Decomposing Crop Loss: The Role of Subsidies and Market Price Uncertainty

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Abstract

Farmers choose to leave between 10% and 60% of harvestable crops on the field in the United States. This paper studies two of the economic drivers of this crop loss: price uncertainty and subsidies. I develop a dynamic stochastic structural framework of crop loss in agricultural production, incorporating subsidy distortions and farmer price expectations. Estimated with wheat data, the baseline model indicates that the presence of subsides targeting downside price risk cause crop loss to be higher relative to a no-subsidy world. However, as the signals over prices received by farmers become noisier, the subsidy distortion decreases in importance relative to price uncertainty. The model provides two possible channels of crop loss that I test in an empirical exercise using wheat and wheat futures data. I find that given a high price expectation at planting, a one standard deviation increase in the price expectation at harvest decreases crop loss by around 8-10%. An additional environmental analysis shows that mean greenhouse gas (GHG) emissions due to crop loss increased after the introduction of the PLC/ARC programs by about 1.48% and that eliminating price uncertainty would reduce GHG from crop loss by about 3.78%.

1 Introduction

Farmers in the United States leave between 10% and 60% of usable crops in the field during any given agricultural season, a phenomenon called crop loss (FAO (2011), Gunders (2017)). Crop loss does not include produce destroyed by weather, pests, or disease. It results solely from farmers' choices to harvest or not harvest ripe acreage.

In this paper, I investigate two economic reasons why farmers leave crops in the field: price uncertainty and subsidies. A low market price for a crop induces a larger amount of loss as marginal costs overtake marginal revenue (Adjemian and Motamed (2019), Hamilton, Richards, and Roe (2022)). As price takers, farmers plant and harvest crops months before they know volatile market prices that change daily. They watch price forecasts from local grain elevators, financial managers, or futures markets to plan their production levels for the year. Subsidies connected to produced acreage can also distort the amount of acres a farmer plants, leading to overproduction and thus crop loss (Henderson and Lankoski (2021)). More modern policy approaches, such as lump-sum transfers of cash based on price levels, may also distort harvest decisions since farmers will produce using their price expectations over both the market and the subsidy.

Little research investigates these relationships either with data or in structural models. My main contribution is thus to show in the data that price uncertainty at both planting and harvest leads to a significant amount of crop loss. I also demonstrate that the introduction of subsidies targeting downside price risk causes crop loss to increase.

Why is crop loss important? The Environmental Protection Agency (EPA) estimates that crop production causes around 5.05% of all greenhouse gas emissions in the United States (EPA (2024)). This means that unharvested, unused crops cause anywhere from 0.5% to 3.03% of greenhouse gas emissions in the United States. Since these crops are usable, leaving them to rot on the field implies a waste of valuable resources. Other environmental externalities of crop loss are fertilizer runoff from wasted planting, which causes destruction of local biomes, and the economic and environmental costs of producing seeds whose fruit is not ultimately harvested (Campbell et al. (2017)). These facts raise several questions important to policymakers: can crop loss be eliminated? If not, could the unused crop be redirected to an economically useful purpose? Answers to these questions rely on an understanding of the fundamental factors leading to crop loss. My paper looks at the price uncertainty and subsidy factors to provide this understanding.

To make these two channels precise, I design a dynamic stochastic model of crop production. A representative farmer forms price expectations from noisy signals over the price rule for infinite agricultural years and a government exogenously administers a subsidy program that eliminates downside price risk. Each agricultural year is divided into three seasons: planting, harvest, and market. Random market prices evolve exogenously and are only revealed to the farmer in the market season. This structure allows a view of how farmer decisions at each season can contribute to crop loss.

The subsidy in the model imitates the recent Price Loss Coverage (PLC) and Agriculture Risk Coverage (ARC) programs that are popular among commodity farmers. Like these programs, the model subsidy provides a lower bound price that the farmer will receive should the true price drop below an "effective price" decided by the government. The model subsidy eliminates downside price risk, guaranteeing the farmer a lower bound income from crop production.

The farmer makes distinct decisions during each season in the agricultural year. In the planting season, she observes a noisy signal over the market price for that year as well as the effective price published by the government. She then uses Bayesian updating to form a price expectation. Using this, she will choose inputs to planting to maximize her current and future expected utility of consumption. The planted crop matures and is ready for harvest at the beginning of the harvest season. The farmer then observes a second signal over market prices and forms a new price expectation. She will use this new expectation to choose inputs to harvest which will be equal to or smaller than the inputs to planting. This results in crop loss. The farmer also chooses consumption in the harvest season. In the marketing season, the market price is revealed, all harvested crop is sold, and the farmer receives income. If the market price is lower than the effective price, the government pays the farmer a lump-sum subsidy which is the difference between the two prices. The new agricultural year then begins.

I estimate parameters in the model with U.S. wheat data from the United States Department of Agriculture (USDA). I use wheat because it acts as a lower bound estimate for crop loss. Wheat is a less risky crop relative to other crops such as fresh fruits or vegetables. It can be stored and can be traded in advanced financial markets.

After estimating the parameters, I turn to a counterfactual analysis of the model. I remove the subsidy completely to isolate its effect on crop loss. I find that the subsidy increases the percentage amount of crop loss relative to a no-subsidy world. The no-subsidy world has a mean crop loss of 17.2% and the subsidy world has a mean crop loss of 21%.

In a second counterfactual analysis, I increase the noisiness of the signals received by the farmer. Crop loss increases to a mean of 38.4%. As the noisiness increases, the subsidy and no-subsidy simulations increase in levels, but do not converge, reducing the role of the subsidy in the crop loss decomposition. This suggests that although the subsidy eliminates downside price risk, noisy signals can be so uninformative over prices that the role of the subsidy diminishes.

The model implies that both price uncertainty and the lump sum subsidy contribute to crop loss, though price uncertainty is a larger factor. To test these predictions in the data, I estimate a pooled OLS regression in first differences. I find evidence that crop loss responds negatively to changes in the price expectations at both planting and harvest: a one standard deviation increase in the planting price expectation translates to a 2.5% decrease in crop loss. A one standard deviation increase in the harvest price expectation translates to a 4.3% decrease in crop loss in the baseline model. To test the role of the subsidy, I use a dummy for the years with the PLC/ARC programs and estimate that the introduction of the PLC/ARC program increased crop loss by 0.5%. I run an additional specification with an interaction term between the price expectation at planting and the price expectation at harvest. This term is highly significant, indicating that, given a high price expectation at planting, a one standard deviation increase in the price expectation at harvest will further decrease crop loss by around 1.0% times the standard deviation change in the price expectation at planting from this year to last year.

In the baseline regression, I find that an increase in the market price at harvest increases crop loss. I hypothesize that this results from the tradeoff between receiving a high price today over a low or relatively low price in the future. To confirm this, I run another series of regressions. I interact the market price at harvest and the two price expectations, finding a more elastic crop loss response to situations in which the price expectation at planting is high. I also find that loss remains high in situations with a greater spot price at harvest.

Since crop loss is a significant contributor to agricultural greenhouse gas emissions (GHG), I conduct an additional analysis of the environmental costs of price uncertainty and the PLC/ARC subsidies using the results from my empirical analysis. After separating and isolating the crop loss due to subsidies and the crop loss due to price uncertainty from my empirical estimations, I use a measure of emissions in CO_2 equivalents from **?** to calculate the relative contribution of each category to crop loss GHG. I find that the introduction of the PLC/ARC program increase GHG due to crop loss by approximately 1.48%, a significant amount. However, price uncertainty still plays the largest role in crop loss emissions. Relative to a world without price uncertainty, price uncertainty increases GHG by about 3.78%. This suggests that a policy targeting the reduction of agricultural GHG from crop loss would focus most effectively on reducing the price uncertainty farmers face through a combination of marketing contracts, hedging with futures markets, and other risk-reduction strategies.

Overall, my results support the hypothesis that crop loss depends strongly on both price uncertainty and subsidies. The structural framework suggests that crop loss can increase through both subsidy distortions and price uncertainty. This paper contributes a structural approach to the crop loss and, more broadly, the food loss literature. In addition, my empirical estimates provide the baseline evidence necessary to address food policy questions at the aggregate level.

1.1 Related Literature

This paper contributes to a recent stream of papers on the relationship between agriculture and the environment at a macroeconomic level. Most notable are two recent papers by Moscona and Sastry (2022) who find that technological improvement helps agriculture adapt to climate change and Hsiao, Moscona, and Sastry (2024) who find climate-change responsive agricultural policies can mitigate or exacerbate its effects depending on the enacted policy. Other papers in this literature include Anderson, Rausser, and Swinnen (2013), who explore global distortions due to domestic policies and Patel (2024) who finds evidence that farmers over- and under-estimate the role of climate factors in response to noisy information about the environment. All four of these papers focus on the adaptation of agriculture to climate change. By contrast, I focus on agriculture's contribution to climate change and how both farm policy and uncertain market factors contribute to aggregate GHG emissions. I incorporate farmer belief updating to noisy market information as well as information communicated through agricultural policy.

This paper contributes more broadly to the agricultural economics literature. It provides a new look into agricultural production by separating planting and harvest decisions in the traditional framework. Typically, a model of agricultural production treats farmers as single-minded decision-makers. They balance risk and price uncertainty at planting to make one decision over production. One such model is explored in Tack and Yu (2021), who develop an asset-pricing framework to investigate agricultural production under price risk, marketing contracts, insurance premiums, and other situations. They find that increasing the variance of prices leads to a decrease in inputs. These models ignore the fact that supply gets determined at harvest when the farmer receives new information about the current and future market. My paper incorporates this insight by allowing farmer expectations over prices to update between planting and harvest.

I contribute to recent studies on the phenomenon of crop loss. Many of these papers attempt to answer the questions I presented in the introduction (e.g., Is crop loss inefficient? Is crop loss avoidable?). While these questions are intriguing, the literature suffers from a lack of empirical investigation of the mechanisms that cause crop loss. Many of the papers in this area describe the problem and its drivers but do not bring data to the theory. Papers of this type include the agricultural economics handbook chapter by Hamilton, Richards, and Roe (2022) who describe crop loss, its reasons, and potential secondary markets. Other papers in the same vein include Kuchler and Minor (2019), Johnson and Dunning (2019), and Adjemian and Motamed (2019), all of whom approach the problem similarly.

Another vein of the crop loss literature focuses on survey-based evidence and field work measuring crop loss. Most surveys are small-scale, focused on farmers in a county or region producing the same or similar crops (e.g. Johnson et al. (2018)). This paper synthesizes the aggregate problem, introduces new sources of data, and provides statistical and structural evidence that price uncertainty can induce crop loss.

1.2 Paper Structure

The rest of the paper is structured as follows. Section 2 describes the model of crop loss with subsidies. Section 3 provides counterfactual analyses with the model. Section 4 presents my empirical findings. Section 5 uses my empirical findings to quantify the environmental impacts of crop loss. Section 6 concludes.

2 A Simple Model of Crop Loss

In this section, I present a simple model for understanding the process of wheat production and harvest decisions. I use simulations of the model's dynamics to explore the relationships between price expectations at planting and harvest, subsidies, and crop loss.

