UNCERTAINTY AT THE FARM–LEVEL: MONTE–CARLO SIMULATIONS FOR FARM PLANNING

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Abstract

This paper uses a partial equilibrium model to explore the options for a U.S. soybean farmer given the heightened uncertainties facing U.S. exports of agricultural products including tariffs, African Swine Fever (ASF), and weather. The goal of this Monte Carlo analysis is to allow the user to explore certain strategic choices available to the farmer and then generate a range of possible revenues. These action choices will be summarized in terms of the expected seasonal revenue. As an experiment, I run this simulation with baseline results and no uncertainty. I find that the optimal output for a farmer is a higher soy to corn profile, lower sales of futures contracts, and lower product storage. I then add uncertainty in terms of weather, tariffs, ASF, market facilitation programs (MFP's), and corn planting. Next I track the changes to the optimal outputs given these uncertainties. This paper contributes to the literature on agricultural modeling and risk modeling by incorporating several different types of farm–related uncertainty and producing realistic farm–level analysis of outcomes. I find that uncertainty from these variables will change how a farmer should plan for their planting year.

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1 Introduction

Given recent changes in the agricultural trade environment–shifting market conditions, policy decisions, and increasingly unpredictable weather, farmers now face additional uncertainty in their planting, storage, and selling decisions. In this paper, I attempt to predict these adjustments in decision–making by taking a bottom–up, or farm–level, approach to modeling the impact of policy changes. Specifically, the model presented in this paper analyzes the optimal choices of a U.S. soy and corn farmer given several sources of uncertainty. Previous work on farm–level modeling has focused singularly on uncertainty or on price changes from tariffs and has generally concluded that uncertainty affects the farmer and their decisions. Therefore, I address this gap in the agricultural economics literature by explicitly modeling a diverse set of uncertain environmental and policy–related external factors for an individual farmer.

Several different methods have been employed to address risk at the farm–level. Bar–Shira et al. (1994) developed an econometric approach to measuring farmers' risk aversion. They estimated Arrow-Pratt coefficients of risk aversion, allocating land among different crops and time between leisure and labor. Bar–Shira et al. (1994) found that farmers exhibit absolute risk aversion regarding wealth (Bar-Shira, Just and Zilberman, 1997). Kaiser and Boehlje (1980) incorporated dynamics by creating a multi–period risk model of farm planning. Their empirical model was built to model a farmer in the U.S. Corn Belt; it demonstrates the applicability of the MOTAD (Minimization of Total Absolute Deviations) modeling framework. While the Kaiser and Boehlje model used utility functions incorporating income to optimize farm planning, it did not address policy changes in its calculations (Kaiser and Boehlje, 1980).

Within the farm planning model literature, Merrill (1965) analyzed three models: a multi–period linear programming model, a stochastic programming model, and a linear team programming model. Merrill found that cash reserves are the most important difference between decision–making structures (Merrill, 1965). Itoh et al. (2003) pointed out that linear programs for farm planning do not capture decision–making, as these programs omit uncertainties such as weather. As a result, the authors built a model with uncertain (stochastic) variables for weather to predict farm decision–making (Itoh, Ishii and Nanseki, 2003). On the agricultural policy side, Zhou et al. (2018) studied the long-run impacts of tariffs on the overall U.S. soybean industry. The authors review the literature on price changes and welfare changes and predict that, while Brazil and Argentina benefit from trade tensions, soybean production in the United States will decline by 11 to 15 percent. In sum, Zhou et al. predict that these trade tension conditions will lead to a global welfare loss of 1.2 to 1.8 billion dollars. However, the authors concluded that for U.S. farmers, the tariffs have long term consequences that are more complicated than welfare loss, particularly regarding anxiety over uncertainty (Zhou, Baylis, Coppess and Xie, 2018). While the literature on farm planning models identifies several factors in farmer decision making, these papers typically analyze just one type of risk in isolation and do not consistently account for major sources of uncertainty, such as policy and environmental change.

