the doubling of the corn yield variation will result in the percent change of standard deviation for year to year corn prices to increase by a factor of approximately 3 to 5 times. The authors also test how corn prices react to the climate shock when the shock is applied with high oil prices, low oil prices, the current ethanol mandate, and the discontinuation of the ethanol mandate.

Diffenbaugh et al. (2012) is a field advancing study, but it still has, and identifies, its limitations. First, it uses average total rainfall as a measure of precipitation, which, as they note, does not account for the "frequency or intensity" of rainfall. This is concerning because the timing of rain is likely more important than the total amount over a six-month period. Second, the study does not allow price to affect yields. For example, if there is a sharp increase in prices, then a farmer might increase fertilizer usage in an effort to increase crop yields, but the model does not allow for this type of response to happen. Third, the study does not explicitly represent the supply and demand for stocks, leaving stock change implicitly as part of aggregate demand. Ending stocks demand is probably more elastic than overall demand, meaning that ending stocks might be able to stabilize prices in future climate scenarios. Diffenbaugh et al. (2012) does not explicitly represent stocks, and because of this choice the possible price stabilizing effect of stocks is missed. Fourth, the study looks only at how climate change will impact one crop, while holding the rest of the crops constant. There are other limitations in the model, but the four noted here are most relevant to this research.

Thompson et al. (2016) identified some of these limitations in a similar study that compared a model that included not only corn, but also soybeans in the US Corn Belt. They acknowledge the value created by Diffenbaugh et al. (2012), but point out that climate does not only effect corn yields. Thompson et al. (2016) expects that focusing only on one crop may underestimate the effect of climate change on agriculture. They use a PE model developed by the Food and Agricultural Policy Research Institute at the University of Missouri (FAPRI-MU) combined with future climate predictions from the North American Regional Climate Change Assessment Program (NARCCAP) in their experiment. Furthermore, the authors allow for stocks to react to the market through an explicit behavioral equation and also incorporate some automatic policy responses into their model. Similar to Diffenbaugh et al. (2012), Thompson et al. (2016) uses the equation developed by Schlenker and Roberts (2009) to estimate the future climate driven changes to yield variability. Thompson et al. (2016) then uses these yield projections in the FAPRI-MU PE model to estimate how the increased yield variability will affect price volatility. They estimate yields under future climate change scenarios for only corn, only soybeans, and then both corn and soybeans. They find that future changes average corn yields will range from +2% to -18% and future changes in corn yield standard deviation will range from -1% to +27%. The changes in corn price that result from the climate driven yield shock are a 5% to 30% increase in average prices and an 11% to 66% change in the corn price standard deviation.

The main purpose of Thompson et al. (2016) is to provide evidence that a single crop model underestimates the impact of climate change, and although it may not seem extremely relevant to the goal of their paper, the omission of changes to the timing of weather variables is still a limitation of their study. The article relies on historical statistics to determine which weather variables affect yields, instead of using a more physiological approach to determine these variables. This method may make more sense for their purpose, but it does not answer the question of how the timing of precipitation may affect markets.

It should be noted here that the results in Thompson et al. (2016) are not directly comparable to Diffenbaugh et al. (2012) for a couple of reasons. First, the studies use different methods in measuring volatility. Diffenbaugh et al. (2012) estimates volatility as the standard deviation of the year-to-year changes in both price and yield, but Thompson et al. (2016) does not explicitly identify a volatility term, and instead just states the averages and standard deviations in their results. An exact comparison between the two is not possible with only the data available in the respective publications. Moving to more fundamental difference, the studies use different time periods in their model estimates. Diffenbaugh et al. (2012) uses the period 2020 to 2040 while Thomson et al. (2016) uses a shorter time period of 2016 to 2026. Next, the two studies impose, similar, but different climate shocks in their model, which might cause their results to differ. A comparison of these two studies with the results in this study is shown in the *RESULTS* section.

To conclude, both of these studies determine that climate change will increase market volatility, but neither of them attempt to determine how climate variability and the timing of precipitation will affect markets, particularly taking into account the impacts on crop yield and area. This study plans to research the market implications of future climate change as set by the IPCC. The study uses methods accepted in previous studies as a starting point, but applies such methods in a different way to measure how the timing of future climate events could affect the volatility of the future market.

Table 2.4: Miao et al. (2015) Climate Variable Coefficients

	Model II - No Price Variables		**Model II - Price Variables**	
Variables	**Coefficient**	**Stand. Error**	**Coefficient**	**Stand. Error**
Precip. in March	0.008	-0.011	0.0194*	-0.011
Precip. in March Sq.	-6.04e-5*	-0.0000363	-0.0001***	-0.0000393
Precip. in April	-0.013	-0.011	-0.018	-0.011
Precip. in April Sq.	0.00000878	-0.0000376	0.000022	-0.000039
Precip. in May	0.039***	-0.01	0.025**	-0.011
Precip. in May Sq.	-0.0002***	-0.000031	-0.0002***	-0.0000313
Precip. in Jun.	0.122***	-0.01	0.121***	-0.01
Precip.in Jun. Sq.	-0.0004***	-0.0000361	-0.0004***	-0.0000359
Precip. in July	0.184***	-0.012	0.176***	-0.012
Precip. in July Sq.	-0.0004***	-0.000042	-0.0004***	-0.000041
Precip. in Aug.	0.0844***	-0.009	0.069***	-0.01
Precip. in Aug. Sq.	-0.0002***	-0.0000288	-0.0002***	-0.0000312
Temp. deviation, Mar.	0.418**	-0.196	0.053	-0.216
Temp. deviation, Apr.	1.160***	-0.213	1.018***	-0.226
Temp. deviation, May	0.311	-0.233	0.802***	-0.262
Temp. deviation, Jun.	-1.079***	-0.233	-1.488***	-0.264
Temp. deviation, Jul.	-1.340***	-0.272	-0.515	-0.324
Temp. deviation, Aug.	-0.502**	-0.229	-0.776***	-0.243

Source: Miao et al. (2015)
* - 10% significance; ** 5% significance; *** 1% significance

III. METHODOLOGY

Model Structure

The model in this study is designed to use both US and rest of world (ROW) Supply (*SUPPLY*) and Demand (*DEMAND*) to calculate a market price that balances the net trade between the two regions (Figure 3.1). The US is a net exporter of corn, while the ROW is a net importer of corn. In the model, a Market Price (*PRICE*) of corn will change until the US net exports ($NETEXP_{US,t}$) balance with ROW net imports ($NETIMP_{ROW,t}$). In order for the $NETEXP_{US,t}$ and $NETIMP_{ROW,t}$ to balance, the *PRICE* is transmitted to the US and ROW and affects the quantity of supply and demand variables. Demand variables include Consumption (*CONSUM*) and Ending Stocks (*ENDSTK*), while supply variables include Production (*PRODUC*) and Beginning Stocks (*BEGSTK*). Although it is not decomposed in Figure 3.1, the *PRODUC* variable calculated from the variables Yield (*YIELD*) and Area Harvested (*AREAHV*), which are used to reflect the timing of producer planting decisions and to estimate the climate impacts of yield more precisely. Different values for *PRICE* are tested until the US and ROW trade balance and there is an equilibrium value for all market variables in the model.

The variables *CONSUM*, *ENDSTK*, *AREAHV*, and *YIELD* for the US and ROW are behavioral equations to be defined in the *Equations* section. The *PRODUC* variables in US and ROW are identities of *AREAHV***YIELD* and the *BEGSTK* variables are *ENDSTK* lagged one year. The variables US Imports ($IMPORTS_{US,t}$) and ROW Exports ($EXPORTS_{ROW,t}$) are exogenous and set at small fixed values based on historical averages.

The rest of the variables in the model are derived from the following identities for US and ROW, which are consistent throughout the literature using similar models:

1. *SUPPLY = DEMAND,*

2. *SUPPLY = PRODUC + BEGSTK + IMPORTS, and*

3. *DEMAND = CONSUM + EXPORTS + ENDSTK.*

From these identities, $SUPPLY_{US,t}$ and $DEMAND_{ROW,t}$ can both be directly calculated because all of the necessary variables for these equations are defined. $DEMAND_{US,t}$ and $SUPPLY_{ROW,t}$ are used to estimate $EXPORTS_{US,t}$ and $IMPORTS_{ROW,t}$. Identities 4 and 5, shown below, rearrange identities 2 and 3 to calculate the implied values for $NETEXP_{US,t}$ and $NETIMP_{ROW,t}$.

4. $NETEXP_{US,t} = SUPPLY_{US,t} – CONSUM_{US,t} – ENDSTK_{US,t}$

5. $NETIMP_{ROW,t} = DEMAND_{ROW,t} - PRODUC_{ROW,t} - BEGSTK_{ROW,t}$.

The model then uses a single *PRICE* to link two regions. The *PRICE* will change until the following identity holds:

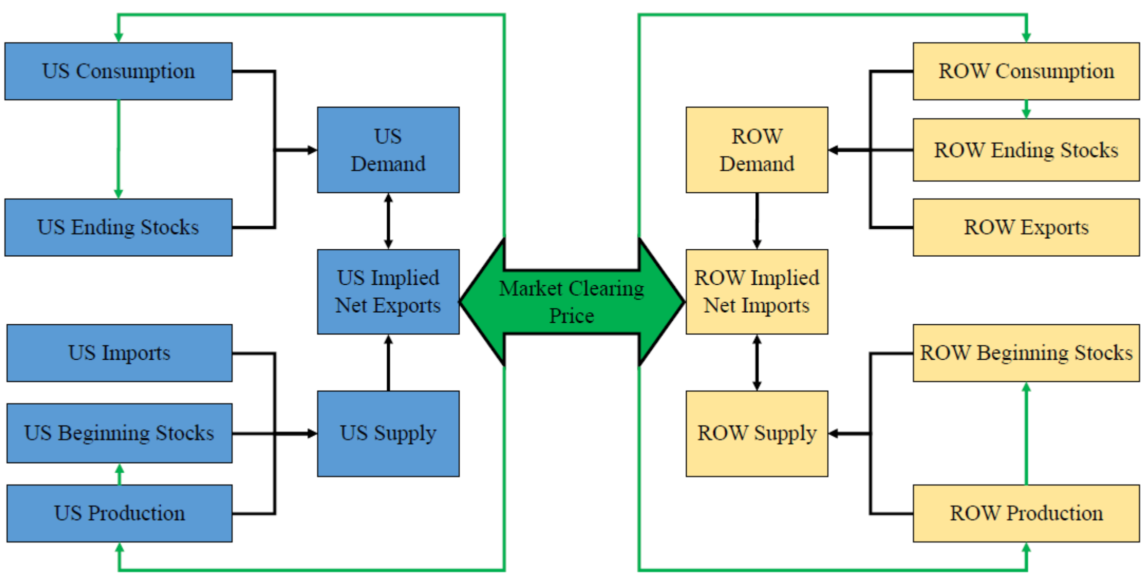
6. $NETEXP_{US,t} = NETIMP_{ROW,t}$

Once the model has solved for the *PRICE* that allows Identity 6 to hold, the model is at equilibrium and will have returned a value for all of the other variables at that price.