2.1 Set-Up

There are infinitely many agricultural years $t = 1, ..., \infty$. Within each agricultural year, there are three seasons s: planting $s = 1$, harvest $s = 2$, and marketing $s = 3$, in which a single crop is planted, harvested, and sold. Market prices for the crop evolve according to an AR(1) process $p_t = \rho p_{t-1} + \sigma \varepsilon_t$ with ε_t an iid normal exogenous shock. There is a representative farmer and a government.

The farmer has one goal: to maximize the expected discounted current and future utility of consumption. To do so, she makes distinct decisions in each season. In the planting season, she chooses farming inputs x_t subject to a fixed marginal cost q_x to plant a crop. The crop will then mature into X_t bushels according to the production technology $X_t = x_t^\eta$. The X_t bushels sit in the field, ready for harvest. In the second season, the farmer chooses inputs to harvest h_t and pays fixed marginal cost q_h to supply $y_t = h_t^\eta$ bushels of the crop to the market. She also chooses consumption c_t. The relation between the unharvested mature bushels and the harvested bushels is $y_t = h_t^\eta = \alpha_t x_t^\eta$, where $\alpha \in [0, 1]$ is the proportion of bushels that are harvested from the crop of ripe bushels. The percentage of crop loss in a given agricultural year t is thus $1 - \left(\frac{h_t}{x_t}\right)^\eta = 1 - \alpha_t$. In the third season, all harvested crop sells and the farmer receives income.

The government exogenously administers a program that pays subsidies to the farmer. At the beginning of agricultural year t, the government releases its forecast of the market price $\hat{p}_t^g$. The government receives some noisy signal of the price $\theta_t^g = p_t + \omega_t^g$ with $\omega_t^g \sim N(0, \tau_{g,\omega}^{-1})$ and uses Bayesian updating to arrive at their expected market price. This leads to a forecast equal to

$$\hat{p}_t^g = \frac{\tau_\varepsilon \rho + \tau_{g,\omega} \theta_t^g}{\tau_\varepsilon + \tau_{g,\omega}} \tag{1}$$

At the end of the year, should the true price drop below the effective price, the government will pay a subsidy to the farmer on her planted acres, X_t, rather than on current production, y_t. The lump sum subsidy follows the piecewise function:

$$\begin{cases} (\hat{p}_t^g - p_t)y_t + \hat{p}_t^g(X_t - y_t) & \hat{p}_t^g > p_t \\ 0 & \hat{p}_t^g \leq p_t \end{cases} \tag{2}$$

Thus, the farmer is guaranteed an income of $\hat{p}_t^g X_t$ if the true price falls below the government's price forecast.

The model subsidy is based primarily on the Price Loss Coverage (PLC) program administered by the USDA[1]. Periodically, the USDA will endow parcels of agricultural land as "base acres", which belong to the current owner of the land. If producing an eligible crop, a farmer in the U.S. can enroll these base acres in the PLC every year. At the beginning of the agricultural year, the USDA sets an "effective price" which equals the higher of the market year average price or the national average loan rate for the covered crop. The USDA also sets an "effective reference price" which is the greater of the reference price or 85 percent of the average of the market year average price from the preceding 5 years, excluding the highest and lowest prices. The "reference price" is a fixed fair price decided in the Farm Bill by congress every four years for each eligible commodity. The reference price is based on historical market prices. If, during the year, the effective price is less than the effective reference price, the USDA will issue direct payments to enrolled farmers equal to the difference between the effective reference price and the effective price times an approximate historical yield of the farmer's base acres as calculated by the USDA. Thus, current payments are "decoupled" from current production and rely only on registered base acreage of the farmer.

At the beginning of each agricultural year, the farmer has income M_t from last year's market sales and knows the market price of wheat from the previous year, p_{t-1}. She also knows the costs of planting and harvest per acre, q_x and q_h. However, the market price p_t that she will receive for this year's production is unknown until the end of the agricultural year. Lastly, she knows the government's price forecast $\hat{p}_t^g$, which she knows is guaranteed to her if the true price is revealed to be lower than the government forecast at the end of the year.

In both the planting and harvest seasons, the farmer seeks to accurately forecast the marketing price p_t, which is the price that the wheat she produces this year will sell

[1]This subsidy also closely follows the Agricultural Risk Coverage (ARC) program.

for on the market at the end of the year. Given a noisy signal at planting, the farmer forms beliefs over the unknown market price. Using these beliefs, she chooses her planting inputs x_t. In the harvest season, the farmer observes a second signal over harvest, updates her expectations over the future market price, and, using this information, chooses her harvest inputs h_t and consumption c_t.

For season $s \in \{1, 2\}$, I denote the signal $\theta_{t,s} = p_t + \omega_{t,s}$ where $\omega_{t,s}$ is iid random noise uncorrelated with ε_t. She uses Bayes' law to calculate the posterior probability distribution of p_t, that is, the conditional distribution of p_t, given $\theta_{t,s}$.

The farmer generates forecasts $\hat{p}^f_{t,s}$ according to the Kalman filtering formula:

$$\hat{p}^f_{t,s} = K_{t,s}\theta_{t,s} + (\rho - K_{t,s})\hat{p}^f_{t,s-1} \tag{3}$$

where $K_{t,s}$ is the Kalman gain in year t, season s and can be found with the following recursive formulas

$$K_{t,s} = \rho \frac{\tau_\omega}{\hat{\Sigma}^{-1}_{t,s} + \tau_\omega} \tag{4}$$

$$\hat{\Sigma}_{t,s} = \rho^2 \frac{1}{\hat{\Sigma}^{-1}_{t,s-1} + \tau_\omega} + \frac{1}{\tau_\varepsilon} \tag{5}$$

The farmer uses the previous year's market price as the initial value for the price in each year. That is, $\hat{p}^f_{t,0} = p_{t-1}$. Thus, for each season, the formulas above can be expressed as follows. In the planting season $s = 1$, the farmer's forecast is

$$\hat{p}^f_{t,1} = K_{t,1}\theta_{t,1} + (\rho - K_{t,1})p_{t-1} \tag{6}$$

$$K_{t,1} = \rho \frac{\tau_\omega}{\hat{\Sigma}^{-1}_{t,1} + \tau_\omega} \tag{7}$$

$$\hat{\Sigma}_{t,1} = \rho^2 \frac{1}{\tau_\varepsilon + \tau_\omega} + \frac{1}{\tau_\varepsilon} \tag{8}$$

The farmer will then finalize her price forecast $\hat{p}_{t,1}$ at planting with the following piecewise function

$$\hat{p}_{t,1} = \begin{cases} \hat{p}^g_t & \hat{p}^f_{t,1} < \hat{p}^g_t \\ \hat{p}^f_{t,1} & \hat{p}^f_{t,1} > \hat{p}^g_t \end{cases} \tag{9}$$

Then, for the harvest season, $s = 2$, the farmer updates using the Kalman formulas. She will set her expected price forecast at harvest as

$$\hat{p}_{t,2} = K_{t,2}\theta_{t,2} + (\rho - K_{t,2})\hat{p}^f_{t,1} \tag{10}$$

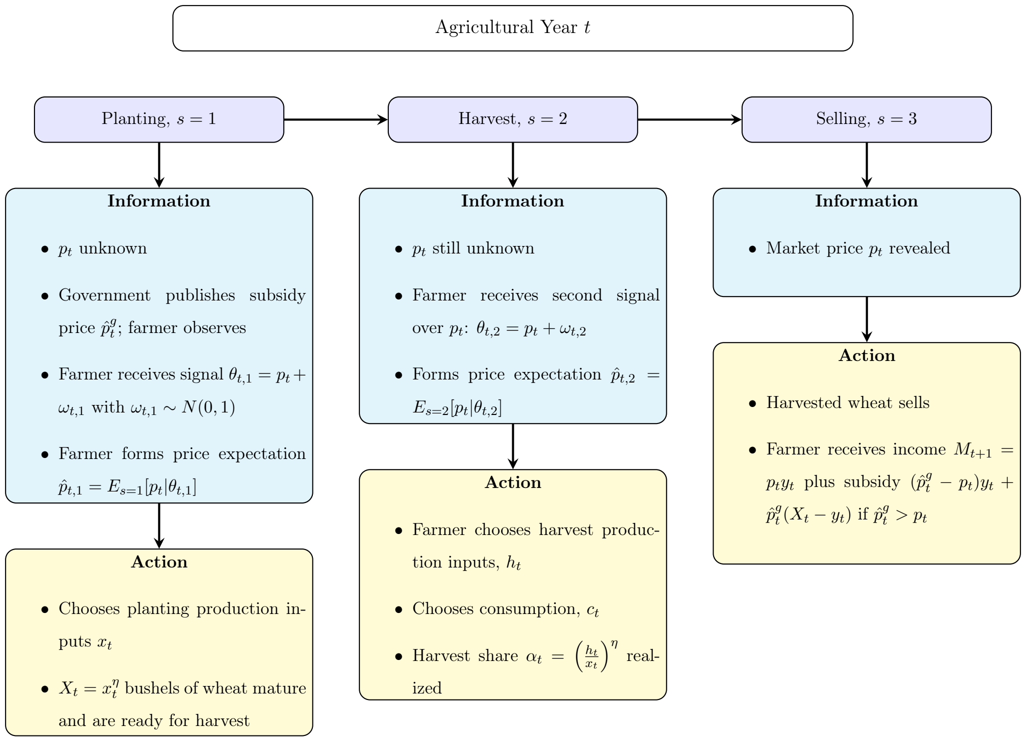


Figure 1: Inside agricultural year t.

In the marketing season $s = 3$, the true price p_t is realized and all the wheat harvested sells at this price. I assume markets fully clear every period, so all wheat is then sold in the market and the farmer receives income $M_{t+1} = p_t y_t$ from the market. If $p_t < \hat{p}_t^g$, the farmer receives an additional lump-sum subsidy $(\hat{p}_t^g - p_t)y_t + \hat{p}_t^g(X_t - y_t)$ from the government, resulting in a total income of $M_{t+1} = p_t y_t + (\hat{p}_t^g - p_t)y_t + \hat{p}_t^g(X_t - y_t) = \hat{p}_t^g X_t$. This means the farmer is getting paid based on her planted acres rather than her final production if the price is lower than the government's price forecast. The process begins over again in the next agricultural year. Figure 1 illustrates the choices and information over an agricultural year.

2.2 Solution Strategy

The farmer's overall problem in agricultural year t is to maximize her utility of consumption based on the current information available in one of two seasons. The farmer solves two sub-problems for an infinite horizon: the planting problem and the harvest-consumption problem.

First I solve the planting problem for an expression of x_t in terms of the model parameters. Full derivations are available in the appendix. Let $u(c_t) = c_t - 1$ (i.e., an isoelastic utility with parameter $\delta = 0$). This will simplify the derivations since $E[u(c_t)] = E[c_t - 1] = \hat{c}_t - 1$. The planting problem is

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) \tag{11}$$

subject to

$$M_t = (q_x + q_h)x_t + \hat{c}_t \tag{12}$$

and

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}_t^g \leq p_t \\ \hat{p}_t^g X_t & \hat{p}_t^g > p_t \end{cases} \tag{13}$$

The first order condition is

$$x_t = \left(\frac{q_x + q_h}{\beta \eta \hat{p}_{t,1}} \right)^{\frac{1}{\eta - 1}} \tag{14}$$

where the price forecast follows the piecewise function in equation (9). Since $0 < \eta < 1$, x_t is increasing in $\hat{p}_{t,1}$. This makes intuitive sense: if the farmer expects a higher return, she will plant more acreage.

