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

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May 6, 2025

Abstract

Farmers choose to leave around 42% 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, and underscores their large environmental impacts. 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. In an empirical exercise, 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%. Mean greenhouse gas (GHG) emissions due to crop loss increased after the introduction of the PLC/ARC programs by about 1.48% Eliminating price uncertainty would reduce GHG from crop loss by about 3.78%.

1 Introduction

Farmers in the United States leave around 42% of usable crops in the field during any given agricultural season, a phenomenon called crop loss (Roe (2019),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. 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. A low market price expectation for a crop induces a larger amount of loss as marginal costs overtake expected marginal revenue (Adjemian and Motamed (2019), Hamilton, Richards, and Roe (2022)). 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)). 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 around 2.12% of all 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 planted crops.

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 by about 14%. The no-subsidy world has an average median crop loss of 5.12% and the subsidy world has an average median crop loss of 19.3%.

In a second counterfactual analysis, I increase the noisiness of the signals received by the farmer. Crop loss increases to an average median value of 34.17%, about 15% higher than in the baseline model. 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 when price forecasts are less accurate. 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 find that loss is lower in situations with a greater spot price at harvest when the price expectation at planting is low relative to when the price expectation at planting is high. This supports my hypothesis.

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 Johnson et al. (2016) 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. 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 Patel (2024), who finds evidence that farmers over- and under-estimate the role of climate factors in response to noisy information about the environment, and Shu and Zhang (2025), who look at farmer belief updating about climate change mitigation strategies after separate subsidy strategies in the cocoa industry in Ghana. Less focused on but related to the environment, Anderson, Rausser, and Swinnen (2013) explore global externalities due to domestic subsidy policies in the agricultural sector. All 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 market 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 create a simple model of crop production. The model incorporates farmer belief updating over uncertain prices and a subsidy program. Unlike a typical agricultural production model, my model allows for crop loss at harvest and provides insight into how price uncertainty and subsidies impact it. I derive results from the model which show that the subsidy program leads to crop loss. I also show that noisy price forecasts impact crop loss up to the second order.

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 market $s = 3$, 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 planting inputs x_t subject to a fixed marginal cost q_x to plant a crop. The crop will then mature into X_t acres according to the decreasing returns production technology $X_t = x_t^\eta$ with $\eta \in [0, 1]$. The X_t acres sit in the field, ready for harvest.

In the second season, the farmer chooses harvest inputs h_t and pays fixed marginal cost q_h to supply $y_t = h_t^\eta$ acres of the crop to the market. She also chooses consumption c_t. The relation between the unharvested mature crop and the harvested crop is $y_t = h_t^\eta = \alpha_t x_t^\eta$, where $\alpha \in [0, 1]$ is the proportion of the crop that is harvested from the ripe planted acreage. 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.

2.2 The Subsidy Program

The government exogenously administers a program that pays subsidies to the farmer. At the beginning of agricultural year t, the government releases the subsidy price $\hat{p}_t^g$ that it will guarantee to the farmer. The government sets its price guarantee as 85% of the average of the market price over the last five agricultural years in the model, less the maximum and the minimum price, which I express as

$$\hat{p}_t^g = \frac{\sum_{t-5}^{t-1} p_k - \max\{p_{t-5}, \ldots, p_{t-1}\} - \min\{p_{t-5}, \ldots, p_{t-1}\}}{3} \tag{1}$$

This calculation is called an Olympic average. It mimics the real-life payment level from two United States subsidy programs that I discuss below.

At the end of the year, should the true market price drop below the government's price guarantee, the government will pay a subsidy to the farmer on her planted acreage, X_t, rather than on current production, y_t. In this case the subsidy equals the difference between the government's price guarantee and the true market price. The lump sum subsidy follows the piecewise function

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

The farmer receives this additional income of $(\hat{p}_t^g - p_t)X_t$ if the true market price falls below the government's price guarantee.

A key feature of the model subsidy program is that the farmers receive subsidy payments on their planted crop X_t rather than their produced crop y_t. This modeling choice reflects the way many subsidies are calculated in the United States. Typically, the United States Department of Agriculture (USDA) pays subsidies to farmers based on their ownership of a crop-specific set of acres called *base acreage*. The USDA endows land as base acreage based on that land's historical planted acreage for a certain crop. In programs relevant to this paper, base acreage is eligible for subsidy payments and non-base acreage is not. The USDA only periodically allows farmers to update a land's base acreage designation to prevent payments from becoming too tied to current production[1]. In the model, y_t is current production and X_t imperfectly but closely reflects the concept of base acreage.

A second feature of the model subsidy program that matters for results is that payment is based on the government's price guarantee $\hat{p}_t^g$. This feature reflects a popular subsidy program called the Price Loss Coverage (PLC) program, which is administered by the USDA and subscribed to by most subsidy-eligible commodity farmers in the U.S. The model subsidy also closely follows the Agricultural Risk Coverage (ARC) program, which is similar to the PLC.

The PLC dispenses payments on base acreage based on two price estimates published by the USDA. The effective price equals the higher of the average of market prices over the previous year or the national average loan rate for the individual crop. The effective *reference* price is the greater of a fixed baseline price set by Congress in the Farm Bill every four years for each commodity or 85 percent of the average of the annual market price from the previous five years, excluding the highest and lowest prices[2].

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. Thus, current payments are decoupled from current production and rely only on registered base acreage of the farmer. In the model, $\hat{p}_t^g$ corresponds to the effective reference price and the true market price p_t corresponds to the effective price.

A final important model feature is that I implicitly assume that planted acres in the model are base acres. This is somewhat unrealistic. Because base acres can only be updated at infrequent intervals, farmers in the U.S. may be receiving payments for one crop on base acreage that they did not plant or base acreage that is growing a different crop entirely. However, since many base acres do still reflect the crop acreage that farmers plant every year relatively well, this model assumption is not an unfair one (Coppess (2023)).

[1]Base acreage was endowed for the first time in the 1996 Farm Bill. It was updated after the passage of the 2002 Farm Bill and again after the 2014 Farm Bill.

[2]The baseline price set by Congress is called the reference price and is based on historical market prices for each subsidy-eligible commodity.

2.3 Farmer Beliefs Over Prices

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 guarantee $\hat{p}^g_t$.

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

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

If the farmer's price forecast is below the government's price guarantee, she will replace her forecast with $\hat{p}_t^g$. This choice maximizes her expected income since she believes she will receive a subsidy payments in the market season.

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

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

Since the subsidy price guarantee only applies to planted acres, the farmer does not take it into account during the harvest season.

In the market season $s = 3$, the true price p_t is realized and all the crop harvested sells at this price. I assume markets fully clear every period, so all crop 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 $(\hat{p}_t^g - p_t)X_t$ from the government, resulting in a total income of $M_{t+1} = p_t y_t + (\hat{p}_t^g - p_t)X_t$. The process begins over again in the next agricultural year. Figure 1 illustrates the choices and information over an agricultural year.

2.4 The Farmer's Problem

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. Together, the solutions to these problems form the backbone of the farmer's crop loss decision.

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 $u(c_t) = c_t - 1$ which is an isoelastic utility with parameter $\delta = 0$. This simplifies the derivations since $E[u(c_t)] =$