Although I use a partial equilibrium model, there has been extensive work on uncertainty using a computable general–equilibrium (CGE) model. In a dynamic stochastic CGE model, the notion of uncertainty is developed by the agent forming expectations that a shock will happen later with some magnitude and direction. Pratt et al. (2013) used a dynamic CGE model to calculate the path of the global economy given several layers of uncertainty, such as tourism demand. The authors explained how their model can be applied to agriculture production risks, especially in modeling welfare losses due to exogenous shocks (Pratt, Blake and Swann, 2013). To calculate risk from another source of uncertainty, Phimister and Roberts (2017) built uncertainty into their CGE model to predict risk in new renewable resource development projects (Phimister and Roberts, 2017). Indeed, several papers more closely related to agriculture focus on climate as a key uncertainty, including Valenzuela et al. (2005) and Berger and Troost (2013). Valenzuela et al incorporated price volatility into their CGE setting to improve predictive power, while Berger and Troost built a multi–agent system, where the agents are other farmers adapting to new land use and resource techniques. Both papers found that the elements incorporated into their CGE setting revealed new aspects of agricultural adaptation (Valenzuela, Hertel, Keeney and Reimer, 2005)(Berger and Troost, 2014).

This paper contributes to the literature by incorporating several different sources of uncertainty in a Monte–Carlo environment to capture mitigating effects of external policy changes and uncertainties to the farmer. I use a partial–equilibrium model to more directly capture the impact on an individual farmer's crops. By using the partial–equilibrium model, I can combine the farmer risk and uncertainty literature with the tariff impact literature. In the context of farm–planning literature, the research question herein examines the optimal choices for a farmer given multiple uncertainties, and how a farmer's choices change with added uncertainty. Thus, my question adds dynamics to the traditional multi–period farm planning model. I also incorporate important methodological findings from previous work, including bounding my parameters and production decisions for the farmers to: (1) capture the farmer's risk aversion, and (2) to make the model more realistic.

Using an industry–specific partial equilibrium model with Monte Carlo sampling, I find that uncertainty from weather, tariffs, downstream demand shocks (such as ASF and other farming effects), market facilitation programs (MFP's), and corn planting will change how a farmer should plan for his/her year. From my baseline results, which do not account for uncertainty from policy or environmental shocks, the farmer would devote most of his/her land to soy, sell a medium amount of his/her crop on the futures market, and retain a small amount of storage. With uncertainty, the farmer would devote almost all of his/her land to corn, sell a large amount on the futures market in period 0 and little in period 1, and thus store much more of his/her crop until the next planting season. In section 2, I explain the model followed by two policy experiments in section 3. I conclude with some uses and implications of this approach.

2 Model

Herein, I employ a farm–level, partial equilibrium planning model, with Monte Carlo sampling. In this context, the term, "farm–level," specifies the impmact or the effects on one particular farmer. In this model, a price–taking, profit maximizing feed farmer optimizes over four periods: periods (0), (1), (2), and (3). These four periods correspond to one entire production year. The farmer has three different action choices that determine their expected revenue: (a) adjusting their soy—corn ratio (portfolio), (b) selling their products on the futures market, and (c) storing their product into the next season.[1] [2] [3] In each period, the farmer encounters random policy and/or environmental shocks: tariffs, weather, ASF, market facilitation programs, and other farming effects. Tariffs and ASF enter as a demand–side shock and will last from periods 1 to 3 (with an initial effect in period 0). Weather and other farming effects (corn planted previous year), enter as a supply–side shock and last the entire model, periods 0 to 3. Market facilitation programs

[1]One action choice that is unavailable to the farmer is that the farmer cannot redirect his/her production to other countries. The model does include a non–subject source of soybeans and corn for the destination country, although not for the producer. One reason for this specific model design is because the farmer usually does not make this decision; rather, the decision is typically made farther downstream with an aggregator. Furthermore, many countries do not import U.S. soy and corn as there are non–tariff barriers in place against GMO soy and corn. These barriers makes trade re–direction difficult in feed markets (Lyons and Oldham, 2014; Pramik, 2018).