The subsidy plays an interesting role. Say that $\hat{p}_{t,1} < \hat{p}_t^g$ and denote by $\overline{x}_t$ the amount of acreage the farmer would have planted if there was no subsidy program. Then, the difference between the two is:

$$\overline{x}_t - x_t = \left(\frac{\beta \eta \hat{p}_{t,1}}{q_x + q_h} \right)^{\frac{1}{1-\eta}} - \left(\frac{\beta \eta \hat{p}_t^g}{q_x + q_h} \right)^{\frac{1}{1-\eta}} < 0 \tag{15}$$

This indicates that when the farmer's forecast is below the government's effective price, the farmer will over-plant relative to the expected income under their own forecast, $\hat{p}_{t,1}$. Thus, the farmers are better off under the subsidy but produce more than they would without the guaranteed income from the subsidy program.

The harvest problem can be expressed as follows:

$$V_{t,s=2}(M_t) = \max_{c_t, h_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) \tag{16}$$

subject to

$$M_t - q_x x_t = q_h h_t - c_t \tag{17}$$

and

$$M_{t+1} = \begin{cases} p_t y_t & p_t > \hat{p}_t^g \\ \hat{p}_t^g X_t & p_t < \hat{p}_t^g \end{cases} \tag{18}$$

Taking first order conditions, we can derive an expression for the optimal choice of h_t, a piecewise function.

$$\frac{1}{\beta} = \frac{E_t[p_t \eta h_t^{\eta-1}]}{q_h} \tag{19}$$

$$\implies h_t = \begin{cases} \left(\frac{q_h}{\beta\eta\hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} & p_t \geq \hat{p}_t^g \\ \left(\frac{\alpha_t q_h}{\beta\eta\hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} & p_t < \hat{p}_t^g \end{cases} \tag{20}$$

where the price forecast follows equation (10). Because $h_t = \alpha_t^{\frac{1}{\eta}} x_t$, we can find a piecewise expression for α_t, which is the variable of empirical interest.

$$\alpha_t = \left(\frac{h_t}{x_t}\right)^{\eta} = \begin{cases} \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h\hat{p}_{t,1}}\right)^{\frac{\eta}{1-\eta}} & p_t \geq \hat{p}_t^g \\ \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h\hat{p}_{t,1}}\right)^{\eta} & p_t < \hat{p}_t^g \end{cases} \tag{21}$$

Since $0 < \eta < 1$, α_t increases in $\hat{p}_{t,2}$. Again, this makes sense: if the expected market price is higher, then the farmer will harvest a larger percentage of her mature crop. In order for $\alpha_t \in [0, 1]$, the following condition must hold:

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} < \frac{q_h}{q_x + q_h} \tag{22}$$

which, since $q_h, q_x > 0$, implies that $\hat{p}_{t,2} < \hat{p}_{t,1}$ in every agricultural year.

We can take a few other insightful observations from these expressions. Firstly, while $1 - \alpha_t$ is the percentage of bushels that are lost, it can also be reframed as the percentage of the crop that was not harvested due to the difference between old information and the newly revealed information at harvest. If the farmer's information was accurate at planting, then all of the crop would be harvested and $\alpha_t = 1$. Since the costs of harvest and planting are fixed over time and known, we can look at the ratio of the second price forecast to the first price forecast. As a first observation, let $\hat{p}_{t,2} > \bar{\hat{p}}_{t,2}$ and $\bar{\hat{p}}_{t,1} > \hat{p}_{t,1}$. Then,

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} > \frac{\bar{\hat{p}}_{t,2}}{\hat{p}_{t,1}} \tag{23}$$

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} > \frac{\hat{p}_{t,2}}{\bar{\hat{p}}_{t,1}} \tag{24}$$

Since $\hat{p}_{t,2} < \hat{p}_{t,1}$ both of the expressions above are less than 1. Then, we can interpret this as meaning the closer the expectations are to each other (i.e., the smaller the revision over price expectations at harvest), the higher the harvest percentage α_t will be. This again, makes sense – if the farmer's forecast revisions are small, this means she believes her original forecast was relatively accurate and the harvest percentage will remain closer to the original harvest expectation of $\alpha_t = 1$.

What is the role of the subsidy for the harvest percentage? I prove the following proposition to demonstrate that the harvest percentage is decreasing in the subsidy. By symmetry, crop loss is increasing in the subsidy.

Proposition 1. *α_t is decreasing in $\hat{p}_t^g$ if $\hat{p}_t^g > \hat{p}_{t,1}^f$. α_t is not responsive to $\hat{p}_t^g$ otherwise.*

Proof. Assume $\hat{p}_t^g > \hat{p}_{t,1}^f$. Then,

$$\alpha_t = \begin{cases} \left(\frac{(q_x+q_h)\hat{p}_{t,2}^f}{q_h\hat{p}_t^g}\right)^{\frac{\eta}{1-\eta}} & p_t \geq \hat{p}_t^g \\ \left(\frac{(q_x+q_h)\hat{p}_{t,2}^f}{q_h\hat{p}_t^g}\right)^{\eta} & p_t < \hat{p}_t^g \end{cases}$$

and the partial derivative of α_t with respect to $\hat{p}_t^g$ is

$$\frac{\partial \alpha_t}{\partial \hat{p}_t^g} = \begin{cases} -\frac{\eta}{1-\eta}\left(\frac{(q_x+q_h)(K_{t,2}\theta_{t,2}+(\rho-K_{t,2})\hat{p}_t^g)}{q_h\hat{p}_t^g}\right)^{\frac{2\eta-1}{1-\eta}} \frac{(q_x+q_h)K_{t,2}\theta_{t,2}}{q_h(\hat{p}_t^g)^2} < 0 & p_t \geq \hat{p}_t^g \\ -\eta\left(\frac{(q_x+q_h)(K_{t,2}\theta_{t,2}+(\rho-K_{t,2})\hat{p}_t^g)}{q_h\hat{p}_t^g}\right)^{\eta-1} \frac{(q_x+q_h)K_{t,2}\theta_{t,2}}{q_h(\hat{p}_t^g)^2} < 0 & p_t < \hat{p}_t^g \end{cases}$$

Since all terms are positive, this partial derivative is negative. Note that if $\hat{p}_t^g > \hat{p}_{t,1}^f$,

$$\frac{\partial \alpha_t}{\partial \hat{p}_t^g} = 0$$

and α_t does not respond to a change in the subsidy price. □

Proposition 1 indicates that an increase in the subsidy, that is, the government's forecast of this year's market price will increase what percentage of the crop is harvested, working through the farmer's forecast. This implies that an increase in the government's price forecast leads to a decrease in crop loss. This makes sense based on the subsidy mechanism: if a farmer is being paid on planted acres rather than current production, she will overplant in the planting stage if she believes the price will end up being lower than the government's forecast. In harvest, the farmer will only produce based on what she can receive in the market since the subsidy is decoupled from production. This will cause a relatively higher crop loss due to the subsidy distortion. I simulate a no-subsidy counterfactual world in the next section.

2.3 Connecting the Model to Empirical Framework

I briefly connect the model to my empirical specification in section 4. Taking the log of the expression for α_t, the model predicts that the percentage of the crop harvested will be related to the price expectations through the following equation:

$$\log(\alpha_t) = c_0 + \frac{\eta}{1-\eta}\log(\hat{p}_{t,2}(\hat{p}^g_t, p_t)) - \frac{\eta}{1-\eta}\log(\hat{p}_{t,1}(\hat{p}^g_t, p_t)) \tag{25}$$

where c_0 is a constant. Since $\alpha_t \in [0,1]$, by symmetry, $\log(1-\alpha_t)$ will relate to the price expectations in the opposite direction as $\log(\alpha_t)$. If $p_t < \hat{p}^g_t$, the coefficients become η and $-\eta$, respectively.

From this result, the model predicts that crop loss and the price expectation at harvest relate negatively and that crop loss and the price expectation at harvest move positively. I will test this result in an empirical specification in Section 4.

2.4 Equilibrium Definition

An equilibrium in this economy is a series $\{x_t\}_{t=0}^{\infty}$ solving the planting problem

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t(c_t - 1) \qquad \text{s.t.} \qquad M_t = (q_x + q_h)x_t + \hat{c}_t$$

subject to (13) and series $\{h_t, c_t\}_{t=0}^{\infty}$ solving the harvest problem given the solutions $\{x_t\}_{t=0}^{\infty}$ to the planting problem:

$$V_{t,s=2}(M_t) = \max_{c_t, h_t} E_0 \sum_{t=0}^{\infty} \beta^t(c_t - 1) \quad \text{s.t.} \quad M_t - q_x x_t = q_h h_t - c_t$$

and (18) and given exogenous processes for $\{\theta_{t,1}, \theta_{t,2}, p_t\}_{t=0}^{\infty}$.

2.5 Model Estimation

So far, I have shown the dynamics of the model mathematically. Now, I simulate the model dynamics. I externally estimate the model parameters η, β, q_x, q_h, ρ, σ with winter wheat data from 1996-2022.

2.5.1 Why Wheat?

I estimate the model to wheat data over other crops for several reasons. Most importantly, more data is available for wheat than for any other crop. The USDA has been tracking the prices and production of wheat since its inception in 1862. A couple decades after, they began tracking wheat storage. Well-known historical agricultural events such as the Dust Bowl in the 1920s tend to revolve around wheat and many original agricultural policies in the United States were intended to target wheat production. Wheat futures markets existed earlier than futures markets for corn and other crops. Wheat farmers have many opportunities to mitigate risks relative to other crops with a variety of marketing options, hedging strategies, and high-technological inputs. In this sense, wheat can be viewed as one of the less risky crops in the United States. In addition, wheat prices are far less volatile than more perishable crops like fruits and vegetables, providing a strong reason to consider wheat a lower-bound for total crop loss (Minor et al. (2020)).

There are three major types of wheat grown in the United States: winter wheat, spring wheat, and durum. Durum composes only a small percentage of the total wheat production, so I focus on winter and spring wheat. Winter wheat is planted around September and spring wheat is planted in the spring, usually around April. Winter wheat tends to be harvested in late May to mid June while spring wheat is usually harvested early August to mid-September.

Winter and spring wheat in the United States can be further split into three classes, or subtypes, of wheat – hard red winter (HRW), soft red winter (SRW), and hard red spring (HRS). Hard red winter wheat is the most common class, composing around 40% of all wheat grown in the United States. Hard red winter wheat is primarily grown in the central plains states, especially Kansas, Oklahoma, Nebraska, and Texas. It is used for flour production and ends up in breads, rolls, and some Asian-style noodles. Soft red winter composes around 20% of total wheat production and is grown mostly in the midwest and plains states. SRW is a high-quality wheat used in pizza doughs, pastries, and other speciality bakery items. Hard red spring wheat also comprises around 20% of total wheat production and is concentrated in northern plains states such as North and South Dakota, Montana, and some parts of Minnesota. It is generally used in the production of crackers, cookies, and some pastries. Because winter wheat makes up the majority of wheat grown in the United States, I estimate the model to moments in winter wheat data. However, my empirical analysis in Section 4 uses a panel of winter and spring wheat data.