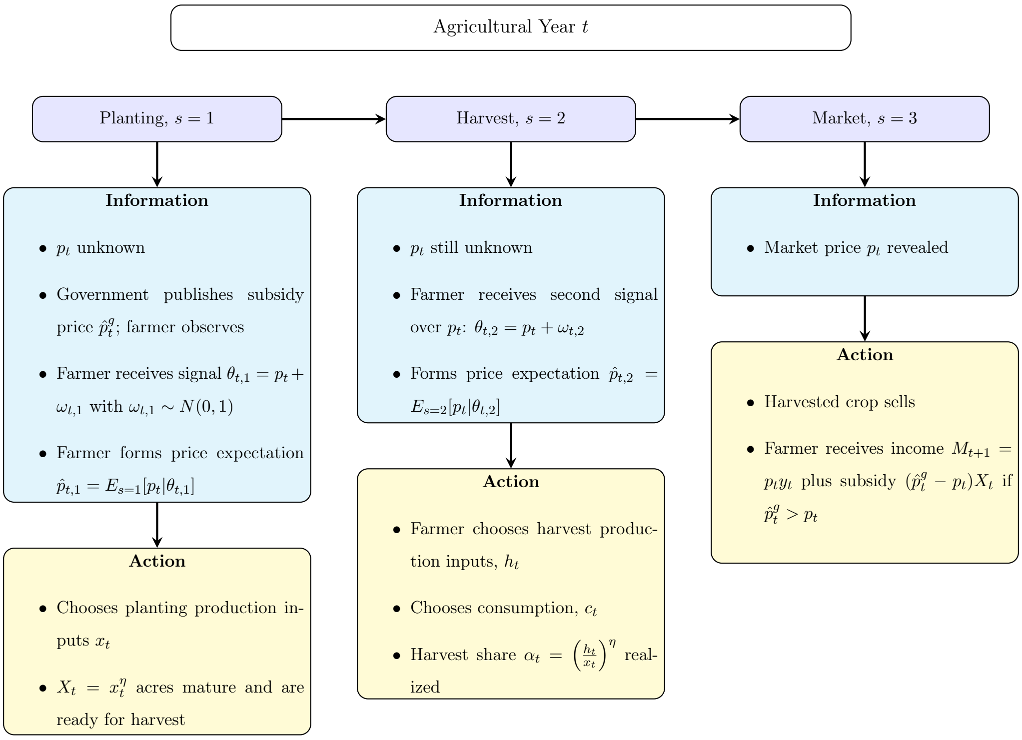


Figure 1: Inside agricultural year t.

$E[c_t - 1] = \hat{c}_t - 1$. 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

$$M_t = (q_x + q_h)x_t + c_t \tag{12}$$

and

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

In the planting season, the farmer expects $\alpha_t = 1$. Otherwise, she would want to plant more to maximize her revenue over the agricultural year. Using this observation, I find the following first order condition

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

where the price forecast $\hat{p}_{t,1}$ 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.

The expression for the planting inputs x_t shows that the subsidy program plays a significant role in the planting season. Say that $\hat{p}^f_{t,1} < \hat{p}^g_t$. Denote by $\overline{x}_t$ the amount of planting inputs the farmer would choose if there was no subsidy program. Then, the difference between the two is greater than zero:

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

This indicates that when the farmer's forecast is below the government's subsidy guarantee, the farmer will over-plant to maximize their revenue from subsidy payments. The farmer is better off under the subsidy but produces more than she would without the guaranteed income from the subsidy program.

After planting, the crop grows and the farmer moves to her harvest problem, which relies on updated information regarding market prices. The harvest problem can be expressed

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

subject to

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

and

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}^g_t \leq p_t \\ p_t y_t + (\hat{p}^g_t - p_t) X_t & \hat{p}^g_t > p_t \end{cases} \tag{18}$$

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

$$h_t = \left(\frac{\beta\eta\hat{p}_{t,2}}{q_h}\right)^{\frac{1}{1-\eta}} \tag{19}$$

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:

$$\alpha_t = \left(\frac{h_t}{x_t}\right)^{\eta} = \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}}\right)^{\frac{\eta}{1-\eta}} \tag{20}$$

where $\hat{p}_{t,1}$ follows the piecewise function in equation (9). Crop loss is $1 - \alpha_t$. Since α_t is a percentage, I show the following lemma.

Lemma 1. *For $\alpha_t \in [0,1]$, the following condition must hold:*

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} < \frac{q_h}{q_x + q_h} \tag{21}$$

Proof. See appendix. □

The harvest percentage depends on the farmer's forecast and the government's subsidy guarantee. The farmer's forecast depends on the noise of the signals she receives. I derive the responses of the harvest percentage to these three variables.

Proposition 1. *α_t increases in $\hat{p}_{t,2}$.*

Proof. Since $\eta \in [0,1]$, α_t increases in $\hat{p}_{t,2}$. □

Proposition (1) indicates that at harvest, the farmer takes more of her crop out of the field when she has a higher expectation of future market prices, whether or not that expectation is higher than the government's subsidy guarantee. This demonstrates that the farmer does not take subsidy values into account at harvest, since the reception of a subsidy relies only on her past planting decision.

However, the harvest percentage does respond to the government's subsidy guarantee since the farmer's forecast at planting may rely on the subsidy value. 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 2. *When $\hat{p}^f_{t,1} \geq \hat{p}^g_t$,*

1. *α_t decreases in $\hat{p}^f_{t,1}$ and*
2. *α_t is unresponsive to $\hat{p}^g_t$.*

Else,

3. *α_t increases in $\hat{p}^f_{t,1}$ and*
4. *α_t decreases in $\hat{p}^g_t$.*

Proof. See appendix. □

The first and last parts of Proposition (2) relate to the interaction between the two price forecasts of the farmer. The harvest percentage α_t is sensitive to the farmer's forecast revision between planting and harvest. If the forecast revision is small, the farmer will harvest more. If it is large, the farmer will harvest less and there will be more crop loss. Since α_t is realized in the harvest season, the value of the planting forecast $\hat{p}_{t,1} \in \{\hat{p}^f_{t,1}, \hat{p}^g_t\}$ is considered fixed by the farmer at harvest. However, if $\hat{p}_{t,1}$ is further in value from the farmer's updated forecast at harvest $\hat{p}_{t,2}$, the difference between the forecasts is higher. This is because $\hat{p}_{t,1} > \hat{p}_{t,2}$ implies $\hat{p}_{t,1} - \hat{p}_{t,2} > 0$ by Lemma (1).

The second part of Proposition (2) states that when the farmer expects high market prices at planting, α_t will not rely on the government's subsidy guarantee. As discussed above, this indicates that the subsidy will not play a large role in the farmer's decision over harvest. The farmer believes in this case that the market will provide a higher return than the government subsidy and will thus not over-plant relative to the expected market price.

The third part of Proposition (2) illustrates the first order dependency of the farmer's price forecast at harvest on the farmer's forecast at planting. In essence, if the farmer forecasts a higher price at planting, this will translate to a certain extent to a higher price expectation at harvest via the Kalman updating formula. This increases in turn the percentage of crop the farmer harvests.

The harvest percentage also depends on the noisiness of the farmer's signals. I prove the following proposition to demonstrate this mechanism behind crop loss fluctuations in the model.

Proposition 3. *α_t is increasing in τ_ω if $\theta_{t,1} > p_{t-1}$ and $\theta_{t,2} > \hat{p}_{t,1}$.*

Proof. See appendix for proof. □

Proposition 3 indicates that, [under certain conditions], the more uncertainty around the market price (i.e., the smaller the precision), the less the farmer will harvest of her mature crop. If the farmer's information is noisy, their harvest percentage will be lower, and thus crop loss is higher. This indicates that a more precise estimate of the market price helps to reduce crop loss. I simulate a noisier-signal counterfactual world in the next section to illustrate this point.

2.5 Equilibrium Definition

An equilibrium in this economy is a partial equilibrium, consisting of series $\{x_t\}_{t=0}^{\infty}$ that solve the planting problem

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

subject to (37) 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 $\{\theta_{t,1}, \theta_{t,2}, p_t\}_{t=0}^{\infty}$.

2.6 Model Estimation

So far, I have shown the model dynamics mathematically. Now, I simulate them with data. I externally estimate the model parameters η, β, q_x, q_h, ρ, σ with winter wheat data from 1996-2022. I use winter wheat specifically because the results can act as a lower bound for overall crop loss across agricultural commodities.

2.6.1 Why Wheat?

I estimate the model to wheat data over other crops for several reasons. Relative to other crops in the United States, wheat is less risky, has highly developed subsidy programs, and has financial futures markets which farmers use as price forecasts. In addition, more data is available for wheat than 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 revolve around wheat shortages 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.

Estimates from wheat can be viewed as a lower bound for crop loss. Wheat farmers in the United States have many opportunities to mitigate risks relative to other crops with a variety of marketing options, hedging strategies, and high-technological inputs. In addition, wheat prices are far less volatile than more perishable crops like fruits and vegetables (Minor et al. (2020)).

For estimating the model, I use winter wheat. There are three major types of wheat grown in the United States: winter wheat, spring wheat, and durum. Winter wheat is the most grown type of wheat in the United States. Durum composes only a small percentage of the total wheat production, so I estimate the model to moments from winter wheat data. However, my empirical analysis in Section 4 uses a joint time series dataset of winter and spring wheat data. 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.