[2]Because we know that farmers are risk averse, the ratio of soy and corn sold between period 0 and period 1 cannot be more than 70 percent of their crop (Turvey and Baker, 1989).

[3]In period 2, the farmer can choose to store some of his/her crop to period 3. The farmer can choose to store between 0 and 100 percent of the remaining production in period 2 (that was not sold in periods 0 or 1) to period 3 (Good, 2011).

enter as a direct price shock, and changes each iteration in the Monte Carlo.

The goal of this model is to investigate how a farmer's optimal behavior changes in response to unforeseen shocks throughout the production year. Therefore, I re–run the model 1000 times and generate a distribution of outcomes. I then observe these outcomes to find how a farmer's decision–making may change given these different risks.

In period 0, suppose the farmer makes their planting decisions and futures market sales decisions. There is an initial user–specified tariff input in this period, as well as an initial ASF effect. I use historical average tariff levels for the experiment. As we move between periods, shocks will be introduced that can change the prices received and quantities produced by the farmer. Tariffs and ASF enter in period 1 as shocks to the market, and their effect on quantities and prices will be calculated through a partial–equilibrium model. Tariffs and ASF will change the producer price received by the farmer, as the farmer is a price–taker. These tariffs and ASF will continue to shock prices in periods 2 and 3. Market facilitation programs only shock the model once in period 0 and reflect a vertical shift in producer price received in all periods.

Weather will influence both the market price and the quantity harvested by the farmer as a supply shock. I determine the weather impact on market prices through trend analysis from 10 years of data for soy and corn, from 2009 to 2019. The quantity shock comes in harvest period 2, where the farmer could harvest up to 30 percent less of soy or corn if the weather is consistently bad throughout periods 0 to 2. Finally, I identify a "corn planting effect," which can be categorized as any environmental factor such as pests, disease, etc., that will only affect the individual farmer and only one of his/her crops. The "corn planting effect" can impact the quantity harvested in period 2 of that crop by up to 10 percent.

Within period 0, prices are determined by a user input of the current spot price, and quantities of soy and corn are determined by a randomly–drawn strategy for the farmer.

How much the farmer sells on the futures market is also randomly drawn. The farmer will receive the delivery price for that contract, calculated by a futures curve (described below). The equivalent pattern applies to period 1; the delivery price on futures contracts evolves according to the futures curve. How much he/she sells on the futures contract is randomly drawn. In period 2, the farmer will sell a randomly–drawn amount of his/her remaining harvest based on the effects of weather and environmental factors, and on the quantity available to said farmers. If there is any amount of his/her harvest that has not been sold in period 2, the farmer will ensure that the unsold portion of harvest will be stored and carried over into period 3. That stored harvest will sell at the period 3 spot price. The farmer incurs a cost to storing the product, by which the farmer loses 2 percent of his/her quantity of stored soy and 3 percent of his/her quantity of stored corn.

The main output of this model is the farmer's profit.

- (P^*) is the delivery or spot price received by the farmer in the relevant period j;
- (Q) is the quantity sold of soy or corn based on the farmer's portfolio allocation;
- (FC) is the fixed cost of the farm; and
- (VC) is the variable cost of soy or corn.

For the futures market sales, in period 0, the farmer will sell a portion of his/her soy or corn at the period 2 delivery price or P^{0^*}. In period 1, the delivery price will adjust based on uncertainties introduced between periods 0 and 1, and the farmer will sell a portion of his/her harvest on the futures market at the new delivery price of P^{1^*}. In periods 2 and 3, the farmer will sell his/her remaining harvest at the spot price or P^2 and P^3. Profit is then calculated as:

$$\pi_j = P_{soy}^{j^*} Q_{soy}^j + P_{corn}^{j^*} Q_{corn}^j - VC_{soy}^j - VC_{corn}^j - FC_j \ \forall j \tag{1}$$

$$\pi = \sum_{j=0}^{3} (\pi_j) \tag{2}$$

The quantities of soy and corn sold in each period are chosen as a percentage of the harvest.