2.5.2 Estimation Details

The costs of planting and harvest are calculated as follows. From the USDA I collect estimates of operating costs per wheat acre over the sample period. I separate the costs into planting and harvest categories. Seeds are categorized as "planting time only". Fuel, lube, and electricity are categorized as both planting and harvest costs. I assign a proportion of this cost to each season based on the ratio of acres harvested or acres planted to the sum of acres planted and acres harvested. All other categories are assigned to harvest costs: custom services, other operating costs, interest paid on operating costs, fertilizer, and chemicals[2]. I find that $q_x = \$19.55$ and $q_h = \$84.65$ per acre.

Parameter	Estimate	Source
q_x	\$19.55 per acre	USDA Costs data
q_h	\$84.65 per acre	USDA Costs data
η	0.975	USDA wheat production data
ρ	0.9035	USDA price data
σ	1.73	USDA price data
β	0.99	N/A

Table 1: Summary of model parameter estimates

I calculate η by first noticing that $h_t = \alpha_t^{\frac{1}{\eta}} x_t$. So then,

$$\eta = \frac{\log(\alpha_t)}{\log(h_t) - \log(x_t)}$$

Recall that h_t and x_t are inputs to production. There is no data on production inputs at an aggregate level, so I use acres harvested and acres planted as proxy measures. Since the data may be contaminated with weather shocks, I drop the two maximum points in each variable. I then use the means of these adjusted measures as the steady state values so that

$$\eta = \frac{\log(\bar{\alpha})}{\log(\bar{h}) - \log(\bar{x})}$$

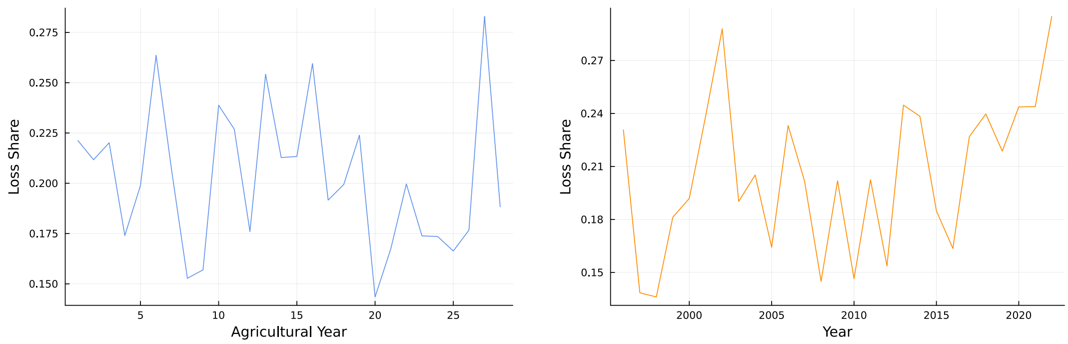
[2]Fertilizer is technically a planting cost, but in order for the model dynamics to work well, I need a larger estimate of q_h, so I include this in harvest costs

where the bars denote steady state values. This expression gives a value of $\eta = 0.975$. I set $\beta = 0.99$ but also test $\beta = 0.8$ and $\beta = 0.5$ for robustness of results. These results are presented in the appendix.

For the price rule, I match the first autocorrelation and standard deviation of the annual spot price for winter wheat. There is no evidence of a trend in the data and since the sample period is relatively short, I calibrate the model to the raw data series which has a first autocorrelation of $\rho = 0.9035$ and a standard deviation of $\sigma = 1.73$. Table 1 summarizes my parameter estimates.

2.6 Simulation Results

In this section, I simulate the time path of bushels lost for 27 years, which is the length of my sample period (1996-2022). Figure 2a shows the mean of 100 simulations.



(a) Mean time path of bushels lost

(b) Log bushels lost, 1996-2022

Figure 2: Mean results from 100 simulations compared to winter wheat data.

The simulated time path matches the data plotted in figure 2b fairly closely: the mean of the simulated crop loss is 20.3% while in the data it is 21%. The standard deviation of the simulated series is 3.56% and the standard deviation of the data is 4.33%.

2.7 Model Extensions

There are several additional extensions that can easily be added to this model. Supply shocks can be modeled with a random variable multiplied by the production function on acres produced given inputs. Another extension that is very easy to add is hedging with futures markets. This extension mimics the approach I take to subsidies as well –

adding a baseline, guaranteed income creates a revenue floor, reducing overall risk. The appendix contains a version of this extension.

A less easy but still possible extension would be to add storage as a state variable. To do so, remove the assumption that the farmer cannot consume out of current market income and add the assumption that the farmer can store some wheat across agricultural years should it not sell. In this case, the farmer would plant and harvest in a similar way but with the additional consideration of the wheat in storage that could also be sold in the market. Years of high storage may induce lower planting and lower harvest. The effect on the percentage of crops left in the field remains unclear without a full analysis.

3 Counterfactual Analyses

There are two mechanisms in the baseline model that contribute to crop loss: the the subsidy program and differences between the price forecasts at planting and at harvest. In this section I explore the counterfactual effects of these two mechanisms. I first eliminate the subsidy from the baseline model and compare the two. Secondly, I run a simulation with noisier signals and no subsidy to isolate the effect of price uncertainty.

3.1 Income Without Subsidies

Take the baseline model and suppose now that there is no subsidy. Thus, the farmer's decision over planting inputs depends on her expected price in the planting period, $\hat{p}^f_{t,1}$. This introduces a downside risk that demand will be lower than forecasted. After planting, the true price is realized as usual and the farmer makes a harvest decision. Then, in the harvest period, income evolves according to the following rule:

$$M_{t+1} = p_t h_t = p_t \alpha_t x_t^\eta$$

The farmer then solves the same problem as in the baseline model except with this new rule and no subsidy.

3.2 Simulation Results with No Subsidy

Figure **??** shows the plot of the dynamics of crop loss in models with and without the subsidy. The crop loss dynamics with a subsidy are the same as in Figure 2a. Under a

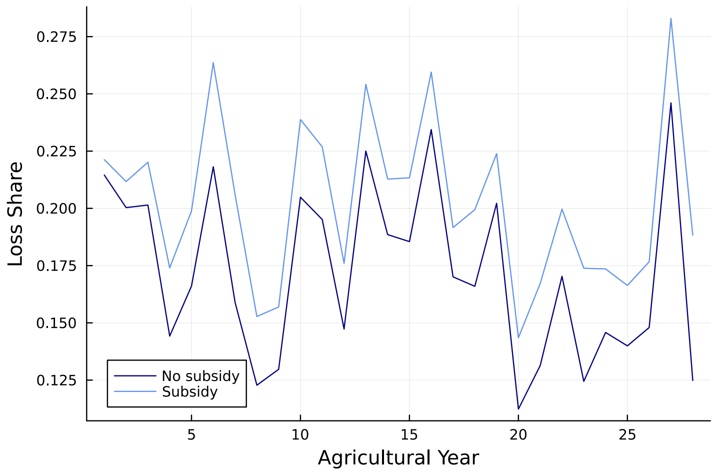


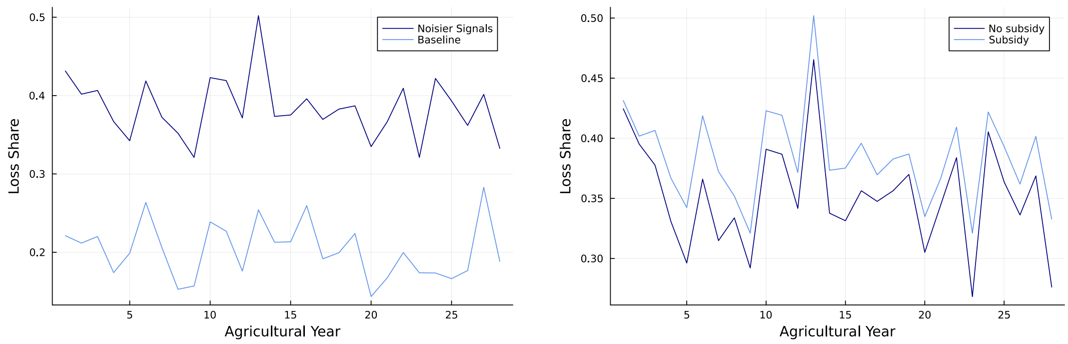
Figure 3: Simulations with and without a subsidy program.

subsidy regime, crop loss is higher on average than in a world without a subsidy. Without a subsidy, average crop loss over the simulated time series is 17.2% and the standard deviation is 3.78%. Under the subsidy, crop loss is higher because, as shown in Section 2, the farmer overplants to receive a higher subsidy if she expects the government's price forecast to be higher than her own. This implies that the subsidy induces overplanting, despite being decoupled from the actual crop brought to market in the third season.

3.3 Noisier Signals

Another way to explore the implications of the model is to increase the noise in the signals or remove it entirely. It would be quite difficult to have a true counterfactual for no signals in this model as this implies that the price expectations for both planting and harvest are the mean of the price rule ρp_{t-1} and $\hat{p}_{t,1} = \hat{p}_{2,t}$. This will imply a constant rate of loss in the model dynamics. Instead, I increase the volatility of the distribution of the signals received by the farmer. Now, instead of being noise, $\omega_{t,s} \sim N(0, 10)$. This will induce more volatile price beliefs.

Figure 4a compares the baseline model simulation results to the simulation results with noisier signals. Clearly, noisier signals increase the percentage of crops that are lost. The average crop loss under the noisier signals is 38.4%, roughly double that of the baseline model. The standard deviation is 3.9%, which is only slightly larger than baseline. This suggests that less accurate price forecasts increase crop loss percentages in levels but will not strongly impact the variance of crop loss.



(a) "Noisier Signals" denotes $\omega_{s,t} \sim N(0, 10)$

(b) Subsidy versus no subsidy.

Figure 4: Simulations with noisier signals.

Figure 4b presents the results of the simulation with noisier signals when there is a subsidy versus when there is no subsidy. Relative to the baseline model, crop loss under the subsidy regime versus the no-subsidy regime remain quite close to each other. This suggests that as price expectations move further away from the true price, the presence of a subsidy continues to impact the incidence of crop loss by approximately the same proportion. However, the large increase in crop loss is due primarily to farmer's uncertainty over market prices, not farmer's receipt of subsidies.

This is an important result. It suggests that production-decoupled subsidies do not matter as strongly as price uncertainty for crop loss. In the model, removing the subsidy would decrease crop loss slightly, but removing all price uncertainty would eliminate crop loss entirely.

4 Empirical Analysis

By how much does wheat crop loss respond to changes in price expectations? Do the PLC/ARC programs matter for crop loss in the data? The model asserts that crop loss is increasing in the subsidy. It also asserts that crop loss is negatively related to the price expectation at harvest and positively related to the price expectation at planting. In this section, I test the validity of these assertions in the data.