2.6.2 Estimation Details

I estimate the model parameters using moments from wheat data. From the USDA I collect estimates of operating costs per wheat acre over the sample period which I use to calculate the costs of planting and harvest. I separate the operating 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 weighted by 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, including but not limited to custom services, other operating costs, interest paid on operating costs, fertilizer, and chemicals, overhead[3]. I find that q_x = \$11.84 and

[3]See the appendix for more justification for this split.

Parameter	Estimate	Source
q_x	\$11.84 per acre	USDA Costs data
q_h	\$411.12 per acre	USDA Costs data
η	0.6373	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

$q_h = \$411.12$ per acre.

I calculate η by first noticing that $y_t = h_t^\eta$. So then,

$$\eta = \frac{\log(y_t)}{\log(h_t)} \tag{22}$$

Recall that h_t is inputs to harvest and y_t are acres harvested. There is no data on production inputs at an aggregate level, so I use bushels harvested data from the USDA multiplied by the marginal harvest cost as proxy measure for h_t. For y_t, I use wheat acres harvested data from the USDA. I then use the means of these adjusted measures as the steady state values so that

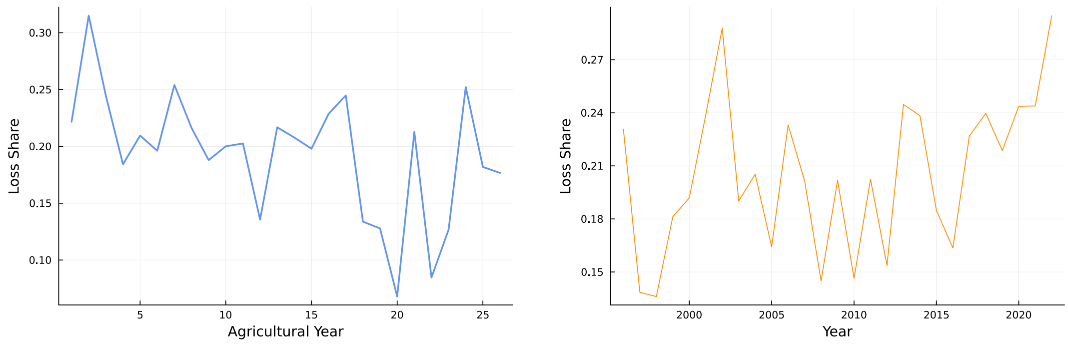
$$\eta = \frac{\log(\bar{y})}{\log(\bar{h})} \tag{23}$$

where the bars denote steady state values. This expression gives a value of $\eta = 0.6373$. I set $\beta = 0.99$.

For the price rule, I match the first autocorrelation and standard deviation of the annual spot price for winter wheat. The data series has a first autocorrelation of $\rho = 0.9035$ and a standard deviation of $\sigma = 1.73$. Table 1 summarizes my parameter estimates.

2.7 Simulation Results

Following the estimate of model parameters, I simulate the time path of crop loss to illustrate the model's close match to the data with a Monte Carlo process. I simulate the crop loss time series for 27 years, which is the length of my sample period (1996-2022).



(a) Median time path of model crop loss.

(b) Log bushels lost, 1996-2022

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

Figure 2a shows the median crop loss time path from 100 simulations. A fan plot of the median time path with the 25th and 75th percentile time paths is available in the appendix.

The simulated median time path matches the data plotted in figure 2b closely: the mean of the simulated crop loss is 19.3% while in the data it is 20.5%. The standard deviation of the simulated crop loss series is 5.48% and the standard deviation of the data is 4.32%. Like in the data, the farmer in model has access to both price forecasts, which I interpret as the futures markets in the data, and subsidies, which are the PLC/ARC programs discussed above. I am able to incorporate all these attributes into the model and match the data well.

2.8 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 farmer must worry primarily about basis risk which is the risk that the futures price will differ from the market price at the end of the year. The appendix contains a version of this extension. The model results do not differ substantially from the baseline model but this version of the model does allow investigation of the role of basis risk in crop loss.

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 main mechanisms of crop loss in the model: price uncertainty and subsidies. I explore the effects of these mechanisms with two counterfactual analyses. I first eliminate subsidies entirely from the baseline model and compare the two. I secondly run a simulation that increases and decreases the noisiness of the signals. I find that, in the baseline model, subsidies cause a more significant portion of crop loss than 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 price forecast in the planting period. This introduces a downside risk to the farmer's income. There is no guarantee of a lower bound income from the government. Income thus evolves according to the following rule:

$$M_{t+1} = p_t y_t$$

The farmer then solves the same problems as in the baseline model except with this new rule and no subsidy. The harvest percentage will never depend on the government's subsidy guarantee. It will always be equal to

$$\alpha_t = \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}} \right) \tag{24}$$

with $\hat{p}_{t,1} = \hat{p}^f_{t,1}$.

3.2 Simulation Results with No Subsidy

Figure 3 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. I reproduce them here for easier comparison.

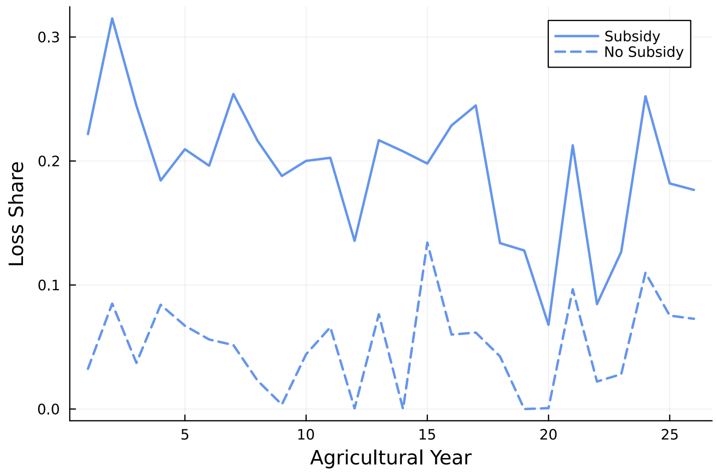
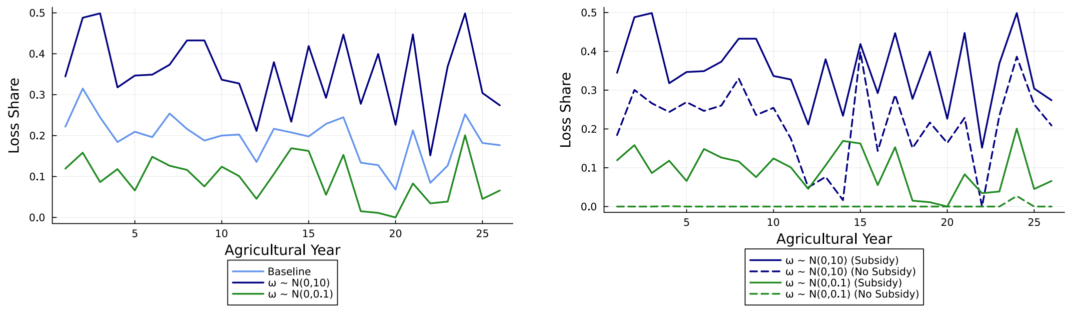


Figure 3: Simulations with and without a subsidy program.

Under a subsidy regime, crop loss is higher on average than in a world without a subsidy. Without a subsidy, the model produces an average crop loss much lower than the baseline model. The average crop loss in the model without a subsidy is 5.12% and the standard deviation is 3.6%. This is about 14% less crop loss than the baseline subsidy model.

In the baseline model, the farmer harvests less because she over-plants to receive a higher income. As discussed in Section 2, this occurs because her price forecast at planting is lower than the subsidy price guarantee. Since the subsidy depends on her planted acres, she will maximize her planted acres to receive the subsidy at the end of the year.

This implies that the subsidy program induces over-planting, despite being decoupled from the farmer's actual production that is sold in the market in the third season. By splitting the planting and harvest seasons, my model is able to show this tradeoff, unlike a traditional agricultural production model in which production occurs at one time (see Tack and Yu (2021) for an example). This type of modeling is more realistic to the decision making process for a farmer in the United States. Farmers will continually update their beliefs around prices by looking at the futures markets or price expectations published by their local grain elevators or distributors. By the very nature of crop growing, decisions over final production do not occur all at once.



(a) Noisier and less noisy signals.

(b) Subsidy versus no subsidy.

Figure 4: Simulations with changes in the signal noise.

3.3 Noisier Signals

Another way to explore the implications of the model is to increase, decrease, or remove entirely the noise in the signals. 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 and decrease the volatility of the distribution of the signals received by the farmer.