- β is the percentage of the acreage chosen for soy;
- (A) is the amount of acres on the farm; and
- (I) is production per acre in bushels:

$$Q_{soy} = \beta A I_{soy} \tag{3}$$

$$Q_{corn} = (1 - \beta) A I_{corn} \tag{4}$$

The quantity sold in each period at the delivery price on the futures market for that period is determined by equation (5), where (α) is a percentage of the total annual quantity:

$$Q_k^j = \alpha_j \bar{Q}_k \in \{corn, soy\} \ \forall \ j \tag{5}$$

Output of corn this season is partially determined by whether corn was planted in the previous season. To account for this, I include a quantity effect in period 1, δ, following Plastina (2018). δ takes a value from (0.0, 0.1) or 0 percent to 10 percent of the harvest, and is drawn from a uniform distribution at the beginning of each simulation. Therefore, output of corn in period 1 is equal to:

$$Q^1_{corn} = Q_{corn}\alpha_1\delta \tag{6}$$

Fixed costs are calculated from the University of Wisconsin Agronomy group (Agronomy, 2014) and are amortized evenly across all periods:

$$FC_j = \frac{FC}{4} \tag{7}$$

Variable costs per acre for soy and corn, respectively, are divided evenly among the periods (for the sake of simplicity)[4]. The numerical values are drawn from 2019 data:

$$VC_j = \frac{VC}{4} \tag{8}$$

Pricing is where much of the uncertainty in the model is introduced. I assume that the farmer knows the prices for both soy and corn at the year's beginning. Agriculture has a robust futures market, where the farmer can create contracts promising a certain amount of his/her harvest at a futures market price, or the delivery price. The delivery price is based on the compound annual growth rate and seasonal effects. The farmer has four options for selling his/her products: he/she may,

1. Sell in period 0 at the period 2 (harvest) delivery price on the futures market,
2. Sell in period 1 at the new period 2 (harvest) delivery price on the futures market,
3. Sell in period 2 at the spot price,
4. Store some product from harvest into the next year and sell at the period 3 spot price.

[4] see Table 1 for numerical values and citations.

In each period, there may be shocks due to Chinese tariffs, ASF, and weather that could alter the spot and delivery prices.

The initial tariff for both soy and corn in period 0 is based on average tariff levels, and will increase in period 1. Periods 2 and 3 price effects are based on a percentage of period 1, where a random variable evenly distributed from 0 to 1, is multiplied by the period 1 tariff. This tariff is added to the period 1 tariff to create a larger effect:

$$T_{t+1} \;=\; c * T_t \text{ for t in } \{1, 2\} \text{ where c } \overset{\text{iid}}{\sim} \cup(0, 1) \tag{9}$$

I implement tariff changes with the standard Armington (1969) assumption which states that products are differentiated by source. The Armington model produces estimates at the industry level, although not at the level of individual producers/farmers (Armington, 1969); it is incorporated into the partial equilibrium model performed within our Monte Carlo simulations via price elasticities of demand that determine how consumers react to a price change from the imposition of a tariff. This model allows for nesting of any Chinese soy or corn feed product and non–subject (Brazil/Argentina) imports, allowing for a higher elasticity of substitution between the two.[5] To see the demand and supply equations that determine the market price, refer to Hallren and Riker (2017).

We base the producer price received in each period on a futures curve. The futures curve is calculated by using 2009–2018 monthly data that I then annualize into a compound annual growth rate. I use monthly, rather than quarterly, data as the 4 periods in this model do not necessarily line up exactly with quarters; the four periods make up one complete growing season. The length of each period is a function of environmental factors such as rainfall, seasonal average temperatures, weather, and the timing of planting decisions. For

[5]We allow a higher elasticity of substitution between Chinese soy and corn production and other sources of supply because Chinese soy and corn is generally used for human consumption, rather than animal feed.

optimal comparison and analysis, I needed to see the differences in the corresponding planting periods, rather than exact quarters in a year. The compound annual growth rate function is as follows:

$$GR_Y = \left(\frac{P_{m+12}}{P_m}\right)^{\left(\frac{1}{12}\right)} - 1 \tag{10}$$

where P_{m+12} is the closing month's price and P_m is the opening month price. I then take the growth rate for each year and calculate the average and standard deviation for month–to–month percent changes in prices. The average and standard deviation for both soy and corn are then placed on an inverse normal distribution.