I find that both the price expectation at planting and the price expectation at harvest matter significantly for wheat crop loss. Differences in price forecasts at planting and harvest account for a smaller, though still significant, portion of crop loss. I find that a one standard deviation increase in price expectations at harvest lead to around a 4.3% decrease in wheat crop loss. Taking into account belief updating between planting and harvest, given a high price expectation at planting, an increase in the price expectation at harvest will decrease crop loss by an addition 1.3% times the change in the price forecast at planting. That is, the higher the price at planting, the more an increase in the price expectation at harvest will decrease crop loss. I also find that the introduction of the PLC/ARC programs accounted for an increase in crop loss of around 0.5%.

4.1 Baseline Regressions

The model of interest is the following pooled OLS regression which I run on an unbalanced panel from 1979-2022:

$$\% \text{ loss}_{it} = c + \beta_1 \hat{p}_{1,i,t} + \beta_2 \hat{p}_{2,i,t} + \Psi X_{it} + \varepsilon_{it} \tag{26}$$

I denote the type of wheat $i \in \{\textit{spring wheat}, \textit{winter wheat}\}$ and the percentage of wheat crops that are lost each year $\% \text{ loss}_{it}$. In addition, $\hat{p}_{1,i,t}$ denotes the price expectation at planting for the spot price in the month after harvest. Similarly, $\hat{p}_{2,i,t}$, is the price expectation at harvest for the spot price in the month after harvest. Controls X_{it} absorb weather effects, harvest spot price effects, and the impact of stored bushels of wheat. β_1, β_2 and Ψ are parameters and ε_{it} is an error term. Summary statistics of the data can be viewed in the appendix.

This specification is the empirical analog of (25). Although the model predicts that the response of crop loss to both price forecasts has the same magnitude, this is somewhat unrealistic. Thus, for the empirical analysis in this section, I allow crop loss to responds with different magnitudes to the different price expectations.

Wheat production has decreased over the sample and production techniques have changed. Due to these trends and wheat-type-specific attributes, there may be omitted variable bias in the above specification. I thus estimate the regression above in first-differences:

$$\Delta\% \text{ loss}_{it} = \alpha + \beta_1 \Delta\hat{p}_{1,i,t} + \beta_2 \Delta\hat{p}_{2,i,t} + \beta_3 D_{\text{subsidy}} + \Psi \Delta X_{it} + \Delta\varepsilon_{it} \tag{27}$$

This specification removes the trend and any time-invariant attributes due to wheat type (spring or winter wheat). I also add a dummy D_{subsidy} for the years after 2015, which was the first year wheat farmers registered in the PLC/ARC programs.

I calculate wheat crop loss with data from the USDA National Agricultural Statistics Service (NASS). I use the difference between the acres planted and acres harvested times the yield in bushels per acre harvested. To find the percentage of bushels lost, I divide this measure by the bushels harvested plus bushels unharvested.[3] Loss as calculated here could over- or under-estimate true crop loss. Overestimation may occur if the researcher does not control for weather, pests, or other natural shocks. Underestimation may occur if the acres counted as "harvested" were only partially harvested. Due to a lack of data, it is difficult to fully eliminate all noise in a measure of crop loss. The measure I use here is most likely the best available to researchers at the moment. In my analysis, I correct for weather by adding controls for county-level volume-weighted averages of temperature and precipitation in my baseline specification. Underestimation is more difficult to control for since there are little to no data on the proportion of an acre that a farmer will not harvest. However, with controls for overestimation, these results provide a lower bound estimate for wheat crop loss response.

One additional consideration is wheat storage utilization. At any given time, the United States hold hundreds of millions of bushels of wheat in storage. In addition, wheat storage is seasonal: it is lower at harvest time and higher post-harvest. At harvest time, there may be varying levels of wheat in storage across years. Some years, the relative amount of wheat in storage may be higher due to a lower demand and vice versa. Figure 5 illustrates this. Due to this fluctuation, farmers may choose to leave more wheat in the field when using relatively higher storage capacity at harvest. They will need sell both stored wheat and new harvest. The table shows that stock level at harvest significantly predicts crop loss.

The last control that I use is the market price at harvest, since it may figure into a farmer's decision to harvest.[4] The market price data comes from the USDA NASS. Farmers harvest winter wheat in June and spring wheat in late August to September, so I use the market prices in June and August, respectively.

For the price expectations, $\hat{p}_{1,i,t}$ and $\hat{p}_{2,i,t}$, I look to wheat commodity futures markets. I use Chicago Board of Trade (CBOT) wheat futures from 1979-2022 and Minneapolis Grain Exchange (MGEX) wheat futures from 1980-2022 for winter and spring wheat,

[3]This measure is also called the harvest success rate.

[4]The market price is also called the spot price.

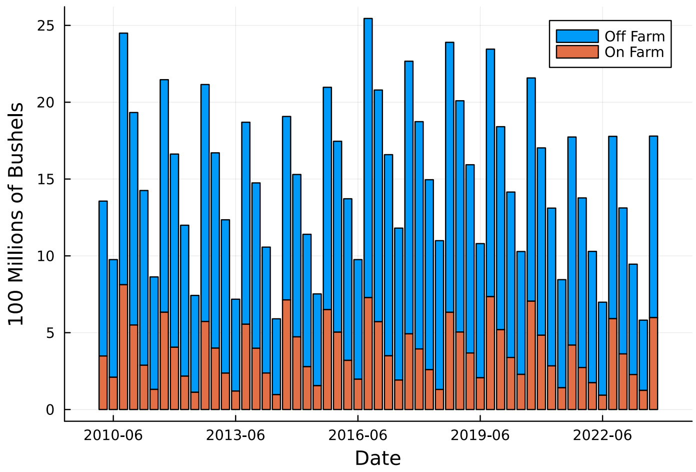


Figure 5: Seasonality of winter wheat storage from 2010-2023. Data source: USDA National Agricultural Statistics Service.

respectively, since the CBOT futures exchange trades winter wheat and the MGEX trades in spring wheat. I assume the futures price is equal to the expected price for wheat at some horizon – in other words, I assume the rational expectations hypothesis holds in the wheat commodities exchanges.[5]

Wheat futures contracts expire approximately every two months in March, May, July, September, and December every year. I use two sets of monthly volume-weighted end of day futures prices: one at planting and one at harvest for each type of wheat. The futures price at planting is the expected market price the month after harvest and the futures price at harvest is the expected price in the month after harvest. The reason I choose the month after harvest is twofold. Firstly, since these are monthly measures, letting the spot price of interest be the spot price in the month after harvest avoids any chance that unknown price information is effecting price beliefs at harvest. Secondly, there is often a delay between when farmers harvest and when farmers deliver their wheat, and using the the month after harvest as the expected spot price may more realistically reflect farmer decisions.

Most winter wheat is harvested in September, while spring wheat is harvested in August. Therefore, the expiry dates for their futures contracts are July for winter wheat and September for spring wheat. This represents the fourth futures contract after the

[5] Futures contracts may not reflect the true price expectation if the market prices are easily predictable (see Piazzesi and Swanson (2008) for a discussion with Fed Funds Futures). I address this problem by removing an estimate of excess returns. See the appendix for details.

planting month for winter wheat and the second for spring wheat.

The first column of Table 2 contains the baseline regression. I standardize all of the independent variables except the subsidy dummy for easier interpretation and provide heteroskedasticity-robust standard errors. The R-squared is 0.231.

This specification demonstrates that a one standard deviation increase in the price expectation at harvest, $\hat{p}_{2,i,t}$, leads to a highly significant decrease in wheat crop loss of about 4.3%. This was predicted by (25). On the other hand, the marginal response to a one standard deviation change in the price expectation at planting $\hat{p}_{1,i,t}$ is a significant decrease in loss of 2.5%. The model predicted the opposite sign in the response. In response to the introduction of the PLC and ARC programs in 2015, there was a highly significant increase in crop loss of 0.5%. This is a much smaller response, as anticipated in the model simulations.

Interestingly, an increase in the spot price at harvest leads to an increase in wheat crop loss. This indicates that a higher spot price at harvest may cause farmers to leave more crop in the field. This seems counterintuitive but I hypothesize that this effect may be because farmers prefer to sell at harvest rather than face storage costs and price risks if the spot price today is high enough, and that the scramble to receive this price may result in a lower harvest percentage. I explore this relationship in the section below.

The second column of Table 2 contains the baseline regression with an additional interaction term between the two variables to test whether changes in price expectations between planting and harvest have an effect on crop loss. The coefficient for $\hat{p}_{2,i,t}$ is significant at the 99% confidence level and nearly identical to the baseline regression at -4.4%. The coefficient on $\hat{p}_{2,i,t}$ is weakly significant at the 90% level with a value of -2.6%. The coefficient on the interaction is significant at the 99% level and has a value of -0.8%. The R-squared increases slightly to 0.255.

These results imply that the total effect of an increase in the price expectation at harvest depends on the price expectation at planting. The response of wheat crop loss due solely to a one standard deviation increase in the price expectation at harvest will lead to a 4.4% decrease in crop loss. However, a nonzero price expectation at planting will amplify the effect by -0.8% times the value of that price expectation. The effect is stronger for a high value of $\Delta\hat{p}_{1,i,t}$. This is in line with the relationships demonstrated with the structural approach in the previous section which say that less belief updating

Table 2: Dependent variable: Δ *% loss*

	(1)	(2)	(3)
$\Delta\hat{p}_{2,i,t}$	-0.043***	-0.044***	-0.043***
	(0.013)	(0.010)	(0.010)
$\Delta\hat{p}_{1,i,t}$	-0.025***	-0.026***	-0.028***
	(0.009)	(0.008)	(0.004)
$D_{subsidy}$	0.005***	0.004***	-0.000
	(0.002)	(0.000)	(0.005)
$\Delta p_{i,t}$	0.074***	0.088***	0.085***
	(0.012)	(0.018)	(0.012)
Δ *Stored Bushels*	0.009	0.012	0.011
	(0.010)	(0.013)	(0.011)
$\Delta\hat{p}_{2,i,t} * \Delta\hat{p}_{1,i,t}$		-0.008***	-0.013**
		(0.009)	(0.006)
$\Delta\hat{p}_{2,i,t}$ * Δ*Stored Bushels*			-0.016***
			(0.000)
Constant	0.001	0.005	0.001
	(0.001)	(0.006)	(0.004)
Controls	X	X	X
N	86	86	86
R^2	0.231	0.255	0.315
Adj R^2	0.152	0.168	0.225

Notes: Each column is a separate regression. Standard errors are robust. The dependent variable is the change in percentage of bushels lost between agricultural years. $\hat{p}_{1,i,t}$ and $\hat{p}_{2,i,t}$ are the variables of interest. p_{it} is the spot price at harvest. Weather controls included in all specification and are volume-weighted averages of precipitation, maximum and minimum temperatures over all counties that produced wheat of type i in growing season of agricultural year t. *Stored Bushels* is the amount of wheat stocks in storage at harvest. All RHS variables are standardized. Three asterisks denotes significance at the 99% level, two denotes the 95% level, and one denotes the 90% level.