The model is designed to represent variation in $YIELD_{US,t}$ and $AREAHV_{US,t}$ as well as $YIELD_{ROW,t}$. The variation in these terms results in changes to *PRODUC*, which affects both *SUPPLY* and *DEMAND* in the model. *PRODUC* affects demand because it is a determining factor of $NETEXP_{US,t}$ and $NETIMP_{ROW,t}$. This results in both *SUPPLY* and *DEMAND* being affected by the variation to the above-mentioned variables.

The remaining variables that have yet to be defined are calculated from behavioral equations that rely on ordinary least squares (OLS) regressions to estimate coefficients for each variable, including economic factors such as *PRICE*. Each of these variables are estimated from an equation that includes a constant (β_0), one or more dependent variables multiplied by some coefficient (β_i), and an error term (μ). The reference period used in the OLS regressions is from the corn marketing year 1995/96 to 2016/17 unless noted otherwise in the *Data* section. The variables defined from these equations are both US and ROW *AREAHV*, *EXPREV*, *YIELD*, *CONSUM*, and *ENDSTK*.

Figure 3.1: Marketing Clearing Price Diagram



Source: Model

US Behavioral Equations

Starting with $AREAHV_{US,t}$, *Equation 3.1*, which is the total acreage of corn harvested throughout the US. US Expected Gross Farm Revenue ($EXPREV_{US,t}$) represents the expected revenue from corn anticipated by the farmer when making their planting decisions. It is defined in more detail below. US May Precipitation ($MAYPCP_{US,t}$) is the state-level average precipitation recorded in the US Corn Belt in the month of May. $MAYPCP_{US,t}$ is used to measure the amount of days a farmer can work in their field.

Equation 3.1. $AREAHV_{US,t} = \beta_0 + \beta_1 (EXPREV_{US,t}) + \beta_2 (MAYPCP_{US,t}) + \mu$

$EXPREV_{US,t}$ is an identity calculated by taking the higher of the Expected Corn Price ($EXPRICE_{US,t}$) or the Marketing Loan Rate ($MLRATE_{US,t}$) and multiplying it by the Expected Yield ($EXPYIELD_{US,t}$), seen in *Equation 3.2*. $EXPRICE_{US,t}$, *Equation 3.3,* is a running average of the two previous years $PRICE_{US,t}$. $EXPYIELD_{US,t}$, *Equation 3.4*, is estimated as a function of a linear trend (*TREND*) and an error term. It should also be noted that the model allows producers to consider the yield effects resulting from changes in climate variability in their planting decisions. To account for this, the model is run twice to allow for producers to change their yield expectations in future climate scenarios. This means that each scenario is run first using $EXPYIELD_{US,t}$ to represent producer yield expectations, and then again using the projected $YIELD_{US,t}$ from the first simulation in place of the $EXPYIELD_{US,t}$ in the second simulation.

Equation 3.2. $EXPREV_{US,t} = MAX[EXPRICE_{US,t}, MLRATE_{US,t}] * EXPYIELD_{US,t}$

Equation 3.3. $EXPRICE_{US,t} = \mathrm{AVERAGE}(PRICE_{US,t-1}, PRICE_{US,t-2})$

Equation 3.4. $EXPYIELD_{US,t} = \beta_0 + \beta_1 (TREND) + \mu$

$YIELD_{US,t}$, *Equation 3.5*, is calculated as a function of July Precipitation ($JULPCP_{US,\ t}$) and a *TREND*. $JULPCP_{US,\ t}$ is the average state-level precipitation in the US Corn Belt during the month of July, and $(JULPCP_{US,\ t})^2$ is the same variable squared used to represent the nonlinearity of rainfall and corn yields (Schlenker and Roberts, 2009). As noted above, the *TREND* term is a general linear trend used to capture technological improvements and better farm practices. A $(TREND)^2$ term was considered to capture a possible nonlinear relationship between yield increases and technological improvements, but due to its extreme statistical insignificance in both the $YIELD_{US,t}$ and the $EXPYIELD_{US,t}$ equations it is not included in either equation.

Equation 3.5. $YIELD_{US,t} = \beta_0 + \beta_1 (JULPCP_{US,t}) + \beta_2 (JULPCP_{US,t})^2 + \beta_3 (TREND) + \mu$

$CONSUM_{US,t}$, *Equation 3.6*, is estimated as a function of $PRICE_{US,t}$, one-year lagged US Corn Consumption ($CONSUM_{US,t-1}$), US Gasoline Price ($GASPRC_{US,t}$) and the Renewable Fuels Standard (RFS) Mandate ($RFSMAN_{US,t}$). $CONSUM_{US,t-1}$ represents the time-delay needed for consumers to change their demands. $GASPRC_{US,t}$ is the annual average RBOB gasoline price during the relevant corn marketing year. This independent variable represents the substitutability between corn based ethanol consumption and conventional gasoline consumption. $RFSMAN_{US,t}$ is used to represent the RFS's effect on corn consumption in the US.

Equation 3.6. $CONSUM_{US} = \beta_0 + \beta_1 (PRICE_{US,t}) + \beta_2 (CONSUM_{US,\ t-1}) + \beta_3 (GASPRC_{US,t}) + \beta_4(RFSMAN_{US,t}) + \mu$

$ENDSTK_{US,\ t}$, *Equation 3.7*, represents US ending stocks, and is a function of $PRICE_{US,t}$ and $PRODUC_{US,t}$. The equation uses the inverse of price, $1/PRICE_{US,t}$, instead of just a $PRICE_{US,t}$ term here because this functional form could capture the ranges in ending stock price response, from very low when depleted to very high if prices fall well below normal ranges, and it also has the practical advantage of maintaining simulated prices in a plausible range.

Equation 3.7. $ENDSTK_{US,t} = \beta_0 + \beta_1 (1/PRICE_{US,t}) + \beta_2 (PRODUC_{US,t}) + \mu$

ROW Behavioral Equations

$AREAHV_{ROW,t}$, *Equation 3.8*, is a function of $EXPREV_{ROW,t}$. Unlike $AREAHV_{US,t}$, the equation does not include explicit weather variables, mainly because there is not enough data of historical ROW precipitation. $EXPREV_{ROW,t}$ is calculated in a similar way as $EXPREV_{US,t}$, but it uses ROW values for everything except the $EXPRICE_{US,t}$. It should also be noted here that the $EXPREV_{ROW,t}$ does not allow for producers to account for climate changes in their planting decisions because of insufficient data, so the $EXYIELD_{ROW,t}$ is based only on a linear trend. The new equations are *Equation 3.9* and *Equation 3.10*.

Equation 3.8. $AREAHV_{ROW,t} = \beta_0 + \beta_1 (EXPREV_{ROW,t}) + \mu$

Equation 3.9. $EXPREV_{ROW,t} = EXPRICE_{US,t} * EXYIELD_{ROW,t}$

Equation 3.10. $EXYIELD_{ROW,t} = \beta_0 + \beta_1 (TREND_t) + \mu$

$YIELD_{ROW,t}$, *Equation 3.11*, is a function of a linear time trend and an error. This equation also does not include explicit weather variables due to insufficient data.

Equation 3.11. $YIELD_{ROW,t} = \beta_0 + \beta_1 (TREND_t) + \mu$

$CONSUM_{ROW,t}$, *Equation 3.12*, is a function of $PRICE_{US,t}$ and ROW GDP ($GDPROW_{ROW,t}$). $PRICE_{US,t}$ is used as a proxy for the ROW corn price. $GDPROW_{ROW,t}$ is used to measure ROW income. The error in this equation does not appear to be random, but instead it looks like it may be autocorrelated and heteroskedastic. This limitation is discussed in more detail later on.

Equation 3.12. $CONSUM_{ROW,t} = \beta_0 + \beta_1 (PRICE_{US,t}) + \beta_2 (GDPROW_{ROW,t}) + \mu$

$ENDSTK_{ROW,t}$, *Equation 3.13*, is a function of $PRICE_{US,t}$ and $PRODUC_{ROW,t}$, and it uses a $1/PRICE_{US,t}$ for the same reason as noted above in the $ENDSTK_{US,t}$ equation.

Equation 3.13. $ENDSTK_{ROW,t} = \beta_0 + \beta_1 (1/PRICE_{US,t}) + \beta_2 (PRODUC_{ROW,t}) + \mu$

Elasticities

The estimation results from the behavioral equations are provided in Table 3.1. Looking first at the US equations, $AREAHV_{US,t}$ has a reasonable price elasticity when compared to Table 3.2, which is adapted from Miao et al. (2015). Miao et al. (2015) also offers a comparison for the relationship of $MAYPCP_{US,t}$ to $AREAHV_{US,t}$; both studies estimated relatively small negative elasticities for the $MAYPCP_{US,t}$ term. As pointed out in Miao et al. (2015), this modest negative effect of May precipitation on corn area suggests that increased $MAYPCP_{US,t}$ encourages the planting of soybeans instead of corn. Furthermore, the independent variables $MAYPCP_{US,t}$ and $EXPREV_{US,t}$ are statistically significant at 1% and the adjusted R^2 of the regression is .65.