I both increase and decrease the noise of the signals to investigate the effects of imperfect price forecasts on model dynamics. For the increase in noise, I let $\omega_{t,s} \sim N(0, 10)$. This will induce less volatile but also less accurate price beliefs as the farmer weights the signal $\theta_{t,s}$ less and trusts her prior p_{t-1} or $\hat{p}^f_{t,1}$ more, depending on the season. For the decrease in noise, I let $\omega_{t,s} \sim N(0, 0.1)$. This will induce the opposite effect.

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 of the median crop loss time path under the noisier signals is 34.17%, roughly 15% more than that of the baseline model. The standard deviation is 9.37%, which is much larger than the baseline model. This suggests that when the farmer receives less accurate price signals, crop loss increases in levels and becomes more volatile.

Similarly, under the less noisy signals, average median crop loss is 8.65% and its standard deviation is 5.74%. The farmer weights her signal higher than her prior because there is less noise in the signal. More precise forecasts that are closer to the true price will then lead to a lower incidence of crop loss since the farmer updates her price forecast at harvest by a smaller amount.

Figure 4b presents the results of the simulation with noisier signals when there is a subsidy versus when there is no subsidy. When signals are noisier, crop loss under the subsidy regime is higher in levels than under the no-subsidy regime. This is exactly how crop loss behaves in the baseline model. The average median crop loss with noisier signals and no subsidy is 20.4%, which is around 14% less – the same proportion less as in the baseline model. 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. Conversely, when signals are less noisy and we remove the subsidy, the average median crop loss is 0.1%. Since crop loss cannot be negative in the model, it runs into the 0% lower bound. Crop loss is thus effectively removed from the model in this case.

3.4 Discussion of Simulation Results

The simulation exercise offers several predictions that I test in the data in the following section. At the heart of the simulation, the model predicts that the subsidy program matters more for the incidence of crop loss than price uncertainty. I compare the relative importance of both the subsidy mechanism and the price signal mechanism by removing each while keeping the other fixed. Removing the subsidy program while keeping price signal noise constant reduces crop loss by about 14% on average. On the other hand, decreasing price uncertainty by 10 times with a subsidy program in place reduces crop loss by only 7%, or half as much. The model also predicts that a joint reduction in signal noise and subsidy program removal.

The model also predicts that the more accurate the price signals become, the more important the subsidy becomes to the incidence of crop loss. Conversely, when forecasts become more and more noisy, crop loss will be reduced by more by eliminating the noise rather than eliminating the subsidy program. As indicated above, when the signals are noisy, removing the subsidy will reduce crop loss by around 15% and removing the subsidy program will reduce crop loss by around 14%. However, as noise decreases, the effect of removing the subsidy remains roughly at 14% while the effects of removing more signal noise consistently decreases.

To put this result more bluntly, the model predicts that the subsidy program has a constant effect on crop loss away from the lower bound. On the other hand, the effects of signal noise decrease non-linearly as the noise decreases. Near the lower bound, elimination of both the subsidy program and price uncertainty reduce crop loss equally.

4 Empirical Analysis

By how much does crop loss respond to changes in price expectations? Do the PLC/ARC subsidy programs matter for crop loss in the data? The model predicts that crop loss reacts differently depending on the size of the farmer's forecast revision between planting and harvest. It also asserts that crop loss increases significantly in the subsidy. In this section, I test the validity of these predictions with wheat data.

I find that both the price expectation at planting and the price expectation at harvest lead to a significant increase in crop loss. Forecast revisions between 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 additional 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. This confirms the model's prediction.

Measuring the impact of the PLC/ARC programs is difficult. However, using a dummy variable for the years these programs were active, I also find that the introduction of the PLC/ARC programs accounted for an increase in crop loss of around 0.5%. This confirms the model's intuition that the subsidy program leads to more crop loss.

4.1 Baseline Regressions

The model of interest is the following pooled OLS regression which I run on a bivariate time series from 1979-2022:

$$\% \text{ loss}_{it} = c + \beta_1 \hat{p}_{1,i,t} + \beta_2 \hat{p}_{2,i,t} + \beta_3 subsidy_{i,t} + \Psi X_{it} + \varepsilon_{it} \tag{25}$$

I denote the type of wheat $i \in \{spring\ wheat,\ winter\ wheat\}$ 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. The variable $subsidy_{i,t}$ captures the effect of the PLC/ARC program introduction in 2014. 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.

This specification allows me to test several of the main model predictions. The first is the relative importance of the farmer's forecasts at both planting and harvest. It also tests the importance of the PLC/ARC subsidy programs for the incidence of crop loss.

Several issues in the data lead me to run the above regression in first-differences. 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. Since there are two types of wheat, I add wheat-type fixed effects. Furthermore, isolating the effect of the PLC/ARC programs is difficult in the data since there are many concurrent subsidy programs that wheat farmers have access to. To mitigate these problems, I run the following regression:

$$\Delta\%\ \text{loss}_{it} = \alpha_i + \beta_1 \Delta \hat{p}_{1,i,t} + \beta_2 \Delta \hat{p}_{2,i,t} + \beta_3 D_{\text{subsidy}} + \Psi \Delta X_{it} + \Delta \varepsilon_{it} \tag{26}$$

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. Summary statistics of the data can be viewed in the appendix.

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.[4] 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

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

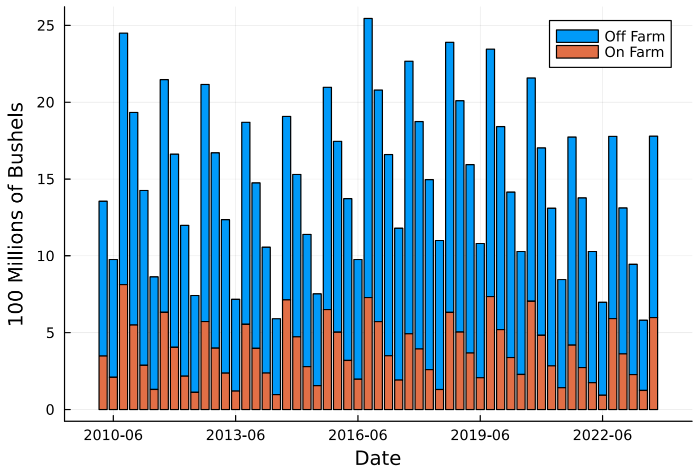


Figure 5: Seasonality of winter wheat storage from 2010-2023. Data source: USDA National Agricultural Statistics Service.

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. Furthermore, 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. Table 2 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.[5] 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.

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

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, 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.[6]

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 June, 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 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 confirms the model prediction in Proposition (1).

On the other hand, the marginal response to a one standard deviation change in the

[6] 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.

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.

price expectation at planting $\hat{p}_{1,i,t}$ is a significant decrease in loss of 2.5%. Although this makes intuitive sense – farmers expecting a higher price at planting will want to harvest more – interpreting this result in the model requires an additional analysis that I explore below. This is because $\hat{p}_{t,1}$ and $\hat{p}_{2,t}$ interact in the model.

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 than anticipated in the model simulations, but I attribute this to a lack of precision in the subsidy dummy. In the appendix, I provide an additional test of the subsidy's contribution to crop loss with a measure using PLC/ARC payments to wheat farmers. I find that crop loss is increasing in these payments by a larger amount – around a 4% increase for a $1 million dollar payment increase. However, these results should be interpreted with caution since I do not control for concurrent subsidy payments and changes to the PLC/ARC programs over time due to data constraints.

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 price forecast 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 $\Delta\hat{p}_{1,i,t}$.

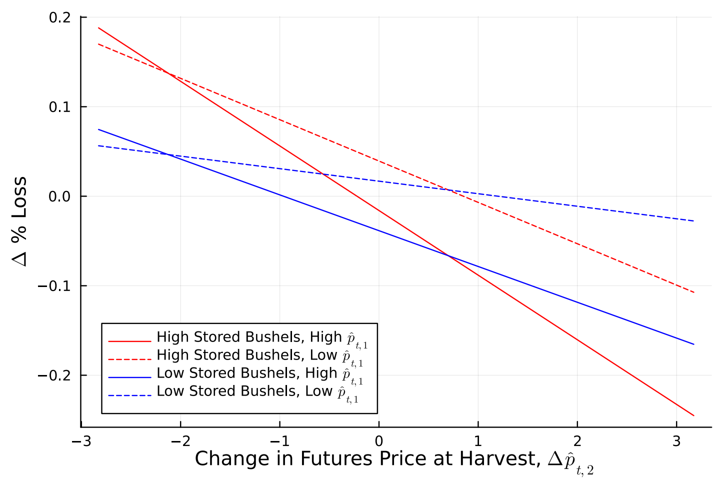


Figure 6: Fitted one standard deviation plots from Table 2, column (3).