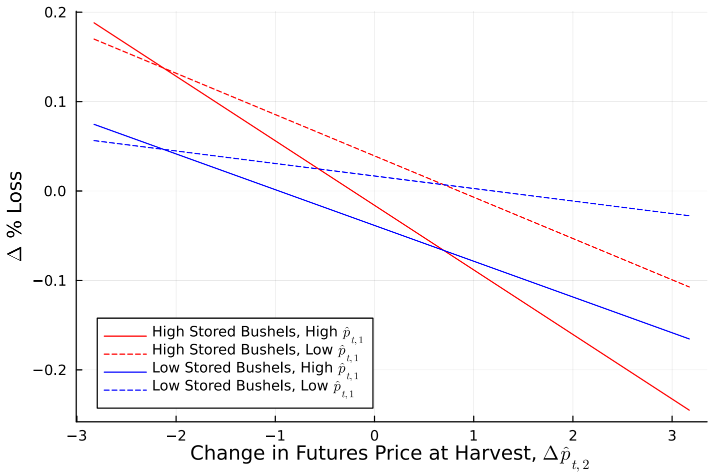


Figure 6: Fitted one standard deviation plots from the regression in column (3) of Table 2.

(i.e., price expectations that are closer in value to each other) will lead to lower crop loss (see equation (23)). To illustrate, say a farmer has a high price expectation at planting and there is an unexpected increase in the price expectation at harvest. Then, the overall effect would be to decrease crop loss by a relatively large amount. Conversely, if the farmer has a low price expectation at planting and there is an unexpected increase in the price expectation at harvest, the effect will be to reduce crop loss but by a smaller amount than if the farmer believes she will receive a high price in the market at planting.

In column (3) of Table 2, I run an additional regression specification by adding interactions between each price expectation and the stored bushels variable as well as a three-way interaction. As mentioned above, farmers may take stored bushels into account as they are harvesting and thus crop loss may be impacted by this information. The R-squared increases slightly to 0.315. The coefficients on both price expectation variables are negative, close to the baseline, and significant at the 99% level. The coefficient on the interaction between the two price expectations is significant at the 95% confidence level. Furthermore, the coefficient on the interaction between the price expectation at harvest and stored bushels is highly significant, indicating that the response of crop loss to an increase in the price at harvest is conditional on not only the price expectation at planting but also the level of bushels in storage.

Figure 6 plots the fitted line of the marginal response of crop loss to a change in $\hat{p}_{2,i,t}$ with the first standard deviations of the data from the results in the third column. The figure illustrates that, conditional on having a high amount of bushels in storage and a high price expectation at planting, an increase in the price expectation at harvest will decrease crop loss more elastically than other states of the world. Conversely, conditional on a low amount of stored bushels and a low price expectation at planting, crop loss responds much less elastically to a change in the price at harvest. Another result is that the level of stored bushels appears to matter very little – when price expectations at planting are low, it takes a much larger increase in the price expectation at harvest to induce a reduction in crop loss and vice versa for a high price expectation at planting.

Overall, these results provide evidence that differences in price expectations between planting and harvest do contribute to loss. However, the strongest effect comes directly from changes in the price expectation at harvest. Given a value of one for the change in the price expectation at harvest, the model predicts that a one standard deviation increase in the price forecast at harvest leads to a decrease of between 4.3% and 7.3% decrease in wheat crop loss in a given year.

4.2 Testing for the Joint Role of Prices and Price Expectations

The coefficient on the spot prices is positive in the results above, indicating that a higher spot price at harvest will result in a higher percentage of crops lost. I hypothesize that this result can be explained by the farmer's decision-making process at harvest.

As a simple example, say that the farmer is at harvest. If the spot price is high at harvest but the expected price in the future is low, then she may wish to harvest less in general, since she will need to face additional price risk as well as storage costs in order to sell later. This results in higher crop loss. Depending on the relative values of the market price and price forecast at harvest, this relationship will be more or less elastic. As the price forecast at harvest increases relative to the market price at harvest, the farmer will harvest more and more as the expected price becomes attractive enough to overcome the risk of waiting to sell later.

I test this hypothesis in a similar way to the section above. I run the following regression:

$$\Delta\%\text{loss}_{it} = \alpha + \beta_1\Delta\hat{p}_{1,i,t} + \beta_2\Delta\hat{p}_{2,i,t} + \beta_3\Delta p_{i,t} + \beta_4\Delta\hat{p}_{1,i,t}\Delta\hat{p}_{2,i,t} \tag{28}$$

$$+ \beta_5\Delta\hat{p}_{1,i,t}\Delta p_{it} + \beta_6\Delta\hat{p}_{1,i,t}\Delta\hat{p}_{2,i,t}\Delta p_{i,t} + \Delta\varepsilon_{i,t} \tag{29}$$

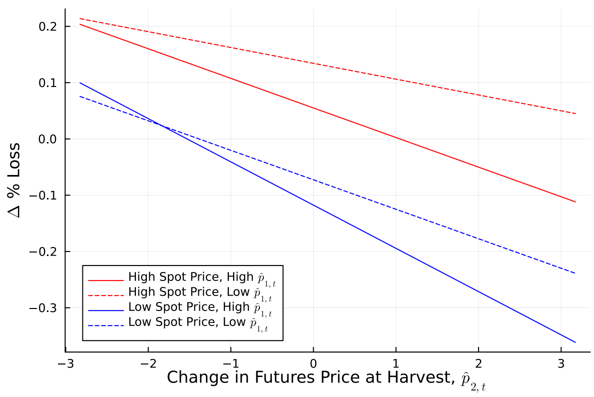


Figure 7: One standard deviation plots of results from column (2) of table 3.

If this hypothesis is correct, I would expect to see a negative relationship that lies above the origin line in the case of a high spot price today, regardless of the value of the futures price at planting. This would mean that increases in expected futures prices at harvest would have to be much greater to be more attractive than the increase in the spot price at harvest for a farmer to harvest more. Conversely, I would expect to see a negative relationship that lies below the origin line in the case of a low spot price at harvest, regardless of the value of the futures price at planting. This means that an increase in the expected price at harvest does not need to be as great to make future sale more attractive than selling at harvest in the market. This is exactly what I find in the data, as discussed below. Table 3 presents the results from the regression.

Column (3) of Table 3 tests the three-way interaction between the market price, the price forecast at planting, and the price forecast at harvest. Columns (1) and (2) of Table 3 present a simplified versions of column (3). The coefficients on all price variables and two-interactions are highly significant, indicating that all three variables matter for explaining crop loss decisions. The three-way interaction is insignificant. The R-squareds fall between 0.309 and 0.317. To more easily interpret the results, figure 7 shows the fitted lines of the marginal response of crop loss to a change in $\hat{p}_{2,i,t}$ with the first standard deviations of the data from the results in the second column of Table 3.

Two attributes of the plot immediately stand out. Firstly, when there is a high spot price, the majority of the plotted lines lie above the horizontal axis, indicating that it takes a much larger increase in the expected price in the future to decrease crop loss. Conversely, when there is a low spot price, the majority of the plotted lines lie below the horizontal axis at zero. This implies under a low spot price, it does not take as much of

Table 3: Dependent variable: Δ *% loss*

	(1)	(2)	(3)
$\Delta\hat{p}_{2,i,t}$	-0.056***	-0.052***	-0.054***
	(0.009)	(0.006)	(0.006)
$\Delta\hat{p}_{1,i,t}$	-0.028***	-0.031***	-0.032***
	(0.009)	(0.004)	(0.003)
$\Delta p_{i,t}$	0.097***	0.100***	0.095***
	(0.016)	(0.005)	(0.013)
$D_{subsidy}$	-0.001	-0.003	-0.002
	(0.002)	(0.003)	(0.003)
Δ *Stored Bushels*	0.013	0.013	0.012
	(0.011)	(0.010)	(0.010)
$\Delta\hat{p}_{2,i,t} * \Delta p_{i,t}$	0.010***	0.012***	0.012***
	(0.000)	(0.002)	(0.002)
$\Delta\hat{p}_{1,i,t} * \Delta p_{i,t}$	-0.018***	-0.009***	-0.009**
	(0.003)	(0.003)	(0.003)
$\Delta\hat{p}_{2,i,t} * \Delta\hat{p}_{1,i,t}$		-0.012***	-0.012***
		(0.002)	(0.001)
$\Delta\hat{p}_{2,i,t} * \Delta\hat{p}_{1,i,t} * \Delta p_{i,t}$			0.001
			(0.001)
Constant	0.004	0.003	0.003
	(0.005)	(0.005)	(0.005)
Controls	X	X	X
N	86	86	86
R^2	0.309	0.312	0.317
Adj R^2	0.219	0.216	0.206

Notes: Each column is a separate regression. Standard errors are robust. The dependent variable is the change in percentage of bushels lost between agricultural years. $\hat{p}_{1,i,t}$ and $\hat{p}_{2,i,t}$ are the variables of interest. p_{it} is the spot price at harvest. Weather controls included in all specification and are volume-weighted averages of precipitation, maximum and minimum temperatures over all counties that produced wheat of type i in growing season of agricultural year t. *Stored Bushels* is the amount of wheat stocks in storage at harvest. All RHS variables are standardized. Three asterisks denotes significance at the 99% level, two denotes the 95% level, and one denotes the 90% level.

an increase in the expected price at harvest to decrease crop loss. This result is exactly as expected, suggesting that farmers prefer to sell at harvest if the price is high enough rather than incur storage costs and additional price risk. The expected price in the future needs to be higher to overcome the attraction of a high price now.

The second observation is that the response of crop loss to a change in the expected price at harvest is more elastic when there is also a high price expectation at planting. The plot indicates this through the steepness of the solid lines relative to the dotted lines. An increase in the price expectation at harvest will cause a greater decrease in loss under a high price expectation at planting than under a low one. This result also makes sense under my hypothesis. Farmers will have a higher incentive to harvest more when the price expectation at harvest is higher.

Overall, these two observations provide evidence for my hypothesis. Farmers value selling right away at harvest rather than storing over several months, especially when prices are expected to decrease in the future. Farmers will be incentivized to harvest less if the market price at harvest is high relative to future expected prices, increasing crop loss.

4.3 Robustness

Both winter wheat and spring may be harvested in months other than June or August. I check whether the results hold with a spot price in May or July for winter wheat and August for spring wheat. This does not significantly change the results and in fact lowers the R^2 on all of the regressions and reduces the significance of the coefficients.

5 The Environmental Impacts of Wheat Crop Loss

In this section, I take the fitted results from my baseline regression and calculate the change in greenhouse gas (GHG) emissions due to the introduction of the PLC/ARC programs. I also use the same fitted regressions to calculate an estimate of the GHG due to price uncertainty in the production cycle. These estimates allow me to compare the two factors' relative contribution to agricultural emissions. I find that, as indicated in the structural approach and in the empirical results in the previous sections, price uncertainty matters much more for GHG emissions than the subsidy programs that are decoupled from current production.