Table 3.1: Behavioral Equation Elasticities

Variables	Coefficient	P-Value	Elasticity	
US Equations				
Dependent Variable: *AREAHV*$_{US,t}$				Adjusted R^2 = .65
Intercept	71.75	0.00		
EXPREV$_{US,t}$	0.02	0.11	0.24	
MAYPCP$_{US,t}$	-1.86	0.04	-0.10	
Dependent Variable: *YIELD*$_{US,t}$				Adjusted R^2 = .78
Intercept	-247.94	0.00		
JULPCP$_{US,t}$	74.80	0.00	1.85	
JULPCP$^2_{US,t}$	-8.37	0.00	-0.88	
TREND$_t$	2.62	0.00		
NEW Dependent Variable: *CONSUM*$_{US,t}$				Adjusted R^2 = .97
Intercept	5328.36	0.00		
PRICE$_{US,t}$	-406.89	0.00	-0.18	
CONSUM$_{US,t-1}$	0.36	0.02	0.35	
GASPRC$_{US,t}$	455.11	0.00	0.12	
RFSMAN$_{US,t}$	189.73	0.00	0.24	
Dependent Variable: *ENDSTK*$_{US,t}$				Adjusted R^2 = .82
Intercept	-1799.55	0.00		
1/PRICE$_{US,t}$	4665.94	0.00	0.70	
PRODUC$_{US,t}$	0.17	0.00	1.56	
ROW Equations				
Dependent Variable: *AREAHV*$_{ROW,t}$				Adjusted R^2 = .73
Intercept	242.24	0.00		
EXPREV$_{ROW,t}$	0.29	0.00	0.29	
Dependent Variable: *YIELD*$_{ROW,t}$				Adjusted R^2 = .94
Intercept	-44.13	0.00		
TREND$_t$	1.15	0.00		
Dependent Variable: *CONSUM*$_{ROW,t}$				Adjusted R^2 = .82
Intercept	5945.19	0.00		
PRICE$_{US,t}$	-980.22	0.02	-0.19	
GDPROW$_{ROW,t}$	375.38	0.00	0.89	
Dependent Variable: *ENDSTK*$_{ROW,t}$				Adjusted R^2 = .94
Intercept	-4609.93	0.00		
1/PRICE$_{US,t}$	10093.96	0.00	0.40	
PRODUC$_{ROW,t}$	0.32	0.00	1.42	

Source: Model Estimates

Table 3.2: Miao et al. (2015) Corn Acreage Elasticity Comparison

Study	**Own-Price Elasticity**
Chavas and Holt (1990)	0.15
Chembezi and Womack (1992)	0.10
Lee and Helmberger (1985)	0.05
Miller and Plantinga (1999)	0.95
Miao et al. (2015)	0.45
This study	0.07

Source: Adapted from Miao et al. (2015)

The elasticities in the $YIELD_{US,t}$ equation are consistent with the previous literature, specifically Schlenker and Roberts (2009) and Miao et al. (2015). The elasticity of July precipitation in Miao et al. (2015) is relatively large and positive, and the elasticity of July precipitation squared is smaller and negative. The $JULPCP_{US,t}$ elasticity indicates a positive relationship between $JULPCP_{US,t}$ and $YIELD_{US,t}$. The negative $(JULPCP_{US,t})^2$ variable indicates a nonlinear relationship between $YIELD_{US,t}$ and $JULPCP_{US,t}$. The combination of the two variables indicates that $JULPCP_{US,t}$ is beneficial for corn yields up until a certain point, but after that point additional rainfall will have a negative effect on yields. Miao et al. (2015) finds similar a similar relationship between July rainfall and corn yields. Schlenker and Roberts (2009) does not compare as nicely with this study because it does not focus on specific months or precipitation, but instead it focuses on temperatures throughout the entire growing season. It does, however, indicate a positive relationship between precipitation and yields, and a similar nonlinearity seen in this study and Miao et al. (2015). Helping to provide further evidence to the validity of the $YIELD_{US,t}$ equation, all of the independent variables are statistically significant at the 1% level and adjusted R^2 is adequate at .78.

The $CONSUM_{US,t}$, $ENDSTK_{US,t}$, and all of the ROW equations do not directly involve weather variables; instead they are derived based solely on economic theory. The $CONSUM_{US,t}$ equation returns a negative elasticity for price, and a positive elasticity for both $GASPRC_{US,t}$ and $RFSMAN_{US,t}$. The equation returns a non-negative coefficient that is less than one for $CONSUM_{US,t-1}$ which is consistent with Nerlove (1958). These elasticities are consistent with the economic theory. It could be argued that the inclusion of both the $GASPRC_{US,t}$ and the $RFSMAN_{US,t}$ could result in multicollinearity, but the very good fit, indicated by the adjusted R^2 of .97, and the statistical significance of both variables suggest that this claim is not a serious concern.. The elasticities in the $ENDSTK_{US,t}$ equation are consistent with economics, the coefficients are statistically significant, and the equation has a good fit. The elasticities for the ROW equations are also provided in Table 3.6, and coefficients on all of the independent variables are statistically significant. Validation for all equations is provided in *Baseline Results and Model Validation* section through a comparison of this model's historical estimates and the actual historical values. Further validation for the US equations is accomplished by comparing projections using this model with the projections developed by FAPRI-MU in their Baseline Model (Westhoff et al., 2017).

Data

The yield, area harvested, import, export, consumption, production, supply, and ending stocks data were obtained from the USDA's Foreign Agricultural Services (FAS) Production, Supply, and Distribution (PSD) database. The data used in this model range from the 1995/96 marketing year to the 2016/17 marketing year and is national or global level data. The corn price data are the average national farm price received in the relevant marketing year, and were obtained from the USDA's National Agricultural Statistics Service (NASS). These prices were then adjusted for inflation by the Bureau of Labor Statistics' (BLS) Producer Price Index (PPI), so that all prices are in terms of the 2017 dollar. Average gas prices for the relevant corn marketing year were obtained from the Energy Information Agency (EIA), and adjusted using the same PPI. The ROW Gross Domestic Product (GDP) data were calculated from the annual nominal GDP data and adjusted by the same PPI as the rest of variables. The GDP data are from the International Monetary Fund (IMF) are measured on a calendar year. Each calendar year was matched up with the second calendar year for each relevant corn marketing year. For example, the 2015 calendar year data would be matched up with the data for the corn marketing year of 2014/15. The RFS data come from the mandates set by the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007.

The data used to estimate the $AREAHV_{ROW,t}$ and the $ENDSTK_{ROW,t}$ equations are from a different period than the rest of the data. The $AREAHV_{ROW,t}$ data are from the 2000/01 marketing year to the 2016/17 marketing year, and the $ENDSTK_{ROW,t}$ equations are from the 2007/08 marketing year to the 2016/17 marketing year. The data periods selected for these equations were chosen to reflect the expected market conditions in the medium-term simulation period, whereas the historical data represent market conditions further in the past which might not be relevant due to changes in policies and behaviors.

The weather data come from a National Oceanic and Atmospheric Administration (NOAA) database. The data is used to calculate the average precipitation of seven Corn Belt states. The states used are Illinois, Indiana, Iowa, Minnesota, Missouri, Wisconsin, and Ohio. The reason these specific states were selected is because they all are in close proximity to each other geographically, but more importantly, they are all significant corn producing states for predominantly rain fed corn, as reported by the NASS.

IV: BASELINE RESULTS AND MODEL VALIDATION

Baseline Results

The baseline results estimated by the model use the historical average and standard deviation of rainfall in the U.S. Corn Belt as parameters in a stochastic simulation to estimate future corn yields and area. The model is designed to draw random values for the variables $MAYPCP_{US,t}$, $JULPCP_{US,t}$, and the $YIELD_{ROW,t}$. The random values for $MAYPCP_{US,t}$ and $JULPCP_{US,t}$ are to represent future precipitation totals, and are generated from the averages and standard deviations of the historical period. The $YIELD_{ROW,t}$ random values represent the uncertainty of climate variation across the ROW, and are used as the error term for future periods. The $YIELD_{ROW,t}$ random values are based off of a mean of zero and the average standard deviation of the data period's error term. The distribution of the random draws for each precipitation variables is a truncated normal distribution, meaning that it is bound by zero and cannot return a negative value for precipitation. The distribution of the $YIELD_{ROW,t}$ error term is drawn from a normal distribution. The model generates random values for each year of the projection period and solves itself with its new values. In order to create a stochastic simulation, it repeats this process 1000 times. The resulting output of the simulation is the yearly average value, average standard deviation, range, and average standard deviation/mean for each variable over the projection period. The model uses Excel VBA and Excel Solver. The remaining projected variables are defined from solving the model or by a linear trend.

The model does make three adjustments that help it solve for more reasonable results. These adjustments, made to the error terms of $AREAHV_{US,t}$, $AREAHV_{ROW,t}$, and $CONSUM_{ROW,t}$, are accepted as limitations of the model. The model estimates that, under the historical climate conditions, the future nominal prices will range between $3.16 and $3.72 (Table 4.1).

As noted, the model adjustments are limitations to the model, but they also serve a purpose. The adjustment to the $AREAHV_{US,t}$ error term was made because the equation has reasonable, and statistically significant, coefficients, but it underestimated actual corn area in recent years. This error might be caused by possible autocorrelation the equation, but the autocorrelation is not tested and is accepted as a limitation. In an effort to return more reasonable values for the $AREAHV_{US,t}$, the error of this equation was adjusted by an amount equal to its historical 10-year average. This adjustment increases $AREAHV_{US,t}$ estimates so they are closer to the FAPRI-MU baseline model, which are discussed in more detail below. (Westhoff et al., 2017). Next, the $AREAHV_{ROW,t}$ equation is similarly adjusted because it underestimates the ROW corn area, especially in recent years. The elasticities of the equation are economically logical and the coefficients on the independent variables are statistically significant, but still the equation returns an unrealistic decrease in corn area. The equation projects the error term from the 2016/17 marketing year into the projection period. The $CONSUM_{ROW,t}$ equation also must be adjusted because the error term is suggesting strong autocorrelation. The suspected autocorrelation means that the estimators in this equation are unlikely to be efficient. The limitation of this inefficiency is that the resulting estimates from the equation may *seem* more accurate than they actually are. No steps are taken at this time to correct for this autocorrelation, so the limitation is accepted, and the projections adjust for it. All three of the limitations need to be considered, but none of the three should be detrimental to this study because they are consistent across all shocks