For each iteration of the Monte Carlo simulation, the model randomly selects a compound annual growth rate along this distribution which will be used for that iteration. Through trend analysis, I also use the data to add seasonal effects. The delivery price in period 1 is always higher than at harvest in period 2; periods 0 and 3 usually fall in the middle. The modeler enters the period 0 spot price, as it is known by the farmer, and then the futures curve price in period 3 is calculated. The period 3 delivery price is adjusted by season and growth to calculate a period 1 and period 2 delivery price.[6] MFP's will then shift that price vertically for soy and corn depending on the level of the programs as a supply–side shock. Between periods, the futures curve changes depending on tariffs, ASF, and weather. Weather can change the magnitude of the seasonal effects and the CAGR, while tariffs, ASF, and weather will vertically shift the market price.[7]

The tariffs are randomly selected in period 1 between 0 and 60 percent (Durisin and Robinson, 2019) (Regmi, 2019). The tariff shocks are specified to illustrate the effect of

[6]While I use the period 2 futures price as the delivery price on futures contracts in periods 0 and 1, I estimate the futures curve in all periods in order to observe changes over time.

[7]Tariffs and ASF will shift the price through the partial–equilibrium model; weather affects the market price based on my trend analysis.

this form of uncertainty on farm-level decisions, and thus are only chosen to reflect a range of possible outcomes for the farmer. These randomized tariff shocks are not in any way meant to match specific recent changes in Chinese tariffs. I chose 60 percent as a reasonable maximum based on historical data and WTO standards. I assume that the farmer knows the intensity of ASF in the initial period 0, by seeing it in the news or hearing from their contractors how the demand for feed is being affected, and can measure the intensity from 0 to 10. That number will be re–calibrated as an ad valorem rate in period 0 between 0 and 70 percent for soy and 0 and 56 percent for corn (Pitts, Whitnall et al., 2019; Singh, 2019; Frost, 2019; Patton, 2019).

In periods 2 and 3, the partial tariff effects will be random between 0 and 100 percent of the price effects in period 1. Both tariffs and ASF will negatively shock sales and the price received by the farmer.[8] The prices, quantities, and growth rate are adjusted for weather.[9]

Simulations are based on 1,000 iterations of calculating profit. Inputs are allowed to vary in each of the 1,000 iterations. The simulations will provide an expected value for profit, and the model maximizes expected profit given inputs. The model then solves the optimization problem by selecting the strategy among the 1,000 iterations which yielded the highest profits. I tested this several times for each of the following Monte Carlo optimizations to ensure accuracy.

[8] In this case, I assume that ASF negatively shocks prices because of the negative demand shock for feed from ASF.

[9] The weather effect is initially valued as an "intensity" in each period between 0 and 1, which will then effect prices and quantity differently depending on the period. The distribution is a normal distribution with the mean being "average" weather, and a high standard deviation. Assumptions include: (1) weather can create damage to up to 20 percent of soy and corn crops with adverse weather conditions, and (2) harvest quantities decrease overall due to poor weather, these conditions will create a direct, positive effect on prices; however, the weather conditions will slightly depress the compound annual growth rate(Willenbockel, 2012).

3 Experiment

3.1 Baseline Results

I use data from December 2019 to calibrate the model. It is run six times, each time adding a new layer of uncertainty. To predict an optimal strategy for the farmer, the model optimizes the agent's choices of portfolio, futures sales, and storage. The inputs that I used for the farm are found in Table 1.

My baseline results assume that there will be no tariffs introduced during the year, no uncertainty from ASF, and no uncertainty from planting corn the previous year.[10] I normalize weather patterns and market facilitation programs (MFP's) down to their average.

I also use industry inputs to calibrate the partial–equilibrium model embedded in the Monte Carlo simulation. These numbers are based upon U.S. soy and corn exports to China, with China and Brazil/Argentina supplying the Chinese soy and corn markets. The industry inputs are found in tables 2 and 3.