This result lines up with the model prediction in the previous section. As in the model, the data suggests that as a farmer's forecast revision decreases, crop loss also decreases. This effect is larger when both price forecasts are high and still exists but is smaller when both price forecasts are low. To illustrate, say a farmer has a high price expectation at planting and her forecast revision at harvest is very small, leading to a high harvest-time price expectation. 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 her forecast revision at harvest is small, her harvest-time price expectation is low. There is thus an upward pressure on crop loss due to a low market price expectation but a downward pressure due to a more accurate price forecast at planting. The overall effect decreases crop loss since the accurate price forecast dominates the low price expectation in the data.

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 to 0.315. The coefficients on both price expectation variables are negative, close to the baseline regression, 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 many bushels in storage, farmers harvest more when they forecast high prices at both planting and harvest. On the other hand, conditional on high bushels in storage, farmers' harvest decisions are less elastic to an increase in the harvest price expectation when their forecast at harvest is low. The flatter curve plotted in the figure illustrates this.

The graphs also illustrates that the level of stored bushels appears to matter very little – farmer respond much more elastically to high price expectations at harvest than low expectations. When prices expectations at planting are low, it takes a much larger increase in the price expectation at harvest to induce a reduction in crop loss.

Overall, these results provide evidence that the size of forecast revisions do matter for farmers' crop loss decisions. However, a strong 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% in wheat crop loss in a given year.

4.2 The Joint Role of Market Prices and Price Expectations

The coefficient on the market price is positive in the results in Table 2, indicating that a higher spot price at harvest will result in a higher percentage of crops lost. This seems somewhat counterintuitive – if the spot price is high, the farmer should want to harvest as much as possible to secure that price in the market. However, I hypothesize that this result can be explained by the farmer's decision-making process at harvest and how farmers sell wheat to limited-capacity grain elevators.

As a simple example, say that the farmer arrives at harvest. Most grain elevators where farmers deliver wheat accept a limited number of bushels based on demand and their storage and processing capacity. Due to an influx of wheat at harvest, they can close with backlogs of grain to process. Because of this, the farmer may choose to harvest less if the spot price is high at harvest but the expected price in the future is low since

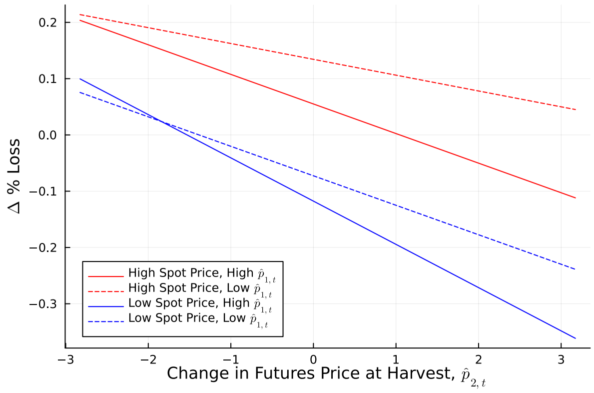


Figure 7: One standard deviation plots of results from column (2) of table 3.

her local grain elevator may not be accepting large quantities of wheat. In addition, she may wish to harvest less since she will need to face additional price risk as well as storage costs in order to sell her wheat 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:

$$\Delta\%\text{loss}_{it} = \alpha + \beta_1 \Delta\hat{p}_{1,i,t} + \beta_2 \Delta\hat{p}_{2,i,t} + \beta_3 \Delta p_{i,t} + \beta_4 \Delta\hat{p}_{1,i,t} \Delta\hat{p}_{2,i,t} \tag{27}$$

$$+ \beta_5 \Delta\hat{p}_{1,i,t} \Delta p_{it} + \beta_6 \Delta\hat{p}_{1,i,t} \Delta\hat{p}_{2,i,t} \Delta p_{i,t} + \Phi X_{i,t} + \Delta\varepsilon_{i,t} \tag{28}$$

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.

The plot illustrates that farmers value high spot prices now over future price risk. When there is a high spot price, the plotted lines lie above the horizontal axis. This

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.

observation indicates that farmers need much larger increase in the expected price in the future to induce them to harvest more. Conversely, when there is a low spot price, farmers increase their harvest in response to much smaller increases in the future price expectation. The graphs shows this observation with the two blue lines that lie below the horizontal axis.

This result supports my hypothesis that farmers avoid future price risk if the spot price is high enough at harvest. They appear to opt for a lower harvest at a higher price in the data. The expected price in the future needs to be higher to overcome the attraction of a high price at harvest.

The graph also confirms the results in the previous subsection 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. 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 price uncertainty matters much more for GHG emissions than the subsidy programs that are decoupled from current production, contrary to my findings from the structural model, but attribute this result to a weak measure of the subsidy program.

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 my crop loss problem. I decompose the 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 (25) less the estimated coefficient of the subsidy dummy variable times the dummy. This value can be expressed:

$$\Delta\%\text{loss}^{\text{NS}} = \Delta\%\widehat{\text{loss}}_{it} - \hat{\beta}_3 D_{\text{subsidy}} \tag{29}$$

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 (25) less the estimated coefficients of each price expectation variable times the price expectations in the data. In mathematical terms, this measure is denoted:

$$\Delta\%\text{loss}^{\text{NPU}} = \Delta\%\widehat{\text{loss}}_{it} - \hat{\beta}_1 \Delta\hat{p}_{1,i,t} - \hat{\beta}_2 \Delta\hat{p}_{2,i,t} \tag{30}$$

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

$$\%\widehat{\text{loss}}_{i,t} = \%\text{loss}_{i,t-1} + \%\Delta\widehat{\text{loss}}_{i,t} \tag{31}$$

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

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

I next calculate an estimate of GHG emissions under loss calculated from the fitted values in Equation 25. I use the following formula:

$$\widehat{GHG}_{it} = \%\ \text{loss}_{it} \times \text{hectares planted}_{it} \times \text{avg emissions}_{it} \tag{34}$$

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 $\text{avg emissions}_{it}$ 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. However, as discussed above, it is difficult to separate the effects of the PLC/ARC programs from other subsidy programs in the data. Thus, the dummy coefficient for the subsidy program may underestimate the true impact of the PLC/ARC programs on crop loss GHG emissions.

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 smaller proportion of total crop loss.

My empirical analysis provides strong evidence that farmers' decisions over crop loss depend heavily on their uncertainty regarding market prices. 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 wheat crop loss. A complete elimination of price risk would decrease emissions from wheat 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 wheat 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, the calculation of subsidy payments on base acreage cause an overproduction of crops as farmers seek to maximize their subsidy receipts. Calculating payments from base acreage may induce over-planting which thus increases crop loss. This suggests that an avenue for future research is to further explore the role of the base acreage designation in farmer decisions over planting.

The empirical analysis of these subsidy programs remains inconclusive. I find that these subsidies do not matter as strongly for crop loss as price uncertainty in the empirical analysis, contrary to the structural model. I attribute this to a weak measure of the subsidy program. I do, however, 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 Derivations

A.1 Solving the Baseline Model

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. Together, the solutions to these problems form the backbone of the farmer's crop loss decision.

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

$$V_{t,s=1}(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) \tag{35}$$

subject to

$$M_t = (q_x + q_h)x_t + c_t \tag{36}$$

and

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}_t^g \leq p_t \\ p_t y_t + (\hat{p}_t^g - p_t)X_t & \hat{p}_t^g > p_t \end{cases} \tag{37}$$

with $y_t = \alpha_t x_t^\eta$ and $X_t = x_t^\eta$. In the planting season, the farmer expects $\alpha_t = 1$. Otherwise, she would want to plant more to maximize her revenue over the agricultural year. So $y_t = X_t$.