Table 4.1: Baseline Model Results

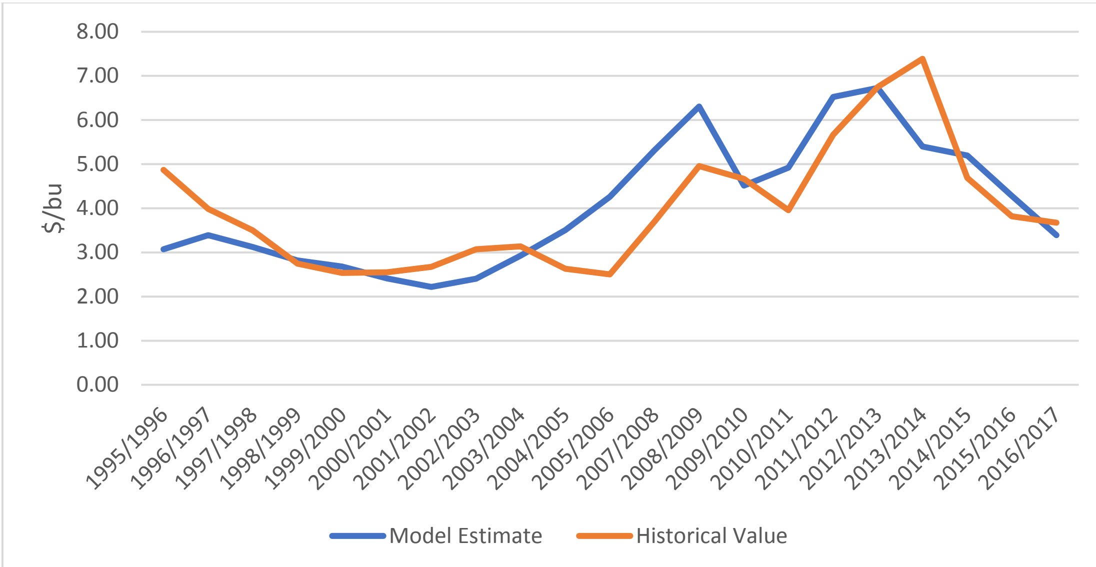
Variable	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ ($)	3.57	3.72	3.59	3.36	3.31	3.35	3.33	3.25	3.18	3.16
US										
$AREAHV_{US,t}$ (mil acres)	79.6	79.6	80.5	80.7	80.2	79.9	80.0	80.4	80.2	80.0
$YIELD_{US,t}$ (bu.)	176.0	177.6	179.6	183.6	185.9	188.0	191.1	193.4	196.3	198.5
$CONSUM_{US,t}$ (mil bu.)	12,187	12,104	12,160	12,307	12,417	12,474	12,539	12,636	12,737	12,824
$ENDSTK_{US,t}$ (mil bu.)	1,892	1,870	1,973	2,125	2,164	2,163	2,216	2,300	2,363	2,401
$NETEXP_{US,t}$ (mil bu.)	2,297	2,065	2,196	2,359	2,450	2,548	2,689	2,832	2,936	3,028
$PRODUC_{US,t}$ (mil bu.)	14,006	14,146	14,459	14,819	14,906	15,021	15,281	15,551	15,736	15,889
$FARMREV_{US,t}$ (mil $)	49,804	52,247	51,486	49,475	48,980	50,003	50,584	50,187	49,769	49,834
ROW										
$AREAHV_{ROW,t}$ (mil acres)	363.4	363.7	368.3	369.7	366.9	364.9	365.9	367.3	367.1	366.4
$YIELD_{ROW,t}$ (bu.)	72.5	73.7	74.9	76.1	77.1	78.3	79.5	80.6	81.8	83.1
$CONSUM_{ROW,t}$ (mil bu.)	28,524	28,829	29,414	30,104	30,634	31,073	31,588	32,177	32,756	33,305
$ENDSTK_{ROW,t}$ (mil bu.)	6,722	6,763	7,116	7,489	7,598	7,644	7,830	8,074	8,285	8,438
$NETIMP_{ROW,t}$ (mil bu.)	2,297	2,065	2,196	2,359	2,450	2,548	2,689	2,832	2,936	3,028
$PRODUC_{ROW,t}$ (mil bu.)	26,363	26,805	27,572	28,118	28,292	28,572	29,085	29,589	30,032	30,431
$FARMREV_{ROW,t}$ (mil $)	94,091	99,604	98,831	94,353	93,395	95,695	96,797	95,943	95,415	95,960

Source: Model Results

Model Validation

The baseline model is validated two ways. First, the model is validated by retroactively applying the model to the marketing years 1995/96 to 2016/17 and then comparing these estimated values to actual values of market (Table 4.2). The historical model is dynamic, so the simulated values are used for any lagged endogenous variables in the model instead of actual historical data. The model also uses the historical averages and standard deviations in a stochastic simulation, which is the same method used for the future projections. The purpose of the experiment is to help show that the model is structurally sound, that the stochastic process operates correctly, and that the elasticities generate results that are reasonably consistent with the historical values. The model is run without adjustments to the estimated historical values, and because the model is dynamic, the errors from the earlier marketing years are carried into the later marketing years. The compounding error terms negatively affect the historical fit of the model, but they do not limit this simulation from showing that the model is structurally sound. The model estimated $PRICE_{US,t}$ term is a good indicator to the validity of the model structure. There may be some departures between the simulated historical prices and actual historical prices, but the two prices look to move in a similar fashion, and that is the important take away from the historical simulation (Figure 4.1).

Figure 4.1: Real Corn Price, Historical vs. Estimate



Source: Source: FAS PSD Data and Model Estimates

The second method of model validation is a comparison of the model's projection period estimates with the FAPRI-MU Baseline Model (Westhoff et al., 2017) (Table 4.3). The values of each respective variable in the comparison are not identical, but they move within similar ranges.

Figure 4.2: Historical Values vs. Historical Estimates

Variable		1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	2005/06
$PRICE_{US,t}$ ($)	Model Estimate	3.07	3.39	3.13	2.82	2.68	2.41	2.22	2.41	2.92	3.51	4.26
	Historical Value	4.87	3.99	3.50	2.74	2.53	2.55	2.67	3.07	3.14	2.63	2.50
US												
$AREAHV_{US,t}$ (mil acres)	Model Estimate	71.6	71.3	71.3	71.4	71.2	71.0	70.9	70.7	70.6	71.0	71.7
	Historical	65.2	72.6	72.6	72.6	70.5	72.4	68.7	69.3	70.9	73.6	75.1
$YIELD_{US,t}$ (bu.)	Model Estimate	118.4	120.4	123.2	126.1	128.4	130.9	133.4	135.8	139.2	140.7	144.3
	Historical	113.5	127.1	126.7	134.5	133.8	136.9	138.2	129.4	142.2	160.4	148.0
$CONSUM_{US,t}$ (mil bu.)	Model Estimate	7,433	7,416	7,425	7,510	7,809	8,077	8,102	8,144	8,062	7,970	8,670
	Historical	6,321	6,991	7,287	7,314	7,578	7,799	7,911	7,903	8,330	8,842	9,134
$ENDSTK_{US,t}$ (mil bu.)	Model Estimate	1,205	1,082	1,232	1,434	1,544	1,772	1,968	1,826	1,519	1,282	1,101
	Historical	426	883	1,308	1,787	1,718	1,899	1,596	1,087	958	2,114	1,967
$NETEXP_{US,t}$ (mil bu.)	Model Estimate	1,391	1,285	1,198	1,286	1,214	986	1,164	1,593	2,073	2,256	1,849
	Historical	2,211	1,784	1,496	1,965	1,922	1,935	1,895	1,573	1,886	1,807	2,125
$SUPPLY/DEMAND_{US,t}$ (mil bu.)	Model Estimate	10,052	9,808	9,876	10,248	10,585	10,854	11,250	11,581	11,671	11,531	11,639
	Historical	8,974	9,672	10,099	11,085	11,232	11,639	11,412	10,578	11,188	12,774	13,235
$FARMREV_{US,t}$ (mil $)	Model Estimate	25,796	28,861	27,215	25,174	24,307	22,188	20,843	22,927	28,563	34,745	43,828
	Historical	36,013	36,799	32,232	26,786	23,876	25,242	25,373	27,569	31,630	31,035	27,807
ROW												
$AREAHV_{ROW,t}$ (mil acres)	Model Estimate	292.4	287.7	288.1	289.6	286.5	284.1	281.8	279.0	279.7	286.3	296.5
	Historical	268.4	276.9	263.9	270.7	272.5	266.3	269.9	270.9	278.9	285.4	284.2
$YIELD_{ROW,t}$ (bu.)	Model Estimate	47.1	48.3	49.4	50.6	51.7	52.9	54.0	55.2	56.3	57.5	58.7
	Historical	48.2	51.0	50.8	52.1	53.2	50.2	52.6	54.7	52.5	57.5	58.0
$CONSUM_{ROW,t}$ (mil bu.)	Model Estimate	16,326	15,411	15,064	15,432	15,606	15,436	15,841	17,251	18,454	19,004	19,430
	Historical	14,625	15,021	15,276	15,569	16,057	16,175	16,594	16,805	17,254	18,271	18,726
$ENDSTK_{ROW,t}$ (mil bu.)	Model Estimate	3,132	2,860	3,226	3,712	3,953	4,452	4,880	4,576	3,943	3,593	3,371
	Historical	4,821	5,664	5,274	5,747	5,936	5,000	4,367	3,907	3,162	3,044	2,893
$NETEXP_{ROW,t}$ (mil bu.)	Model Estimate	1,205	1,256	1,192	1,271	1,030	912	1,040	1,550	2,060	2,188	1,816
	Historical	2,025	1,755	1,490	1,950	1,737	1,861	1,771	1,530	1,873	1,739	2,091
$SUPPLY/DEMAND_{ROW,t}$ (mil bu.)	Model Estimate	20,242	19,260	18,942	20,181	20,638	20,919	22,154	22,964	23,637	23,650	24,373
	Historical	19,991	21,469	21,540	21,967	23,030	22,254	21,992	22,146	21,552	22,554	22,673
$FARMREV_{ROW,t}$ (mil $)	Model Estimate	42,277	47,064	44,514	41,281	39,751	36,221	33,782	37,084	46,099	57,778	74,100
	Historical	62,985	56,233	46,900	38,678	36,733	34,057	37,890	45,549	45,892	43,150	41,249

Source: Model Results and FAS PSD Data (2017)