This model predicts that the maximum profit strategy for a farmer with no uncertainties will be a slightly higher soy profile over corn, low futures sales, and medium-low storage (Table 4).

3.2 With Uncertainty from Weather

I begin my experiments by allowing weather to vary with uncertainty. In each period, the weather varies, which in turn will change prices, quantities, and the growth rate of prices. The farmer's optimal strategy is similar to the baseline results with uncertainty from

[10] With 1000 iterations of the Monte Carlo, outputs were stable across the following experiments.

weather in terms of the soy to corn profile, storage, and futures sales, suggesting that weather affects soy and corn in the same way (Table 5).

3.3 With Uncertainty from Tariffs

In this paper's second experiment, I add uncertainty from tariffs into the model. There will be an unexpected shock in period 1 that will then continue to shock prices throughout periods 2 and 3 depending on a random distribution. With uncertainty from both weather and tariffs, the optimal strategy for the farmer changes to a higher soy profile, lower futures sales, and much higher levels of storage (Table 6). I attribute the changing results from adding tariffs to the price shocks from the tariffs and the different elasticities between soy and corn.

3.4 With Uncertainty from ASF

Now I add uncertainty from ASF as an additional ad valorem shock to foreign demand which will act as a proxy shock to export demand. As swine producers favor soy over corn–based feed, the ASF shock has a disproportionate effect on soy, leading to a change in the optimal strategy toward a more even soy-corn profile, with low futures sales and medium storage (Table 7).

3.5 With Uncertainty from MFP's

Next, I add uncertainty from Market Facilitation Programs as a direct shock to prices depending on the level (levels are based on past 20-year ranges). There is a range of outputs depending on the levels of MFP's; however, I conclude that there will be a higher ratio of corn to soy, medium–low futures sales, low storage of soy, and high storage of corn (Table 8).

3.6 With Uncertainty from Corn Planting

The final layer of uncertainty in this analysis is from corn planting, or environmental factors that only affect one crop, which, in this case is corn. Farmers run a certain level of risk by choosing to plant corn more than one year in a row, as mineral–depletion in the soil is a concern. If the farmer planted corn the year before (an input in the model), there will be a random shock to quantity harvested. I find further that there is a high corn to soy ratio and medium-low futures sales, but with lower storage of corn and higher storage of soy (Table 9).

4 Conclusions

In this paper, I report a series of farm–level Monte Carlo simulations that model optimal farm planning decisions for a farmer given uncertain variables such as tariffs, African Swine Fever, and weather. This model incorporates partial–equilibrium modeling to simulate the effects of policy changes on a price–taking farmer.

In a simulation for a large farm in the United States with China as the destination country and Brazil or Argentina as alternative sources of supply over China, with current price levels and common output levels for soy and corn, this model finds that the optimal choice for farmers will depend on the level of uncertainty between certain variables. This paper's baseline results with no uncertainty indicate that a high ratio of soy to corn, low futures sales, and low storage will be optimal for the farmer to maximize their profit. With the added layers of uncertainty from tariffs, ASF, MFP's, corn, and weather, the optimal choice reverses to a high corn to soy ratio, medium futures sales, and lower levels of storage.

This paper contributes to the literature on agricultural modeling by introducing several different types of uncertainty into a farmer's profit planning. This model does not attempt to determine which tariff or non–tariff measure is optimal, nor does it try to determine which overall price or tariff levels are optimal. This model is focusing on the decisions of individual farmers; it does not estimate the overall welfare effects on U.S. farmers.

In future research, this model can be used to explore how different policy experiments may affect producer decision–making and what policy changes to make that may be profit–maximizing for a farmer. As this model is built for changing inputs, this model can also be used year–by–year to simulate farmers decisions given the current level of uncertainty in agriculture.