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

$$V(M_t) = \max_{x_t} E_0 \sum_{t=0}^{\infty} \beta^t (p_{t-1}x_{t-1}^\eta + \max\{0, (\hat{p}_{t-1}^g - p_{t-1})x_{t-1}^\eta\} - (q_x + q_h)x_t - 1)$$

The first order condition is then:

$$\frac{\partial V}{\partial x_t} = -\beta^t(q_x + q_h) + \beta^{t+1} E_{t,s=1}[p_t \eta x_t^{\eta-1} + \max\{0, \eta(\hat{p}_t^g - p_t)x^{\eta-1}\}] = 0$$

I split the first order condition into cases to simplify:

$$\frac{\partial V}{\partial x_t} = \begin{cases} q_x + q_h = \beta\eta E_{t,s=1}[p_t]x_t^{\eta-1} & \hat{p}_t^g \leq E_{t,s=1}[p_t] = \hat{p}_{t,1}^f \\ q_x + q_h = \beta\eta\hat{p}_t^g x_t^{\eta-1} & \hat{p}_t^g > E_{t,s=1}[p_t] = \hat{p}_{t,1}^f \end{cases}$$

$$\implies x_t = \begin{cases} \left(\frac{q_x+q_h}{\beta\eta\hat{p}_{t,1}^f}\right)^{\frac{1}{\eta-1}} & \hat{p}_t^g \leq \hat{p}_t^f \\ \left(\frac{q_x+q_h}{\beta\eta\hat{p}_t^g}\right)^{\frac{1}{\eta-1}} & \hat{p}_t^g > \hat{p}_{t,1}^f \end{cases}$$

This can be rewritten as in the main text as

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

with

$$\hat{p}_{t,1} = \begin{cases} \hat{p}^f_{t,1} & \hat{p}^g_t \leq \hat{p}^f_{t,1} \\ \hat{p}^g_t & \hat{p}^g_t > \hat{p}^f_{t,1} \end{cases}.$$

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

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

$$M_{t+1} = \begin{cases} p_t y_t & \hat{p}^g_t \leq p_t \\ p_t y_t + (\hat{p}^g_t - p_t) X_t & \hat{p}^g_t > p_t \end{cases}$$

with $y_t = h_t^\eta$ and $X_t = x_t^\eta$. Since x_t was already chosen, the farmer treats it as fixed.

I set this up as a Lagrangian:

$$\mathcal{L} = \max_{c_t,h_t} E_0 \sum_{t=0}^{\infty} \beta^t (c_t - 1) - \lambda_t (p_{t-1} h_{t-1}^\eta + \max\{0, (\hat{p}^g_{t-1} - p_{t-1}) x_{t-1}^\eta\} - q_x x_t - q_h h_t - c_t)$$

Taking first order conditions, I derive an expression for the optimal choices of h_t and c_t:

$$\frac{\partial \mathcal{L}}{\partial c_t} = \beta^t + \lambda_t = 0$$
$$\frac{\partial \mathcal{L}}{\partial c_{t+1}} = \beta^{t+1} + \lambda_{t+1} = 0$$
$$\frac{\partial \mathcal{L}}{\partial h_t} = \lambda_t q_h - \lambda_{t+1} E_t[p_t \eta h_t^{\eta-1}] = 0$$

Substituting and rearranging:

$$\implies h_t = \left(\frac{q_h}{\beta \eta \hat{p}_{t,2}} \right)^{\frac{1}{\eta-1}}$$

Now, 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.

$$\alpha_t = \begin{cases} \left(\frac{h_t}{x_t}\right)^\eta = \left(\left(\frac{q_h}{\beta\eta\hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} \cdot \left(\frac{q_x+q_h}{\beta\eta\hat{p}^f_{t,1}}\right)^{-\frac{1}{\eta-1}}\right)^\eta & \hat{p}^g_t \leq \hat{p}^f_{t,1} \\ \left(\frac{h_t}{x_t}\right)^\eta = \left(\left(\frac{q_h}{\beta\eta\hat{p}_{t,2}}\right)^{\frac{1}{\eta-1}} \cdot \left(\frac{q_x+q_h}{\beta\eta\hat{p}^g_t}\right)^{-\frac{1}{\eta-1}}\right)^\eta & \hat{p}^g_t > \hat{p}^f_{t,1} \end{cases}$$

$$= \begin{cases} \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h\hat{p}^f_{t,1}}\right)^{\frac{\eta}{1-\eta}} & \hat{p}^g_t \leq \hat{p}^f_{t,1} \\ \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h\hat{p}^g_t}\right)^\eta & \hat{p}^g_t > \hat{p}^f_{t,1} \end{cases}$$

Since $0 < \eta < 1$, α_t is increasing in $\hat{p}_{t,2}$.

A.2 Lemma 1 Proof

I reproduce Lemma 1 and provide its proof.

Lemma 1. For $\alpha_t \in [0, 1]$, the following condition must hold:

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} < \frac{q_h}{q_x + q_h} \tag{38}$$

Proof.

$$\begin{aligned} &0 < \alpha_t < 1 \\ &0 < \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h\hat{p}_{t,1}}\right)^{\frac{\eta}{1-\eta}} < 1 \\ &0 < \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h\hat{p}_{t,1}}\right) < 1 \\ &0 < (q_x + q_h)\hat{p}_{t,2} < q_h\hat{p}_{t,1} \\ &0 < \frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} < \frac{q_h}{q_x + q_h} \end{aligned}$$

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

A.3 Proposition 2 Proof

I reproduce Proposition 2 and provide its proof.

Proposition 2. When $\hat{p}^f_{t,1} \geq \hat{p}^g_t$,

1. α_t decreases in $\hat{p}^f_{t,1}$ and

2. α_t is unresponsive to $\hat{p}^g_t$.

Else,

3. α_t increases in $\hat{p}^f_{t,1}$ and

4. α_t decreases in $\hat{p}^g_t$.

Proof. Let $\hat{p}^f_{t,1} \geq \hat{p}^g_t$. Then, $\alpha_t = \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h \hat{p}^f_{t,1}}\right)^{\frac{\eta}{1-\eta}}$, where $\hat{p}_{t,1} = \hat{p}^f_{t,1}$. Then, notice that

$$\begin{aligned}
\alpha_t &= \left(\frac{(q_x+q_h)(K_{t,2}\theta_{t,2} + (\rho - K_{t,2})\hat{p}^f_{t,1})}{q_h \hat{p}^f_{t,1}}\right)^{\frac{\eta}{1-\eta}} \\
&= \left(\frac{(q_x+q_h)K_{t,2}\theta_{t,2}}{q_h \hat{p}^f_{t,1}} + \frac{(q_x+q_h)(\rho - K_{t,2})}{q_h}\right)^{\frac{\eta}{1-\eta}}
\end{aligned}$$

Taking the partial derivative gives

$$\frac{\partial \alpha_t}{\partial \hat{p}^f_{t,1}} = \frac{\eta}{1-\eta}\left(\frac{(q_x+q_h)K_{t,2}\theta_{t,2}}{q_h \hat{p}^f_{t,1}} + \frac{(q_x+q_h)(\rho - K_{t,2})}{q_h}\right)^{\frac{-1}{1-\eta}} \frac{(q_x+q_h)(\rho - K_{t,2})}{q_h \hat{p}^g_t} > 0$$

where the inequality follows from the fact that $\rho - K_{t,2} > 0$. Note also that α_t does not depend on $\hat{p}^g_t$ in this case, so it is unresponsive to $\hat{p}^g_t$.

On the other hand, let $\hat{p}^f_{t,2} < \hat{p}^g_t$. Then $\alpha_t = \left(\frac{(q_x+q_h)(K_{t,2}\theta_{t,2} + (\rho - K_{t,2})\hat{p}^f_{t,1})}{q_h \hat{p}^g_t}\right)^{\frac{\eta}{1-\eta}}$. Since $\eta \in [0,1]$, α_t is increasing in $\hat{p}^f_{t,1}$ and decreasing in $\hat{p}^g_t$. $\square$

A.4 Proposition 3 Proof

I provide the proof of Proposition 3.

Proposition 3. α_t is increasing in τ_ω if $\theta_{t,1} > p_{t-1}$ and $\theta_{t,2} > \hat{p}_{t,1}$.

Proof. There are two cases.