Figure 4.2: Historical Values vs. Historical Estimates *continued*

Variable		2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17
$PRICE_{US,t}$ ($)	Model Estimate	5.32	6.30	4.52	4.92	6.52	6.73	5.40	5.20	4.28	3.39	4.15
	Historical Value	3.70	4.95	4.67	3.96	5.66	6.75	7.39	4.68	3.82	3.67	3.40
US												
$AREAHV_{US,t}$ (mil acres)	Model Estimate	72.3	73.3	74.5	74.1	73.5	74.6	75.8	75.2	74.4	73.9	72.9
	Historical	70.6	86.5	78.5	79.5	81.4	83.8	87.3	87.4	83.1	80.7	86.7
$YIELD_{US,t}$ (bu.)	Model Estimate	146.3	149.2	151.7	154.2	156.8	159.9	162.3	165.2	167.8	171.0	172.6
	Historical	149.1	150.8	153.3	164.5	152.6	146.9	123.2	158.2	171.1	168.5	174.7
$CONSUM_{US,t}$ (mil bu.)	Model Estimate	8,560	9,282	10,009	10,530	10,478	10,592	11,261	11,618	11,844	12,026	11,806
	Historical	9,081	10,300	10,159	11,062	11,202	10,943	10,353	11,533	11,881	11,763	12,345
$ENDSTK_{US,t}$ (mil bu.)	Model Estimate	924	848	1,205	1,143	923	972	1,209	1,264	1,469	1,782	1,521
	Historical	1,304	1,624	1,673	1,708	1,128	989	821	1,232	1,731	1,737	2,370
$NETEXP_{US,t}$ (mil bu.)	Model Estimate	2,189	1,722	927	953	1,251	1,275	798	739	435	289	1,034
	Historical	2,113	2,417	1,835	1,971	1,803	1,510	570	1,885	1,835	1,833	2,170
$SUPPLY/DEMAND_{US,t}$ (mil bu.)	Model Estimate	11,701	11,882	12,159	12,648	12,676	12,860	13,286	13,638	13,765	14,112	14,377
	Historical	12,510	14,361	13,681	14,749	14,161	13,471	11,904	14,686	15,479	15,401	16,940
$FARMREV_{US,t}$ (mil $)	Model Estimate	55,911	68,569	50,711	55,869	74,708	79,777	66,062	64,159	53,187	42,655	51,957
	Historical	38,984	64,601	56,239	51,718	70,378	83,119	79,446	64,787	54,275	49,925	51,503
ROW												
$AREAHV_{ROW,t}$ (mil acres)	Model Estimate	309.1	326.3	346.2	340.8	329.7	350.2	369.5	360.8	347.6	338.1	321.1
	Historical	301.0	309.3	313.7	312.2	325.8	341.9	352.3	359.8	362.2	360.0	366.7
$YIELD_{ROW,t}$ (bu.)	Model Estimate	59.8	61.0	62.1	63.3	64.4	65.6	66.7	67.9	69.0	70.2	71.4
	Historical	58.7	59.1	62.0	62.4	63.0	66.7	67.0	70.4	71.6	68.2	73.4
$CONSUM_{ROW,t}$ (mil bu.)	Model Estimate	20,649	21,435	21,223	22,438	23,183	23,094	24,705	24,954	23,500	24,264	23,861
	Historical	19,542	20,239	20,661	21,333	22,533	23,328	23,974	25,728	26,208	27,030	28,254
$ENDSTK_{ROW,t}$ (mil bu.)	Model Estimate	3,249	3,401	4,560	4,395	3,783	4,291	5,207	5,228	5,487	6,024	5,214
	Historical	2,976	3,396	3,981	3,844	3,725	4,049	4,422	5,652	6,519	6,639	6,586
$NETEXP_{ROW,t}$ (mil bu.)	Model Estimate	2,041	1,695	878	712	1,325	631	962	481	(242)	1,068	137
	Historical	1,965	2,391	1,787	1,729	1,877	866	734	1,627	1,159	2,612	1,273
$SUPPLY/DEMAND_{ROW,t}$ (mil bu.)	Model Estimate	25,355	26,283	27,607	28,607	30,031	30,411	33,165	33,919	31,794	34,351	33,202
	Historical	24,090	25,092	26,089	27,002	28,031	30,442	31,423	34,632	36,465	36,477	38,904
$FARMREV_{ROW,t}$ (mil $)	Model Estimate	98,325	125,392	97,055	106,076	138,503	154,442	133,089	127,244	102,779	80,480	95,141
	Historical	65,370	90,521	90,871	77,048	116,323	153,807	174,425	118,670	98,952	90,067	91,556

Source: Model Results and FAS PSD Data (2017)

Table 4.3: FAPRI-MU vs. Baseline

Variable	Study	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ ($)	This Study	3.57	3.72	3.59	3.36	3.31	3.35	3.33	3.25	3.18	3.16
	FAPRI Baseline	3.60	3.77	3.76	3.71	3.70	3.71	3.70	3.70	3.69	3.65
US											
$AREAHV_{US,t}$ (mil acres)	This Study	79.6	79.6	80.5	80.7	80.2	79.9	80.0	80.4	80.2	80.0
	FAPRI Baseline	84.1	84.9	85.4	85.4	85.2	85.5	85.4	85.4	85.5	85.5
$YIELD_{US,t}$ (bu.)	This Study	176.0	177.6	179.6	183.6	185.9	188.0	191.1	193.4	196.3	198.5
	FAPRI Baseline	168.6	170.1	172.0	173.8	175.6	177.2	178.8	180.6	182.6	184.6
$CONSUM_{US,t}$ (mil bu.)	This Study	12,187	12,104	12,160	12,307	12,417	12,474	12,539	12,636	12,737	12,824
	FAPRI Baseline	12,382	12,460	12,525	12,579	12,640	12,729	12,834	12,938	13,041	13,138
$ENDSTK_{US,t}$ (mil bu.)	This Study	1,892	1,870	1,973	2,125	2,164	2,163	2,216	2,300	2,363	2,401
	FAPRI Baseline	2,116	2,067	2,114	2,164	2,174	2,203	2,238	2,261	2,307	2,358
$NETEXP_{US,t}$ (mil bu.)	This Study	2,297	2,065	2,196	2,359	2,450	2,548	2,689	2,832	2,936	3,028
	FAPRI Baseline[1]	1,973	2,030	2,124	2,211	2,306	2,385	2,408	2,478	2,533	2,608
$SUPPLY/DEMAND_{US,t}$ (mil bu.)	This Study	16,377	16,039	16,329	16,792	17,031	17,185	17,445	17,768	18,036	18,252
	FAPRI Baseline	16,471	16,557	16,763	16,954	17,120	17,317	17,480	17,677	17,881	18,104
$FARMREV_{US,t}$ ($/acre)	This Study	629	661	645	617	615	631	637	628	625	627
	FAPRI Baseline	607	641	647	645	650	657	662	668	674	674

Source: Model Results and Westhoff et al., 2017

[1] Calculated from FAPRI-MU Results as US Exports - US Imports

V. CLIMATE SCENARIO RESULTS

Shocks

In an attempt to capture how future climate variability could affect market volatility, the following shocks based on possible climate scenarios were imposed onto the baseline model:

(i) 20% increase of US Corn Belt precipitation standard deviation,

(ii) 40% increase of US Corn Belt precipitation standard deviation,

(iii) 20% increase of US Corn Belt precipitation standard deviation and a 20% increase in the standard deviation of the $YIELD_{ROW,t}$ error term, and

(iv) 40% increase of US Corn Belt precipitation standard deviation and a 40% increase in the standard deviation of the $YIELD_{ROW,t}$ error term.

The shocks noted above do not reflect an exact future climate scenario, but instead they represent a logical change based on the predictions set by the IPCC. The shock to the $YIELD_{ROW,t}$ error is meant to represent increased uncertainty of worldwide corn yields at a similar level of the US.

The results in the following tables use averages and standard deviations to summarize the stochastic simulations. Tables 5.1-5.4 present the results of each scenario. Tables 5.5 and 5.6 provide a summary of the same results, but Table 5.5 displays the average results for each scenarios and Table 5.6 displays the percent change from the baseline in each scenario. Tables 5.7 shows the average volatilities in each scenario and Table 5.8 shows the percent change in volatilities between each scenario and the baseline.

Table 5.1: Scenario (i) Results

Variable	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ (\$)	3.70	3.81	3.61	3.40	3.39	3.40	3.38	3.33	3.26	3.20
US										
$AREAHV_{US,t}$ (mil acres)	79.3	79.7	80.6	80.8	80.1	79.8	80.0	80.3	80.3	80.2
$YIELD_{US,t}$ (bu.)	172.4	175.9	178.3	180.9	183.2	186.4	189.2	190.6	193.4	196.9
$CONSUM_{US,t}$ (mil bu.)	12,137	12,050	12,134	12,282	12,376	12,439	12,508	12,594	12,692	12,792
$ENDSTK_{US,t}$ (mil bu.)	1,805	1,825	1,961	2,089	2,105	2,127	2,182	2,236	2,309	2,375
$NETEXP_{US,t}$ (mil bu.)	2,101	1,955	2,098	2,216	2,270	2,415	2,574	2,654	2,763	2,926
$PRODUC_{US,t}$ (mil bu.)	13,674	14,025	14,368	14,626	14,662	14,876	15,138	15,302	15,528	15,784
$FARMREV_{US,t}$ (mil \$)	49,914	52,860	51,202	49,101	48,969	50,147	50,653	50,292	49,915	49,967
ROW										
$AREAHV_{ROW,t}$ (mil acres)	363.4	365.0	370.5	370.9	367.5	366.2	367.4	368.4	368.6	368.2
$YIELD_{ROW,t}$ (bu.)	72.5	73.6	74.9	75.9	77.2	78.3	79.3	80.6	81.8	82.9
$CONSUM_{ROW,t}$ (mil bu.)	28,404	28,743	29,397	30,065	30,555	31,025	31,543	32,101	32,684	33,268
$ENDSTK_{ROW,t}$ (mil bu.)	6,649	6,728	7,176	7,491	7,580	7,657	7,826	8,054	8,280	8,445
$NETIMP_{ROW,t}$ (mil bu.)	2,101	1,955	2,098	2,216	2,270	2,415	2,574	2,654	2,763	2,926
$PRODUC_{ROW,t}$ (mil bu.)	26,366	26,867	27,747	28,164	28,374	28,687	29,137	29,675	30,147	30,507
$FARMREV_{ROW,t}$ (mil \$)	97,321	102,196	99,880	95,636	95,908	97,419	98,288	98,502	97,965	97,327