5.1 Data and Methods

I conduct an analysis that is similar in spirit to the damage mitigation analysis in Moscona and Sastry (2022) but adapted to the crop loss problem. I decompose my fitted baseline regressions into two categories: loss under a no-subsidy regime and loss in a world without price uncertainty.

I define loss without the PLC and ARC programs or no subsidy (NS) as the fitted values of (26) less the estimated coefficient of the subsidy dummy variable times the dummy. This value can be expressed:

$$\Delta\%\text{loss}^{\text{NS}} = \Delta\%\widehat{\text{loss}}_{it} - \hat{\beta}_3 D_{\text{subsidy}} \tag{30}$$

where $\Delta\%\widehat{\text{loss}}_{it}$ is the vector of fitted values.

I define emissions under a no price uncertainty (NPU) regime similarly, as the fitted values of (26) less the estimated coefficients of each price expectation variable times the price expectations in the data. In mathematical terms, this measure is denoted:

$$\Delta\%\text{loss}^{\text{NPU}} = \Delta\%\widehat{\text{loss}}_{it} - \hat{\beta}_1 \Delta\hat{p}_{1,i,t} - \hat{\beta}_2 \Delta\hat{p}_{2,i,t} \tag{31}$$

To calculate the emissions due to loss, I calculate the predicted crop loss rather than the change in crop loss with the following formulas

$$\%\widehat{\text{loss}}_{i,t} = \%\text{loss}_{i,t-1} + \%\Delta\widehat{\text{loss}}_{i,t} \tag{32}$$

$$\%\widehat{\text{loss}}_{i,t}^{\text{NS}} = \%\text{loss}_{i,t-1} + \%\Delta\widehat{\text{loss}}_{i,t}^{\text{NS}} \tag{33}$$

$$\%\widehat{\text{loss}}_{i,t}^{\text{NPU}} = \%\text{loss}_{i,t-1} + \%\Delta\widehat{\text{loss}}_{i,t}^{\text{NPU}} \tag{34}$$

I next calculate an estimate of GHG emissions under loss calculated from the fitted values in Equation 26. I use the following formula:

$$\widehat{GHG}_{it} = \%\ \text{loss}_{it} \times \text{hectares planted}_{it} \times \text{avg emissions}_{it} \tag{35}$$

where $\%\ \text{loss}_{it}$ is the crop loss for wheat type $i \in \{\text{spring, winter}\}$ in year t. The measure hectares planted is the hectares of wheat of type i planted in year t and avg emissions_{it} is an estimate of mean emissions per hectare of planted wheat.

For the measure of emissions, I take the estimate of the mean emissions per hectare by crop type from Johnson et al. (2016). They create a normalized measure in CO_2 equivalents of all GHG emissions from the production of one hectare of wheat. They define their life cycle boundaries from raw material extraction for inputs such as fertilizers, chemicals, electricity, and fuels to the farm gate, or the moment the wheat has left the farm. While this slightly over-estimates the emissions from a hectare of crop loss, the researchers also find that inputs used before and during the growing season such as pesticides and fertilizers account for approximately 75%+ of all emissions while fuels and electricity which are used through planting, growing, and harvest account for a much smaller percentage (around 10-15%). Thus, this is a decent estimate of total emissions for ripe, unharvested wheat. Their mean measures are 2.776 tons of CO_2 equivalents per hectare of winter wheat and 3.385 tons of CO_2 equivalents per hectare of spring wheat.

Additionally, I convert measures of acres planted from the USDA to hectares and use this measure in the equation above. Over time, from the beginning of the full sample in 1979 to the end of the sample, this measure trends downward. Because of this, emissions have decreased over time since there are fewer hectares of wheat produced in general. In order to mitigate the trend's effect, I restrict my sample for my estimate of emissions to 8 years before and after 2015, from 2007 to 2022.

Finally, I aggregate this measure by taking the mean of the total sample and denote it as $\widehat{\text{GHG}}$. I repeat this process with the measures for the no subsidy regime emissions GHG^{NS} and the no price uncertainty regime emissions GHG^{NPU}.

I define the following measure. Denote the percentage change in crop loss emissions due to the introduction of the PLC/ARC programs by

$$\%\Delta\text{GHG} = \frac{\widehat{\text{GHG}} - \text{GHG}^{\text{NS}}}{\text{GHG}^{\text{NS}}} \times 100$$

Using the data described above, I calculate a value of this measure of approximately 1.48%.

I also calculate the change in crop loss emissions due to price uncertainty, which is denoted:

$$\%\Delta\text{GHG}^{\text{NPU}} = \frac{\text{GHG} - \text{GHG}^{\text{NPU}}}{\text{GHG}^{\text{NPU}}} \times 100$$

The value of this measure is 3.78%.

While both measures are large, it is clear that price uncertainty matters more than the PLC and ARC subsidies for emissions. This implies that policies targeting the reduction of price uncertainty would have a much larger effect than the removal of the PLC or ARC programs.

6 Policy Recommendations and Conclusion

In this paper, I provided evidence that crop loss results from subsidies and price uncertainty at both planting and harvest. The model demonstrates that subsidies decoupled from production can increase crop loss by eliminating downside price risk. However, as forecasting becomes less accurate, the subsidy contributes to a small proportion of total crop loss.

My empirical analysis provides strong evidence that farmers' decisions over crop loss depend heavily on price uncertainty. An increase in the price expectation at harvest decreases crop loss. However, there must be a much larger increase in this price expectation in the case when the price expectation at planting is low. Similarly, in a world with a high spot price today, it takes a much larger increase in the expected future price to entice farmers to harvest more crop to sell later. I also calculate measures of the greenhouse gas contributions from both price uncertainty and the PLC/ARC subsidy.

The analysis suggests several avenues for policy. Overall, price uncertainty matters quite strongly for crop loss. A complete elimination of price risk would decrease emissions from crop loss by around 3.78% according to my estimates. This implies that encouragement or emphasis on farmer use of tools to reduce price risk will reduce crop loss. These tools include marketing contracts, which lock in a price pre-planting, and the use of futures markets for hedging price risk. Wheat farmers specifically do not appear to use these tools as much as corn or soybean farmers (Prager et al. (2020)).

The structural analysis suggests that the PLC and ARC subsidies play a role in keeping crop loss unnaturally high. Firstly, production requirements for subsidies cause an overproduction of crops, implying that these policies will increase crop loss. The suggestion from the world where the subsidy is not tied to production is that if farmers use the effective price or the subsidy level as a signal about unknown prices, it is quite possible that they will not incorporate better information over prices into their expectations. This suggests that an avenue for future research is to learn the role of the effective price in farmer price expectations. While I find that these subsidies do not matter as strongly for crop loss in the empirical analysis, I do find that the removal of these subsidies would result in a decrease in emissions from crop loss of around 1.48%.

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A Additional Simulations

I simulate the model with $\beta = 0.8$ and $\beta = 0.5$. The results are very close to the baseline model and are plotted below.

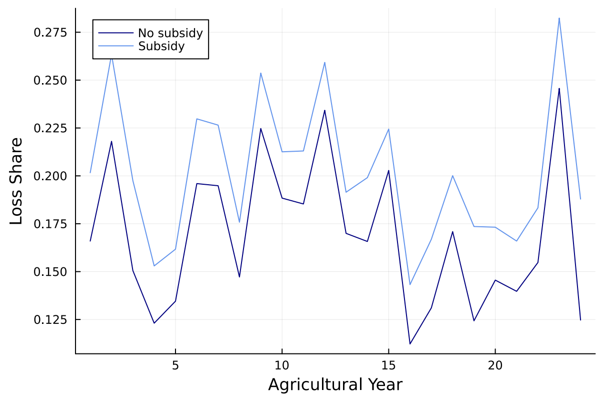

Figure 8: Baseline simulation with $\beta = 0.8$.

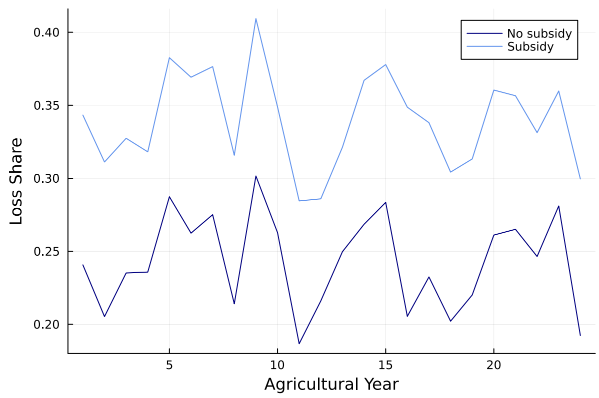

Figure 9: Baseline simulation with $\beta = 0.5$.

B Agricultural Subsidies in the United States

This appendix provides a summary of historical and current agricultural subsidies in the U.S.

The United States has financially aided farmers through various programs since the 1800s. Modern subsidy programs developed when Franklin D. Roosevelt signed the Agricultural Adjustment Act into law in 1933. Considered the first "farm bill", this act attempted to increase rapidly declining agricultural prices to historical level through subsidies that were given to farmers when they planted less acreage of their crop, also known as supply control. The legislation was largely successful at reducing supply surpluses – wheat acreage was reduced from 81 million acres in 1937 to 63 million acres in 1938 (Bowers, Rasmussen, and Baker (1984)).

Throughout the decades of the 1940s, 50s, and 60s, agricultural production technology improved at a rapid rate. Wheat yields per acre increased from 17 bushels per acre in 1945 to 26.1 bushels in 1960 (Bowers, Rasmussen, and Baker (1984)). This led to massive surpluses of wheat – approximately 1.4 billion bushels a year that was held by the government. By the beginning of the 1970s, however, demand for U.S. exports of wheat skyrocketed. This depleted supply, including surplus held by the government. The Agricultural and Consumer Protection Act of 1973 changed the direction of agricultural subsidy policy, instead promoting higher production and transfers based on rising input costs. In addition to reducing the maximum transfer amount, the bill instituted a "target price", above which no payments would be made to farmers.

Under the Reagan, Bush, and Clinton administrations, USDA policy moved away from direct control toward market-based incentives. The biggest shift in agricultural policy since the 1933 bill occurred in the 1996 Farm Bill. For the nearly 65 years, the primary focus of agricultural policy was on supply control. The main programs attempted to control surpluses of crops. In this legislation, supply controls were completely removed as a policy, and a new form of income support arrived through payments that were"decoupled" from current production. After farmers continued receiving payments despite a strong market price during the Great Recession, the 2014 Farm Bill responded by eliminating the direct payments and starting two new programs – the Price Loss Coverage (PLC) program and the Agriculture Risk Coverage (ARC) program. Both programs implemented direct payments based on historical production that only took effect once the market price dipped below an "effective price" determined by the USDA. These last programs are the programs most closely related to the subsidy in my model.

Today, if producing an eligible crop, a farmer can enroll acres in either the PLC or ARC programs but not both. The enrollment used to occur once every few years but as of 2021 occurs every year. The programs are very similar, the main difference being that ARC payments are based on county-level revenue guarantees or individual revenue guarantees depending on the program. The ARC programs are less widely adopted than the PLC program (Turner et al. (2023)).