5 Tables

Table 1: Model Inputs

Input	**Value**	**Source**
Period 0 current price per bushel, soy	\$9.04	Business Insider (n.d.b)
Period 0 current price per bushel, corn	\$3.70	Business Insider (n.d.a)
Farm Acreage	1300	MacDonald and Hoppe (2017)
Fixed costs (farm)	\$15,000	Plastina (2020)
Fixed costs (per acre)	\$50	Plastina (2020)
Variable cost per acre, soy	\$400	Plastina (2020)
Variable cost per acre, corn	\$300	Plastina (2020)
Storage cost, soy	3 percent	Russell (2001)
Storage cost, corn	2 percent	Russell (2001)
Production per acre, soy (bushels)	58	Plastina (2020)
Production per acre, corn (bushels)	140	Plastina (2020)

Table 2: Soy Industry Inputs

Input	**Value** [11]
Share of Chinese production	10
Share of U.S. production	40
Share of Brazil/Argentina Production	50
Supply Elasticity, China	3
Import Supply Elasticity, U.S.	8
Import Supply Elasticity, Brazil/Argentina	3
Total Industry Demand Elasticity	-1
Elasticity of Substitution, U.S. and Nest	5
Elasticity of Substitution, China and Brazil/Argentina	7

[11] The current values for these inputs are based on Soderbery (2015) and a qualitative analysis of the soy and corn industries.

Table 3: Corn Industry Inputs

Input	Value [12]
Share of Chinese production	10
Share of U.S. production	45
Share of Brazil/Argentina Production	35
Supply Elasticity, China	3
Import Supply Elasticity, U.S.	7
Import Supply Elasticity, Brazil/Argentina	5
Total Industry Demand Elasticity	-1
Elasticity of Substitution, U.S. and Nest	4
Elasticity of Substitution, China and Brazil/Argentina	8

Table 4: Baseline Results

Action Choice	Optimal Strategy
Soy portfolio, percent	75.97
Corn portfolio, percent	24.03
Period 0 sales, futures market, share of total	4.20
Period 1 sales, futures market, share of total	11.09
Production stored from period 2 to period 3, soy, percent	30.00
Production stored from period 2 to period 3, corn, percent	11.82

[12] The current values for these inputs are based on Soderbery (2015) and a qualitative analysis of the soy and corn industries.

Table 5: Results with Weather

Action Choice	**Optimal Strategy**
Soy portfolio, percent	72.92
Corn portfolio, percent	27.08
Period 0 sales, futures market, share of total	2.88
Period 1 sales, futures market, share of total	17.20
Production stored from period 2 to period 3, soy, percent	35.76
Production stored from period 2 to period 3, corn, percent	32.51

Table 6: Results with Weather and Tariffs

Action Choice	**Optimal Strategy**
Soy portfolio, percent	89.63
Corn portfolio, percent	10.37
Period 0 sales, futures market, share of total	2.26
Period 1 sales, futures market, share of total	6.92
Production stored from period 2 to period 3, soy, percent	76.20
Production stored from period 2 to period 3, corn, percent	60.05

Table 7: Results with Weather, Tariffs, and ASF

Action Choice	**Optimal Strategy**
Soy portfolio, percent	49.95
Corn portfolio, percent	50.05
Period 0 sales, futures market, share of total	0.09
Period 1 sales, futures market, share of total	28.63
Production stored from period 2 to period 3, soy, percent	37.51
Production stored from period 2 to period 3, corn, percent	66.31

Table 8: Results with Weather, Tariffs, ASF, and MFP's

Action Choice	**Optimal Strategy**
Soy portfolio, percent	3.97
Corn portfolio, percent	96.03
Period 0 sales, futures market, share of total	15.18
Period 1 sales, futures market, share of total	2.33
Production stored from period 2 to period 3, soy, percent	29.29
Production stored from period 2 to period 3, corn, percent	84.79

Table 9: Results with Weather, Tariffs, ASF, MFP's, and Corn Planting

Action Choice	**Optimal Strategy**
Soy portfolio, percent	3.22
Corn portfolio, percent	96.78
Period 0 sales, futures market, share of total	22.04
Period 1 sales, futures market, share of total	1.72
Production stored from period 2 to period 3, soy, percent	47.07
Production stored from period 2 to period 3, corn, percent	63.64

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