Source: Model Results

Table 5.2: Scenario (ii) Results

Variable	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ ($)	3.79	3.97	3.67	3.45	3.41	3.51	3.47	3.35	3.27	3.27
US										
$AREAHV_{US,t}$ (mil acres)	79.1	79.7	80.9	80.7	80.2	79.8	80.0	80.3	80.4	80.0
$YIELD_{US,t}$ (bu.)	170.0	171.4	175.1	177.5	181.0	182.5	185.5	188.2	191.3	193.6
$CONSUM_{US,t}$ (mil bu.)	12,100	11,971	12,078	12,240	12,351	12,388	12,454	12,563	12,674	12,755
$ENDSTK_{US,t}$ (mil bu.)	1,747	1,741	1,925	2,036	2,083	2,064	2,120	2,211	2,296	2,309
$NETEXP_{US,t}$ (mil bu.)	1,974	1,693	1,908	1,981	2,117	2,185	2,330	2,466	2,624	2,717
$PRODUC_{US,t}$ (mil bu.)	13,451	13,658	14,171	14,333	14,515	14,554	14,840	15,121	15,383	15,485
$FARMREV_{US,t}$ (mil $)	49,985	52,875	50,966	48,677	48,724	49,826	50,438	49,860	49,538	49,830
ROW										
$AREAHV_{ROW,t}$ (mil acres)	363.4	366.0	373.3	373.4	368.9	367.1	368.8	370.6	370.0	368.7
$YIELD_{ROW,t}$ (bu.)	72.5	73.8	74.9	75.9	77.2	78.3	79.5	80.7	81.7	82.9
$CONSUM_{ROW,t}$ (mil bu.)	28,313	28,585	29,330	30,013	30,531	30,924	31,454	32,075	32,667	33,195
$ENDSTK_{ROW,t}$ (mil bu.)	6,592	6,692	7,225	7,545	7,624	7,644	7,852	8,134	8,335	8,430
$NETIMP_{ROW,t}$ (mil bu.)	1,974	1,693	1,908	1,981	2,117	2,185	2,330	2,466	2,624	2,717
$PRODUC_{ROW,t}$ (mil bu.)	26,345	26,991	27,955	28,351	28,494	28,760	29,333	29,891	30,243	30,572
$FARMREV_{ROW,t}$ (mil $)	99,676	107,046	102,435	97,670	97,002	100,549	101,531	99,862	98,739	99,791

Source: Model Results

Table 5.3: Scenario (iii) Results

Variable	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ ($)	3.66	3.83	3.63	3.40	3.35	3.43	3.39	3.30	3.24	3.23
US										
$AREAHV_{US,t}$ (mil acres)	79.4	79.7	80.7	80.8	80.2	79.8	80.1	80.3	80.3	80.0
$YIELD_{US,t}$ (bu.)	173.7	174.9	178.3	181.0	183.5	185.8	189.0	191.4	193.5	196.2
$CONSUM_{US,t}$ (mil bu.)	12,152	12,047	12,123	12,278	12,389	12,433	12,502	12,602	12,702	12,784
$ENDSTK_{US,t}$ (mil bu.)	1,832	1,808	1,955	2,083	2,123	2,115	2,182	2,262	2,322	2,350
$NETEXP_{US,t}$ (mil bu.)	2,168	1,924	2,118	2,210	2,291	2,399	2,575	2,679	2,770	2,895
$PRODUC_{US,t}$ (mil bu.)	13,782	13,947	14,387	14,616	14,720	14,824	15,144	15,361	15,532	15,707
$FARMREV_{US,t}$ (mil $)	49,971	52,825	51,668	49,261	48,821	50,199	50,781	50,135	49,668	50,205
ROW										
$AREAHV_{ROW,t}$ (mil acres)	363.4	364.6	370.4	371.4	367.8	365.8	367.3	368.8	368.4	367.7
$YIELD_{ROW,t}$ (bu.)	72.5	73.6	74.7	76.0	77.2	78.2	79.4	80.6	81.8	82.8
$CONSUM_{ROW,t}$ (mil bu.)	28,439	28,723	29,371	30,065	30,590	31,000	31,531	32,127	32,700	33,239
$ENDSTK_{ROW,t}$ (mil bu.)	6,669	6,713	7,135	7,509	7,615	7,618	7,832	8,098	8,302	8,401
$NETIMP_{ROW,t}$ (mil bu.)	2,168	1,924	2,118	2,210	2,291	2,399	2,575	2,679	2,770	2,895
$PRODUC_{ROW,t}$ (mil bu.)	26,354	26,843	27,675	28,229	28,405	28,604	29,170	29,714	30,134	30,443
$FARMREV_{ROW,t}$ (mil $)	96,257	102,604	100,305	95,781	94,959	97,863	98,667	97,776	97,373	97,986

Source: Model Results

Table 5.4: Scenario (iv) Results

Variable	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	2025/26	2026/27
$PRICE_{US,t}$ ($)	3.83	3.90	3.72	3.47	3.43	3.47	3.50	3.36	3.32	3.29
US										
$AREAHV_{US,t}$ (mil acres)	79.0	79.5	80.8	80.9	80.2	79.9	80.1	80.4	80.3	80.0
$YIELD_{US,t}$ (bu.)	169.1	173.7	173.5	177.3	180.2	183.1	184.5	188.3	189.7	193.8
$CONSUM_{US,t}$ (mil bu.)	12,085	11,993	12,068	12,230	12,342	12,398	12,445	12,558	12,652	12,741
$ENDSTK_{US,t}$ (mil bu.)	1,734	1,774	1,898	2,047	2,085	2,088	2,114	2,218	2,268	2,327
$NETEXP_{US,t}$ (mil bu.)	1,915	1,783	1,822	1,967	2,086	2,225	2,307	2,467	2,528	2,706
$PRODUC_{US,t}$ (mil bu.)	13,364	13,816	14,014	14,346	14,465	14,627	14,777	15,129	15,230	15,506
$FARMREV_{US,t}$ (mil $)	49,933	53,048	50,766	48,613	48,534	49,920	50,512	49,945	49,432	49,921
ROW										
$AREAHV_{ROW,t}$ (mil acres)	363.4	366.4	372.9	373.2	369.6	367.4	368.6	370.6	370.4	369.4
$YIELD_{ROW,t}$ (bu.)	72.5	73.7	74.9	76.0	77.2	78.3	79.4	80.7	81.7	82.9
$CONSUM_{ROW,t}$ (mil bu.)	28,277	28,650	29,286	29,996	30,518	30,956	31,425	32,070	32,619	33,179
$ENDSTK_{ROW,t}$ (mil bu.)	6,588	6,733	7,209	7,559	7,657	7,679	7,843	8,154	8,324	8,471
$NETIMP_{ROW,t}$ (mil bu.)	1,915	1,783	1,822	1,967	2,087	2,225	2,307	2,467	2,528	2,706
$PRODUC_{ROW,t}$ (mil bu.)	26,364	27,012	27,940	28,378	28,530	28,752	29,282	29,914	30,262	30,620
$FARMREV_{ROW,t}$ (mil $)	100,618	105,209	103,533	98,161	97,285	99,537	102,017	100,038	100,141	100,242

Source: Model Results

Table 5.5: Baseline vs. Scenarios as Average Results

Variable	Baseline			Scenario (i)			Scenario (ii)			Scenario (iii)			Scenario (iv)		
	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio
$MAYPCP_{US,t}$ (in.)	4.62	1.08	0.23	4.63	1.30	0.28	4.62	1.51	0.33	4.61	1.30	0.28	4.65	1.51	0.32
$JULPCP_{US,t}$ (in.)	3.97	0.86	0.22	4.00	1.02	0.26	4.01	1.20	0.30	3.99	1.02	0.26	3.97	1.19	0.30
$PRICE_{US,t}$ ($)	3.38	0.44	0.13	3.45	0.55	0.16	3.52	0.71	0.20	3.45	0.55	0.16	3.53	0.78	0.22
US															
$AREAHV_{US,t}$ (mil acres)	80.1	2.4	0.03	80.1	2.9	0.04	80.1	3.5	0.04	80.1	3.0	0.04	80.1	3.6	0.05
$YIELD_{US,t}$ (bu.)	187.0	11.5	0.06	184.7	14.7	0.08	181.6	18.9	0.10	184.7	14.3	0.08	181.3	19.7	0.11
$CONSUM_{US,t}$ (mil bu.)	12,439	189	0.02	12,401	235	0.02	12,358	302	0.02	12,401	239	0.02	12,351	335	0.03
$ENDSTK_{US,t}$ (mil bu.)	2,147	317	0.15	2,101	389	0.19	2,053	476	0.23	2,103	388	0.18	2,055	499	0.24
$NETEXP_{US,t}$ (mil bu.)	2,540	601	0.24	2,397	761	0.32	2,200	967	0.45	2,403	750	0.32	2,181	1,024	0.48
$PRODUC_{US,t}$ (mil bu.)	14,982	1,021	0.07	14,798	1,304	0.09	14,551	1,649	0.11	14,802	1,275	0.09	14,527	1,716	0.12
$FARMREV_{US,t}$ (mil $)	50,237	4,199	0.08	50,302	4,621	0.09	50,072	5,367	0.11	50,353	5,141	0.10	50,062	6,244	0.13
ROW															
$AREAHV_{ROW,t}$ (mil acres)	366.4	6.5	0.02	367.6	8.1	0.02	369.0	10.4	0.03	367.6	8.2	0.02	369.2	11.4	0.03
$YIELD_{ROW,t}$ (bu.)	77.7	1.8	0.02	77.7	1.8	0.02	77.7	1.8	0.02	77.7	2.2	0.03	77.7	2.6	0.03
$CONSUM_{ROW,t}$ (mil bu.)	30,840	427	0.01	30,779	538	0.02	30,709	699	0.02	30,779	543	0.02	30,698	769	0.03
$ENDSTK_{ROW,t}$ (mil bu.)	7,596	550	0.07	7,589	625	0.08	7,607	755	0.10	7,589	676	0.09	7,622	878	0.11
$NETEXP_{ROW,t}$ (mil bu.)	2,540	601	0.24	2,397	761	0.32	2,200	967	0.45	2,403	750	0.32	2,181	1,024	0.48
$PRODUC_{ROW,t}$ (mil bu.)	28,486	856	0.03	28,567	936	0.03	28,693	1,092	0.04	28,557	1,057	0.04	28,705	1,334	0.05
$FARMREV_{ROW,t}$ (mil $)	96,008	11,566	0.12	98,044	14,914	0.15	100,430	19,624	0.20	97,957	14,806	0.15	100,678	21,312	0.21