If producing an eligible crop, a farmer in the U.S. can enroll acres in the PLC every year. At the beginning of the agricultural year, the USDA sets an "effective price" which equals the higher of the market year average price or the national average loan rate for the covered crop. The USDA also set an "effective reference price" which is the greater of the reference price or 85 percent of the average of the market year average price from the preceding 5 years, excluding the highest and lowest prices. The "reference price" is a fixed fair price published by the USDA for each eligible commodity and is based on historical market prices. If, during the year, the effective price is less than the effective reference price, the USDA will issue direct payments to enrolled equal to the difference between the effective reference price and the effective price times an approximate historical yield of the farmer's base acres, calculated by the USDA.

C Derivations for the Theoretical Results

I reproduce the main text here, with further derivations and assumptions included.

The farmer's overall problem in agricultural year t is to maximize her utility of consumption based on the current information available in one of two seasons. The farmer solves two sub-problems for an infinite horizon: the planting problem and the harvest-consumption problem.

First I solve the planting problem for an expression for x_t in terms of the model parameters. Let $u(c_t) = c_t - 1$ (i.e., an isoelastic utility with parameter $\delta = 0$). This will simplify the derivations since $E[u(c_t)] = E[c_t - 1] = \hat{c}_t - 1$.

The planting problem is

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1)$$

subject to

$$M_t = (q_x + q_h)x_t + \hat{c}_t$$

with

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}_t^g \leq p_t \\ \hat{p}_t^g X_t & \hat{p}_t^g > p_t \end{cases} \tag{36}$$

The problem can be rewritten from above by substituting in the constraints:

$$\max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (p_{t-1}\alpha_{t-1}x_{t-1}^{\eta} - (q_x + q_h)x_t - 1)$$

The first order conditions are then:

$$\begin{aligned}
\frac{\partial V}{\partial x_t} &= -(q_x + q_h) + \beta E_{t,s=1}[p_t \eta (x_t \alpha_t)^{\eta-1}\alpha_t] = 0 \\
&\implies q_x + q_h = \beta\eta E_{t,s=1}[p_t \alpha_t^{\eta}](x_t)^{\eta-1} \\
&\implies q_x + q_h = \beta\eta \hat{p}_{t,1} x_t^{\eta-1} \\
&\implies x_t = \left(\frac{q_x + q_h}{\beta\eta\hat{p}_{t,1}}\right)^{\frac{1}{\eta-1}}
\end{aligned}$$

where the second to last line follows from the fact that $E_{t,s=1}[\alpha_t] = 1$ and

$$\hat{p}_{t,1} \begin{cases} \hat{p}_{t,1}^f & \hat{p}_{t,1}^f \geq \hat{p}_t^g \\ \hat{p}_t^g & \hat{p}_{t,1}^f < \hat{p}_t^g \end{cases}$$

Similarly, the harvest problem can be expressed as follows:

$$V_{t,s=2}(M_t) = \max_{c_t,h_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1)$$

subject to

$$M_t - q_x x_t = q_h h_t - c_t$$

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}_t^g \leq p_t \\ \hat{p}_t^g X_t & \hat{p}_t^g > p_t \end{cases}$$

We can set this up as a Lagrangian:

$$\mathcal{L} = \begin{cases} \max_{c_t,h_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) - \lambda_t (p_{t-1} h_{t-1}^{\eta} - q_x x_t - q_h h_t - c_t) & p_t \geq \hat{p}_t^g \\ \max_{c_t,h_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) - \lambda_t (\hat{p}_t^g \frac{h_t^{\eta}}{\alpha_t} - q_x x_t - q_h h_t - c_t) & p_t < \hat{p}_t^g \end{cases}$$

Taking first order conditions, we can derive an expression for the optimal choice of α_t:

$$\frac{\partial \mathcal{L}}{\partial c_t} = \beta^t + \lambda_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial c_{t+1}} = \beta^{t+1} + \lambda_{t+1} = 0$$

$$\frac{\partial \mathcal{L}}{\partial h_t} = \begin{cases} \lambda_t q_h - \lambda_{t+1} E_t[p_t \eta h_t^{\eta-1}] = 0 & p_t \geq \hat{p}_t^g \\ \lambda_t q_h - \lambda_{t+1} E_t[\hat{p}_t^g \frac{\eta}{\alpha_t} h_t^{\eta-1}] = 0 & p_t < \hat{p}_t^g \end{cases}$$

Substituting and rearranging:

$$\implies h_t = \begin{cases} \left(\frac{q_h}{\beta \eta \hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} & p_t \geq \hat{p}_t^g \\ \left(\frac{\alpha_t q_h}{\beta \eta \hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} & p_t < \hat{p}_t^g \end{cases}$$

In the second case, h_t depends on α_t, which is the variable of interest. Noticing that $h_t = \alpha_t^{\frac{1}{\eta}} x_t$, we can find an expression for α_t in terms of the model parameters.

$$\alpha_t = \begin{cases} \left(\frac{h_t}{x_t}\right)^{\eta} = \left(\left(\frac{q_h}{\beta \eta \hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} \cdot \frac{1}{x_t}\right)^{\eta} & p_t \geq \hat{p}_t^g \\ \left(\frac{h_t}{x_t}\right)^{\eta} = \left(\left(\frac{\alpha_t q_h}{\beta \eta \hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} \cdot \frac{1}{x_t}\right)^{\eta} & p_t < \hat{p}_t^g \end{cases}$$

$$= \begin{cases} \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}}\right)^{\frac{\eta}{1-\eta}} & p_t \geq \hat{p}_t^g \\ \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}}\right)^{\eta} & p_t < \hat{p}_t^g \end{cases}$$

Since $0 < \eta < 1$, α_t is increasing in $\hat{p}_{t,2}$. Again, this makes sense: if the expected market price is higher, then the farmer will harvest a larger percentage of her mature crop. In order for $\alpha_t \in [0,1]$, the following condition must hold:

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} < \frac{q_h}{q_x + q_h}$$

Which, since $q_h, q_x > 0$, implies that $\hat{p}_{t,2} < \hat{p}_{t,1}$ in every agricultural year.

D Data Summary Statistics

Table 5 gives the summary statistics for the data used in the regressions. The regressors are standardized in the regression but I put the pre-standardized summary statistics here. Table 6 summarizes the weather control variables.

Table 4: Summary Statistics

Statistic	Δ% Bushels Lost	$\Delta\hat{p}_{1,i,t}$	$\Delta\hat{p}_{2,i,t}$
mean	0.002	0.000	0.000
std	0.053	0.990	0.990
min	-0.123	-2.880	-2.290
q25	-0.030	-0.669	-0.580
median	0.000	-0.039	-0.069
q75	0.046	0.568	0.327
max	0.113	2.370	3.043

Table 5: Summary Statistics

Statistic	$\Delta p_{i,t}$	Δ Bushels Stored
mean	0.000	-0.179
std	0.990	2.267
min	-1.994	-5.601
q25	-0.611	-1.291
median	-0.095	-0.247
q75	0.544	1.246
max	2.681	4.797

Table 6: Summary Statistics: Weather Controls

Statistic	ΔPrecipitation	ΔMax Temperature	ΔMin Temperature
mean	-0.113	0.154	0.188
std	3.709	3.024	4.458
min	-6.478	-6.475	-9.197
q25	-2.610	-1.709	-2.409
median	-0.468	0.841	0.025
q75	2.200	1.918	2.987
max	8.607	7.413	12.453

E Removing Excess Returns

For the futures prices data, I remove an estimate of excess returns to correct for predictable market prices in the data. To do this, I complete the following steps for each futures price time series:

1. Subtract the futures price at harvest from the futures price of interest to obtain the excess return.

2. Regress the excess return on the futures price, i.e.,

$$\text{excess returns}_{1,i,t} = \beta\hat{p}_{1,i,t}$$

3. Obtain the fitted values, which are the portion of the futures price that is predictable.

4. Subtract the fitted values from the futures price to obtain the adjusted measure of the futures price.

I conduct my analysis in the main text with both adjusted and unadjusted measures. The results to do not change. The results in the main text use the adjusted measures.

F Model Extension: Hedging

There are several additional extensions that can easily be added to this model. One such extension is farmer use of futures contracts to hedge price risk. I model this version of the model similarly to Tack and Yu (2021).

Assume now that there is no subsidy program and instead the farmer hedges price risk at the beginning of each year t by selling a futures contract f_{t-1} for ξ units of wheat each agricultural year at the previous year's futures price before harvest. Let f_t denote the futures price at the time that p_t is revealed. Then, the price p_t can be decomposed into the futures price and an adjustment called the basis which I denote b_t:

$$p_t = f_t + b_t$$

In practice, farmers will purchase a contract at futures price f_t to close out their hedge position at f_{t-1} while selling their production in the market at p_t. Thus, for ξ units of wheat, the farmer will obtain the price adjustment $f_{t-1} - f_t$ each year. For the remaining production excess or deficit, the farmer obtains the market price p_t.

The farmer's revenue at the end of the period will thus be

$$M_{t+1} = p_t\xi + p_t(y_t - \xi) + (f_{t-1} - f_t)\xi$$

This expression can be rearranged to

$$M_{t+1} = p_t(y_t - \xi) + f_{t-1}\xi + b_t\xi$$

Notice that income then depends on the basis, and the farmer bears some risk over the direction of the basis by using a hedging instrument. She also must plant at least the amount of the wheat specified in the contract.

The planting problem is now

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1)$$

subject to

$$M_t = (q_x + q_h)x_t + \hat{c}_t$$
$$M_{t+1} = f_t(x_t^\eta - \xi) + b_t x_t^\eta + f_{t-1}\xi$$

Rearranging and replacing gives us

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (f_{t-1}(x_{t-1}^\eta - \xi) + b_{t-1}x_{t-1}^\eta + f_{t-1}) - (q_x + q_h)x_t - c_t)$$

where $y_t = x_t^\eta$ (i.e., $\alpha = 1$) by the same assumption in the baseline model.

The algebra is nearly identical to the derivation above with the final result being equal to:

$$x_t = \left(\frac{q_x + q_h}{\beta \eta E_{t,1}[f_t + b_t]} \right)^{\frac{1}{\eta - 1}}$$

The harvest problem follows similarly:

$$V_{t,s=1}(M_t) = \max_{h_t, c_t} E_0 \sum_{t=0}^{\infty} \beta^t \left[(c_t - 1) \right]$$

subject to

$$M_t = q_x x_t + q_h h_t + c_t$$
$$M_{t+1} = f_t(h_t^\eta - \xi) + b_t h_t^\eta + f_{t-1}\xi$$

Setting up the lagrangian:

$$\mathcal{L}_{t,s=2}(M_t) = \max_{h_t, c_t} E_0 \sum_{t=0}^{\infty} \beta^t \left[(c_t - 1) - \lambda_t (f_{t-1}(h_{t-1}^\eta - \xi) + b_{t-1}h_{t-1}^\eta + f_{t-2}\xi - q_x x_t - q_h h_t - c_t) \right]$$

This results in the following expression:

$$h_t = \left(\frac{q_h}{\beta \eta E_{t,2}[f_t + b_t]} \right)^{\frac{1}{\eta - 1}}$$