In the first case, let $\alpha_t = \left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h \hat{p}^g_t}\right)^{\frac{\eta}{1-\eta}}$. Then,

$$\frac{\partial \alpha_t}{\partial \tau_\omega} = \frac{\eta}{1-\eta}\left(\frac{(q_x+q_h)\hat{p}_{t,2}}{q_h \hat{p}^g_t}\right)^{\frac{2\eta-1}{1-\eta}} \cdot \frac{q_x+q_h}{q_h \hat{p}^g_t} \cdot \frac{\partial \hat{p}_{t,2}}{\partial \tau_\omega}$$

Since every part of this expression is positive, it suffices to find the sign of $\frac{\partial \hat{p}_{t,2}}{\partial \tau_\omega}$. Recall that

$$\begin{aligned}
\hat{p}_{t,2} &= K_{t,2}\theta_{t,2} + (\rho - K_{t,2})\hat{p}_{t,1} \\
&= \hat{p}_{t,1} + K_{t,2}(\theta_{t,2} - \hat{p}_{t,1}).
\end{aligned}$$

Thus,

$$\frac{\partial \hat{p}_{t,2}}{\partial \tau_\omega} = \frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} + \frac{\partial K_{t,2}}{\partial \tau_\omega} \cdot (\theta_{t,2} - \hat{p}_{t,1}) - K_{t,2} \cdot \frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega}.$$

There are two derivatives that need to be evaluated. I attack the derivative of $\hat{p}_{t,1}$ first. Recall that

$$\begin{aligned}
\hat{p}_{t,1} &= K_{t,1}\theta_{t,1} + (\rho - K_{t,1})p_{t-1} \\
K_{t,1} &= \rho \cdot \frac{\tau_\omega}{\hat{\Sigma}_{t,1}^{-1} + \tau_\omega} \\
\Sigma_{t,1}^{-1} &= \rho^2 \cdot \frac{1}{\tau_\varepsilon + \tau_\omega} + \frac{1}{\tau_\varepsilon}
\end{aligned}$$

The derivative of $\hat{p}_{t,1}$ wrt τ_ω is

$$\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} = \frac{\partial K_{t,1}}{\partial \tau_\omega} \cdot (\theta_{t,1} - p_{t-1})$$

and the derivative of $K_{t,1}$ wrt τ_ω can be calculated as follows. Let $S = \hat{\Sigma}_{t,1}^{-1} + \tau_\omega$. Then,

$$\frac{\partial K_{t,1}}{\partial \tau_\omega} = \rho \cdot \left(\frac{1 \cdot S - \tau_\omega \cdot \frac{\partial S}{\partial \tau_\omega}}{S^2} \right)$$

Then,

$$\frac{\partial \hat{\Sigma}_{t,1}^{-1}}{\partial \tau_\omega} = \left(\hat{\Sigma}_{t,1}^{-1}\right)^2 \cdot \rho^2 \cdot \frac{1}{(\tau_\varepsilon + \tau_\omega)^2}$$

which means that

$$\frac{\partial K_{t,1}}{\partial \tau_\omega} = \rho \cdot \left(\frac{\hat{\Sigma}_{t,1}^{-1} + \tau_\omega - \tau_\omega \cdot \frac{\partial \hat{\Sigma}_{t,1}^{-1}}{\partial \tau_\omega}}{\left(\hat{\Sigma}_{t,1}^{-1} + \tau_\omega\right)^2} \right).$$

This leads to the following expression:

$$\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} = \left[\rho \cdot \left(\frac{\hat{\Sigma}_{t,1}^{-1} + \tau_\omega - \tau_\omega \cdot \frac{\partial \hat{\Sigma}_{t,1}^{-1}}{\partial \tau_\omega}}{\left(\hat{\Sigma}_{t,1}^{-1} + \tau_\omega\right)^2} \right) \right] \cdot (\theta_{t,1} - p_{t-1})$$

Under what conditions is this positive? Since, in the Kalman filter, the a higher signal precision increases the weight the farmer places on the signal, $\frac{\partial K_{t,1}}{\partial \tau_\omega} > 0$.

So the sign of $\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega}$ depends on the sign of $\theta_{t,1} - p_{t-1}$, implying that $\hat{p}_{t,1}$ increases in τ_ω when the signal is greater than last year's price (which is also the farmer's prior) and vice versa.

I move on to $\frac{\partial K_{t,2}}{\partial \tau_\omega}$. $K_{t,2}$ is

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

Then, similarly to $\frac{\partial K_{t,1}}{\partial \tau_\omega}$,

$$\frac{\partial K_{t,2}}{\partial \tau_\omega} = \rho \cdot \left(\frac{\hat{\Sigma}_{t,2}^{-1} + \tau_\omega - \tau_\omega \cdot \frac{\partial \hat{\Sigma}_{t,2}^{-1}}{\partial \tau_\omega}}{(\hat{\Sigma}_{t,2}^{-1} + \tau_\omega)^2} \right)$$

which is positive for the same reasons as $\frac{\partial K_{t,1}}{\partial \tau_\omega}$.
Returning to $\hat{p}_{t,2}$ and simplifying a bit gives:

$$\frac{\partial \hat{p}_{t,2}}{\partial \tau_\omega} = (1 - K_{t,2}) \cdot \frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} + \frac{\partial K_{t,2}}{\partial \tau_\omega} \cdot (\theta_{t,2} - \hat{p}_{t,1})$$

Note that $1 - K_{t,2} > 0$. The derivative will be positive if $\theta_{t,1} > p_{t-1}$ and $\theta_{t,2} > \hat{p}_{t,1}$ or, if either $\theta_{t,1} < p_{t-1}$ or $\theta_{t,2} < \hat{p}_{t,1}$, the opposite term in the overall expression is greater than the other. Thus, in this case, α_t's response to τ_ω is ambiguous since it depends on the value of the two signals.

In the second case, let $\alpha_t = \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}} \right)^{\frac{\eta}{1-\eta}}$. Then,

$$\frac{\partial \alpha_t}{\partial \tau_\omega} = \frac{\eta}{1-\eta} \left(\frac{(q_x + q_h)\hat{p}_{t,2}}{q_h \hat{p}_{t,1}} \right)^{\frac{2\eta-1}{1-\eta}} \cdot \frac{q_x + q_h}{q_h} \cdot \frac{\partial}{\partial \tau_\omega} \left(\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} \right)$$

It suffices to show the sign of the last part of the partial derivative. This compares how the harvest season forecast changes relative to the planting season forecast as the signal precision τ_ω increase. Note that we can write the ratio as:

$$\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} = 1 - K_{t,2} + K_{t,2} \cdot \frac{\theta_{t,2}}{\hat{p}_{t,1}}$$

Then its derivative can be rewritten:

$$\frac{\partial}{\partial \tau_\omega} \left(\frac{\hat{p}_{t,2}}{\hat{p}_{t,1}} \right) = \frac{\partial K_{t,2}}{\partial \tau_\omega} \left(\frac{\theta_{t,2} - \hat{p}_{t,1}}{\hat{p}_{t,1}} \right) - \left(K_{t,2} \cdot \frac{\theta_{t,2}}{\hat{p}_{t,1}^2} + \frac{1 - K_{t,2} + K_{t,2} \cdot \frac{\theta_{t,2}}{\hat{p}_{t,1}}}{\hat{p}_{t,1}} \right) \cdot \frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega}.$$

Recall that $\frac{\partial K_{t,2}}{\partial \tau_\omega} > 0$. Then, the sign of this derivative depends on two separate factors. The first factor is the term $\theta_{t,2} - \hat{p}_{t,1}$. The first term of the overall expression will be positive if $\theta_{t,2} > \hat{p}_{t,1}$, or if the signal in the harvest season is greater than the price forecast in the planting period. The second factor is the sign of $\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega}$, which we established is positive if $\theta_{t,1} > p_{t-1}$.

If both of these factors are positive, then the question becomes whether the second term of the overall expression (which is negative in this case) dominates the first, positive term and α_t's response to τ_ω is ambiguous. Similarly, if $\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} < 0$ and $\theta_{t,2} < \hat{p}_{t,1}$, the response of α_t to τ_ω is ambiguous.

If $\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} > 0$ and $\theta_{t,2} < \hat{p}_{t,1}$ then the whole expression is negative and α_t decreases in τ_ω. If $\frac{\partial \hat{p}_{t,1}}{\partial \tau_\omega} < 0$ and $\theta_{t,2} > \hat{p}_{t,1}$, then the whole expression is positive and α_t increases in τ_ω.