Source: Model Results

Table 5.6: Baseline vs. Scenarios as % Change

Variable	Scenario (i)			Scenario (ii)			Scenario (iii)			Scenario (iv)		
	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio	Average	Standard Deviation	Volatility Ratio
$MAYPCP_{US,t}$ (in.)	0.2%	20.5%	20.3%	-0.1%	39.5%	39.7%	-0.2%	19.7%	19.9%	0.6%	39.2%	38.5%
$JULPCP_{US,t}$ (in.)	0.7%	18.5%	17.7%	1.0%	38.5%	37.1%	0.4%	17.8%	17.3%	0.0%	38.1%	38.1%
$PRICE_{US,t}$ ($)	1.9%	26.1%	23.8%	4.0%	63.9%	57.2%	1.9%	27.4%	25.0%	4.3%	80.2%	72.8%
US												
$AREAHV_{US,t}$ (mil acres)	0.0%	20.6%	20.6%	0.0%	43.5%	43.5%	0.0%	21.3%	21.3%	0.0%	48.6%	48.6%
$YIELD_{US,t}$ (bu.)	-1.2%	28.7%	30.5%	-2.9%	65.0%	70.3%	-1.2%	25.0%	26.5%	-3.0%	72.4%	78.0%
$CONSUM_{US,t}$ (mil bu.)	-0.3%	24.8%	25.2%	-0.7%	60.1%	61.4%	-0.3%	26.7%	27.1%	-0.7%	77.6%	78.9%
$ENDSTK_{US,t}$ (mil bu.)	-2.1%	22.8%	25.5%	-4.4%	50.2%	57.2%	-2.0%	22.7%	25.2%	-4.3%	57.7%	64.5%
$NETEXP_{US,t}$ (mil bu.)	-5.6%	26.7%	34.6%	-13.4%	60.9%	88.0%	-5.4%	24.8%	31.8%	-14.1%	70.5%	99.5%
$PRODUC_{US,t}$ (mil bu.)	-1.2%	27.7%	29.4%	-2.9%	61.5%	66.6%	-1.2%	24.8%	26.3%	-3.0%	68.0%	73.4%
$FARMREV_{US,t}$ (mil $)	0.1%	10.1%	9.9%	-0.3%	27.8%	28.3%	0.2%	22.4%	22.2%	-0.3%	48.7%	49.3%
ROW												
$AREAHV_{ROW,t}$ (mil acres)	0.3%	25.0%	24.6%	0.7%	60.8%	59.5%	0.3%	26.7%	26.2%	0.8%	76.2%	74.8%
$YIELD_{ROW,t}$ (bu.)	-0.1%	-0.6%	-0.5%	0.0%	-0.1%	0.0%	-0.1%	21.1%	21.3%	0.0%	42.0%	41.9%
$CONSUM_{ROW,t}$ (mil bu.)	-0.2%	26.1%	26.6%	-0.4%	63.9%	65.1%	-0.2%	27.4%	27.6%	-0.5%	80.2%	81.2%
$ENDSTK_{ROW,t}$ (mil bu.)	-0.1%	13.7%	13.7%	0.1%	37.2%	36.6%	-0.1%	23.0%	23.0%	0.3%	59.5%	58.6%
$NETEXP_{ROW,t}$ (mil bu.)	-5.6%	26.7%	34.6%	-13.4%	60.9%	88.0%	-5.4%	24.8%	31.8%	-14.1%	70.5%	99.5%
$PRODUC_{ROW,t}$ (mil bu.)	0.3%	9.3%	8.9%	0.7%	27.5%	26.3%	0.3%	23.5%	23.1%	0.8%	55.7%	54.4%
$FARMREV_{ROW,t}$ (mil $)	2.1%	29.0%	26.4%	4.6%	69.7%	62.2%	2.0%	28.0%	25.5%	4.9%	84.3%	75.9%

Source: Model Results

Results

Starting with the shocked variables $YIELD_{US,t}$ and $AREAHV_{US,t}$, the results estimate that average $YIELD_{US,t}$ will be lower in all scenarios and the average $AREAHV_{US,t}$ will remain unchanged or slightly increase in all scenarios. This is a logical result because the nonlinear relationship between precipitation and corn yields causes an increase in both average $PRICE_{US,t}$ and average $EXPRICE_{US,t}$. In this case, the average $EXPRICE_{US,t}$ increase is greater than the average $EXYIELD_{US,t}$ reduction, so expected gross receipts per acre increases which would result in producers wanting to increase corn acreage – absent the effect of $MAYPCP_{US,t}$. The fact that average $AREAHV_{US,t}$ would increase due to higher average $EXPRICE_{US,t}$ could be plausible because it may incentivize producers to farm more total land, but the limitations of a single crop model suggest that more research must be done for this result to be conclusive. The decrease in average $YIELD_{US,t}$ is larger than the slight increase in average $AREAHV_{US,t}$, so the average $PRODUC_{US,t}$ decreases in all four scenarios. As mentioned above, the average $PRICE_{US,t}$ term does increase in all four scenarios. The increased variability of the $PRICE_{US,t}$, $AREAHV_{US,t}$, and $YIELD_{US,t}$ results in an unexpected change in $FARMREV_{US,t}$. If only considering averages of the scenario results, $FARMREV_{US,t}$ increases because the average $PRICE_{US,t}$ term increases enough to offset the average decrease in the $YIELD_{US,t}$ term. The model assumes that this is the method a producer would use to calculate his expected $EXPREV_{US,t}$, which leads to the previously mentioned slight increase in $AREAHV_{US,t}$. The unexpected finding is that when $FARMREV_{US,t}$ is calculated in each specific iteration and then averaged, the $FARMREV_{US,t}$ looks to decrease because of the nonlinear relationship between precipitation and yields.

A result present in all four scenarios is a decrease in average $ENDSTK_{US,t}$. The decreased average $PRODUC_{US,t}$ and the increased average $PRICE_{US,t}$ serve as a basic, but likely accurate, explanation for the decrease in average $ENDSTK_{US,t}$. There are a couple of possible market reactions that need to be mentioned here, although they are not tested in this model. First, one might assume that increased uncertainty would result in a greater holding of stocks for speculation or for security, and this is certainly a plausible, if not likely, prediction for the long term. On the other hand, especially in the near term, there is a physical limitation of how much grain can actually be stored, and it is unrealistic to assume storage can be built immediately or endlessly, at least in this study's projection period. This means if prices are high, stocks could be completely diminished in that year, but in a year with high yields and low prices there is a maximum amount of grain that can physically be stored. Both of these scenarios are interesting, but unfortunately beyond the scope of this study. The point of explaining both possibilities is to acknowledge the limitation of the ending stocks equation in this study, but also to provide evidence that the results in this study are plausibility.

Moving on, the study estimates a slight decrease in average $CONSUM_{US,t}$, which is likely due to an increased average $PRICE_{US,t}$ term. This decrease, however, is small due to the inelastic nature of $CONSUM_{US,t}$. Average $NETEXP_{US,t}$ also decrease, which is likely a result of the higher average $PRICE_{US,t}$ term, as well as decrease to average $SUPPLY_{US,t}$. Overall, the average $SUPPLY_{US,t}$ and $DEMAND_{US,t}$ both decrease in each of the four scenarios.

The explanations of the absolute changes projected in the future scenarios are helpful to demonstrate what this research accomplishes, but not the focus. The main focus of this study is to measure how increased climate variability will affect the volatility of the corn market. In this study, volatility is defined as the standard deviation of the respective data set divided by the average of that data set. The estimates of the relevant volatilities are shown in Tables 5.5 and 5.6, but they are summarized in Tables 5.7 and 5.8.

Table 5.7 Volatility Ratios

Variables	Baseline	Scenario (i)	Scenario (ii)	Scenario (iii)	Scenario (iv)
$PRICE_{US,t}$ ($)	0.13	0.16	0.20	0.16	0.22
$FARMREV_{US,t}$ (mil $)	0.08	0.09	0.11	0.10	0.13
$AREAHV_{US,t}$ (mil acres)	0.03	0.04	0.04	0.04	0.05
$YIELD_{US,t}$ (bu.)	0.06	0.08	0.10	0.08	0.11
$CONSUM_{US,t}$ (mil bu.)	0.02	0.02	0.02	0.02	0.03
$ENDSTK_{US,t}$ (mil bu.)	0.15	0.19	0.23	0.18	0.24
$NETEXP_{US,t}$ (mil bu.)	0.24	0.32	0.45	0.32	0.48

Source: Model Results

Table 5.8 Volatility Ratios as % Change from Baseline

Variables	Scenario (i)	Scenario (ii)	Scenario (iii)	Scenario (iv)
$PRICE_{US,t}$ ($)	24%	57%	25%	73%
$FARMREV_{US,t}$ (mil $)	10%	28%	22%	49%
$AREAHV_{US,t}$ (mil acres)	21%	43%	21%	49%
$YIELD_{US,t}$ (bu.)	30%	70%	27%	78%
$CONSUM_{US,t}$ (mil bu.)	25%	61%	27%	79%
$ENDSTK_{US,t}$ (mil bu.)	26%	57%	25%	65%
$NETEXP_{US,t}$ (mil bu.)	35%	88%	32%	99%

Source: Model Results

The effects of the climate variability shocks, as expected, increase volatility for every variable in all four scenarios. Although there are changes to the average values of some the variables, most of the change comes from the increases in each respective standard deviation. Much of the change to the standard deviations will be discussed later in the text during the volatility discussion, but a few points should be made specifically about the standard deviations. First, they are included to ensure the completeness of the study. Second, they show how the changes in standard deviation to the shocked variables are consistent with the actual shocks. Meaning, that a 20% increase in the standard deviation of a term used in the stochastic shock will translate to an approximately 20% increase in the standard deviation of the resulting estimated values. Lastly, listing the standard deviations makes it clear that they are the main driver behind the changes in volatility, not the average. The increased standard deviations result in a higher volatility for all variables, under all future scenarios when they are compared to the baseline.

The changes in volatility here provide evidence to the main conclusions of this paper. Looking first at $YIELD_{US,t}$, the results suggest that corn yield volatility will increase between 27% and 78%. These increases are approximately double the shock to the weather variables in each respective scenario. Logically, the increased variability is explained by the nonlinear relationship between corn yields and weather variables. The increased variability of $YIELD_{US,t}$ is the main driver behind the increased volatility of $PRICE_{US,t}$, which is estimated to increase between 24% and 73% from the shocks. When a comparison is made using the respective price volatility measure, the estimates in this study are much less severe than the results published by Diffenbaugh et al. (2012) and slightly more severe than Thompson et al. (2016) (Table 5.9). The increased price volatility shows that even if climate averages stay the same, changing the variability of weather patterns will result in a significantly more volatile market, which is due to a combination of the nonlinear relationship between corn yields and weather and the inelasticity of the short-run supply and demand for corn.

Table 5.9: Volatility Comparison: This Study vs. Previous Literature

Study	**Thompson et al. (2016) Method**[1]	**Diffenbaugh et al. (2012) Method**[2]
This Study	26% to 80%	25% to 70%
Thompson et al. (2016)	11% to 66%	n/a
Diffenbaugh et al. (2012)	n/a	310% to 530%

Sources: Model Results; Thompson et al. (2016); Diffenbaugh et al. (2012)
[1]% change in the standard deviation of price
[2]Standard deviation of the year-to-year change in price

$AREAHV_{US,t}$ also becomes more volatile in all scenarios, which is largely due to increased variability in $MAYPCP_{US,t}$ and the previously mentioned change in $PRICE_{US,t}$. Even though the volatility ratio indicates significant increases, the actual year to year change in $AREAHV_{US,t}$ is likely to be fairly consistent in the short term because of the low standard deviation in $AREAHV_{US,t}$. In other words, corn area is fairly inelastic, especially in the short term, and it is not likely for there to be a huge drop off in $AREAHV_{US,t}$. $CONSUM_{US,t}$ has a similar result. The volatility may look increase significantly, but because of the inelasticity of corn consumption, it is unlikely that the shocks result in a huge change in $CONSUM_{US,t}$.

The increased volatility in $AREAHV_{US,t}$, $YIELD_{US,t}$, and $PRICE_{US,t}$ all contribute to an increase in the volatility of $FARMREV_{US,t}$. This volatility increase in $FARMREV_{US,t}$ could result in the Marketing Loan program becoming active more frequently, which would result in changes to the taxpayer cost and producer value of the policy (Table 5.10). Whereas there are Marketing Loan program benefits to producers in only 0.03% of the simulations in the baseline, there are benefits in as many as 0.76% of the simulated outcomes in scenario (iv). More specifically, the projected increase in climate variability could increase the amount of money transferred from taxpayers to producers through the Marketing Loan program.

Table 5.10: Scenario Effects to the Marketing Loan Program

	Baseline	**Scenario (i)**	**Scenario (ii)**	**Scenario (iii)**	**Scenario (iv)**
Frequency of active Marketing Loan Program (%)	0.03%	0.16%	0.52%	0.13%	0.76%
Estimated Annual Cost/Producer Value (mil/$)	0.5	2.9	11.9	1.6	17.6

Source: Model Results

Other agricultural policies, specifically Price Loss Coverage (PLC) and Agricultural Risk Coverage (ARC), also might be affected by an increase climate variability. Under future climate variability, lower or more volatile prices could cause an increase in the transfer of monies from taxpayers to producers under PLC because this program is directly tied to the market price. The effect of increased climate variability to ARC is more uncertain because payments under this program depends on the 5-year Olympic average of US market prices and average county level yields. Furthermore, the dynamic reference price and yield of ARC make the effects of increased price and yield volatility more unclear, but the policy might still be affected by increased climate variation. Crop insurance might also be affected by increased climate variability, but the research in this study does not attempt to determine these affects.

In all four future climate scenarios, the results indicate that $ENDSTK_{US,t}$ will become more volatile. Increased $PRICE_{US,t}$ volatility will likely result in an increase in the sale of stocks during upswings in the market, and a decrease in the sale of stocks during downtrends in the market. Increased $YIELD_{US,t}$ volatility will also contribute to the increased volatility of $ENDSTK_{US,t}$, meaning if corn production becomes more variable then the amount of stored corn is also likely to become more variable. For example, if there is a very large corn crop with concurrently low prices one year, then a large amount of stocks would be expected. If there is small crop the next year, and prices increase due to this, then it is safe to assume the stocks will have significantly fallen the next year. This is nothing new, but if the frequency of highs and lows in the market increase then so will the volatility of stocks, and this is worth acknowledging.

As pointed out by Diffenbaugh et al. (2012), stocks can be difficult to deal with in research like this. Instead of assuming that stocks are implicitly represented in the supply and demand equations, like Diffenbaugh et al. (2012), this study follows Thompson et al. (2016) and represents stocks explicitly with its own behavioral equation. Unfortunately, there are still a couple concerns with the $ENDSTK_{US,t}$ equation in this study. The first problem, as previously noted, is that stocks have a physical restriction as to what can actually be stored. It is difficult to estimate if and how quickly market players can build new storage, so for this study is omitted and accepted as a limitation. Next, in a market with more volatile corn prices it is plausible, and perhaps likely, that there would be increased speculation in the market. For example, if a market player expects prices to move more frequently, then they may be more likely to store their grain longer in an attempt to sell at their desired price. As a result of this increased speculation, the historical price elasticity of stocks may no longer be relevant in future climate scenarios. Again, this study accepts this limitation and does not incorporate any changes to future attitudes that market players may have towards risk. This possibility of increased speculation also brings up another point that has not be largely considered. Stocks are inversely related with the market price, and the market price is inversely related to yields. More simply, if prices are high due to low yields then stocks are likely to be dumped into the market, which would offset some of the low yield price impact. This study accounts for this by including price in the ending stocks behavioral equation, but, as noted above, it does not account for a change in the attitude toward stocks. The limitation here is that a market with an increased appetite for speculation would likely offset some of the price effects of low yields, and this study does not change that magnitude to which stocks can stabilize the market. It should be noted, that stocks would not be able to stabilize the market if there were consecutive years high or low yields (Thompson et al., 2016). This study accepts the stated limitations, and determines that under increased climate variability, stocks, and storage space, will become more valuable in future years.

Moving next to $NETEXP_{US,t}$, which are estimated to become much more volatile in the future climate scenarios. This is no surprise because it is unlikely that the US would import a significant amount of corn, even in a year with low production. Instead, the US will likely continue to meet the demands of their domestic consumption, and allow their exports to absorb most of the supply shock.

VI. LIMITATIONS

This study is not without its limitations. The necessary use of information from three complicated sciences, plant physiology, climatology, and applied economics, results in sacrificing absolute completeness. The model does not include all regions of the world or every commodity in its estimates. A key example of this limitation, as noted by Thompson et al. (2016), is that single commodity models may underestimate the impact of climate change. Next, the model does not allow for corn yields to be impacted by any price term. For example, if corn prices spike a farmer may be more likely to increase the effort they put into producing a high yield, but the model in this study does not explicitly account for such changes. Diffenbaugh et al. (2012) accepts the same limitation. The model does not include temperature data, which is partly justified above, but nonetheless a limitation. For example, July rainfall accompanied by extreme temperatures would likely result in yield loss and the model omits that. Next, the model does not account for a change in the attitude of farmers in their decision making. As noted above, future price volatility may cause farmers to increase storage space at a rate that is not consistent with historical values, resulting in a higher stock retention rate than in the past. Due to the data available, the model also does not account for intra-month weather changes. Along the same lines, it does not account for an exact time frame of when rain is valuable for the corn. Finally, the model used in the study has some possible statistical limitations, such as autocorrelation, and they are noted above.

VII. CONCLUSION

The findings in this study provide evidence to support certain conclusions about climate variation and crop price volatility. The study finds that increased precipitation variability in the US Corn Belt, which is a possible under future climate scenarios, will increase the volatility of corn prices. Previous studies, like Diffenbaugh et al. (2012), also find that under future climate scenarios US corn price volatility will increase. The key conclusion found in this study is that the timing and intensity of weather events, represented in the model by May and July precipitation, will also increase the volatility of US corn prices. This conclusion suggests that research only measuring future climate change by changes to seasonal averages might over or under estimate these effects on corn price volatility. Furthermore, by merging of two separate themes in the literature, the present study allows us to conclude that the effect of planting season precipitation on planted area can also be a factor in determining crop market volatility. Future research could be conducted to determine how the average changes in weather variables, combined with changes to the variability of these same variables will affect corn price volatility. More specifically, future research is needed to first determine if increased weather variability will intensify or offset the projected changes to the averages of climate variables, and second to apply economics to these future findings to assess the changes to future corn price volatility. Other questions for future research may include how different crops, such as wheat or soybeans, are likely to be affected by climate variability, and how these other crops interact with corn.

Although the methodologies of the studies are different, Diffenbaugh et al. (2012), Thompson et al. (2016), and this study all find that future climate changes are likely to increase crop price volatility. The increased crop price volatility could have notable effects to stockholding behaviors, price risk management, and agricultural policies. Although it has limitations, the findings of this study lead to the expectation that stocks would increase in response to greater price volatility. It may be logical to assume that this would lead to increased storage space at a pace faster than is normal, but this study does not specifically test for that. Price risk management and agricultural policy could also be affected from this increased price volatility. Price risk management tools, specifically option contracts, may become more expensive because their value is tied to volatility. Agricultural policies that are tied directly to crop prices could also prove to be more valuable to producers under a scenario of increased crop price volatility. As noted above, an increase to the frequency of low crop prices might cause the Marketing Loan program to be active more often. Climate driven changes in yield, area, price, and revenue would probably affect the amount of tax payer money transferred to producers under other agricultural policies as well. Although the claims in this study remain at least somewhat uncertain, they provide a valuable contribution to the research community by suggesting possibilities of future agricultural markets as well as demonstrating the need for further research on this topic.

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