Thus, in both cases, α_t is increasing in τ_ω if $\theta_{t,1} > p_{t-1}$ and $\theta_{t,2} > \hat{p}_{t,1}$, implying that if the signals are consistently biased upward, the farmer will harvest more. $\square$

B Model Estimation: Additional Details

In this section, I describe the model estimation in more detail. From the USDA, I collect estimates of operating and overhead costs per wheat acre over the same period which I use to calculate the costs of planting and harvest. The categories included in this data are

- Seed
- Fertilizer
- Chemicals
- Custom services
- Fuel, lube, and electricity
- Repairs
- Other variable expenses
- Interest on operating inputs
- Hired labor
- Opportunity cost of unpaid labor

- Capital recovery of machinery and equipment
- Opportunity cost of land
- Taxes and insurance
- General farm overhead

I am constrained by Lemma 1 in the estimation of the model. To match the data well, I need $\frac{q_h}{q_h+q_x}$ to be a large proportion. In order to ensure this, I set the cost of planting q_x equal to the average marginal cost of seed over the sample period and let all other categories fall into the cost of harvest q_h. While this is not entirely accurate to the actual split of production costs toward planting and harvest, it is the case that most farmers will take out loans for planting and repay them post-harvest, so it is not inaccurate to say that most expenses are paid around the harvest season.

For η, I assume that the proportion of bushels to acres will be the same as the proportion of acres to units of crop as in the model. I am agnostic on the crop units in the model, this could be acre/ton, acre/bushel, etc. However, y_t is in acres in the model. Since I assume the proportions remain the same, for the calibration, I have a proxy using bushels for h_t that is equal to bushels produced times the cost per acre. I implicitly assume that the harvest cost per bushel will be the proportional to the cost per acre. In place of y_t I use acres harvested. Using the formula $\eta = \frac{\log(\bar{y})}{\log(\bar{h})}$, I find $\eta = 0.6373$.

The rest of the parameter estimation details are explained in text.

C Additional Simulations

I simulate the model with $\beta = 0.8$ and $\beta = 0.5$. The results are identical to the the baseline model since α_t does not depend on β.

As mentioned in the text, I provide the fan plot of the median time path with the 25th and 75th percentile time paths below.

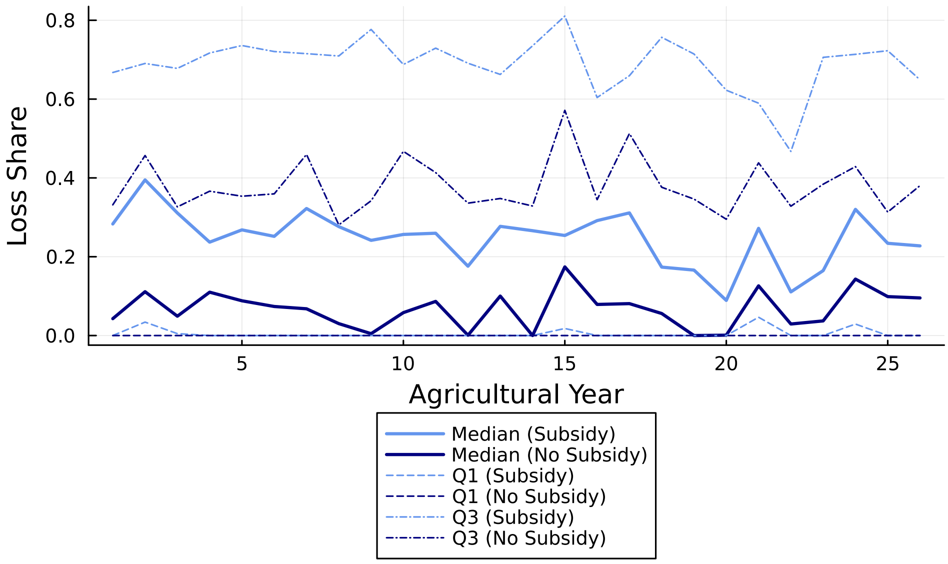

Figure 8: Fan plot of the median, 25th percentile, and 75th percentile time paths.

The plot shows that the baseline model's dynamics tend to land around the median simulation. The 25th percentile hovers around the zero percent lower bound as expected. The 75th percentile simulation hovers around 70% crop loss. The model's results do not change at the 25th and 75th percentiles when I remove the subsidy.

D 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_t units of wheat each agricultural year at the previous year's futures price before harvest. The farmer also takes the cuurrent futures price as the expected price rather than receiving a signal over market prices. 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_t 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

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

This expression can be rearranged to

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

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

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

subject to

$$\begin{aligned} M_t &= (q_x + q_h)x_t + c_t \\ M_{t+1} &= f_t(x_t^\eta - \xi_t) + b_t x_t^\eta + f_{t-1}\xi_t \end{aligned}$$

Rearranging and replacing gives us

$$V_{t,s=1}(M_t) = \max_{x_t, \xi_t} E_0 \sum_{t=0}^{\infty} \beta^t (f_{t-1}(x_{t-1}^\eta - \xi_{t-1}) + b_{t-1}x_{t-1}^\eta + f_{t-2}\xi_{t-1}) - (q_x + q_h)x_t - c_t)$$

where $y_t = x_t^\eta$ (i.e., $\alpha_t = 1$) 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 first order condition for ξ_t is

$$\beta^{t+1}(f_{t-1} - f_t) = 0$$

which implies that the optimal choice of ξ_t occurs when the price adjustment is equal to zero or $f_{t-1} = f_t$ or $p_{t-1} - b_{t-1} = p_t - b_t$ and $p_t - p_{t-1} = b_t - b_{t-1}$. In other words, the optimal choice of ξ_t occurs when the difference between the market price is equal to the difference in the bases.

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

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

Setting up the lagrangian:

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

This results in the following expression:

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

The FOC for c_t is identical to the baseline model.

An expression for α_t is then

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

The harvest percentage is thus subject to basis risk in addition to price risk. All the results of this model follow the baseline model, however, it is now possible to test for basis risk's role in crop loss decisions.

E 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.1 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 Additional Regression Results: PLC/ARC Subsidy Payments

F.1 Different harvest months: baseline

I re-run the main results from the baseline regressions in the text, this time letting the harvest month be July for winter wheat and September for spring wheat. This tests the robustness of the results if wheat is harvested later than I indicate in the text.

Table 7: Dependent variable: Δ *% loss*

	(1)	(2)	(3)
$\Delta\hat{p}_{2,i,t}$	-0.063***	-0.062***	-0.064***
	(0.016)	(0.013)	(0.015)
$\Delta\hat{p}_{1,i,t}$	-0.026***	-0.025***	-0.029***
	(0.005)	(0.006)	(0.002)
$D_{subsidy}$	0.004***	0.004***	0.004*
	(0.000)	(0.001)	(0.002)
$\Delta p_{i,t}$	0.085***	0.085***	0.090***
	(0.014)	(0.015)	(0.018)
Δ *Stored Bushels*	0.007	0.007	0.006
	(0.009)	(0.009)	(0.008)
$\Delta\hat{p}_{2,i,t} * \Delta\hat{p}_{1,i,t}$		-0.005	-0.009*
		(0.010)	(0.004)
$\Delta\hat{p}_{2,i,t}$ * Δ*Stored Bushels*			-0.016***
			(0.002)
Constant	0.001	0.002	-0.004
	(0.001)	(0.006)	(0.003)
Controls	X	X	X
N	87	87	87
R^2	0.274	0.281	0.347
Adj R^2	0.199	0.197	0.261

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.

The results are very similar to the baseline results.

F.2 PLC/ARC payments

In the following table, I re-run the baseline regressions, using data on PLC and ARC program payments to wheat farmers, as reported by the USDA's Economic Research Service (ERS). The complete data is not available after 2018, so I shorten my sample to accommodate this limitation.

Table 8: Dependent variable: Δ *% loss*

	(1)	(2)	(3)
$\Delta\hat{p}_{2,i,t}$	-0.060***	-0.071***	-0.067***
	(0.012)	(0.008)	(0.010)
$\Delta\hat{p}_{1,i,t}$	-0.026**	-0.028***	-0.030***
	(0.012)	(0.009)	(0.005)
$\Delta subsidy$	0.031*	0.039**	0.042***
	(0.018)	(0.016)	(0.015)
$\Delta p_{i,t}$	0.092***	0.112***	0.113***
	(0.010)	(0.014)	(0.016)
Δ *Stored Bushels*	0.009	0.013	0.012
	(0.011)	(0.012)	(0.010)
$\Delta\hat{p}_{2,i,t} * \Delta\hat{p}_{1,i,t}$		-0.013**	-0.017***
		(0.006)	(0.005)
$\Delta\hat{p}_{2,i,t}$ * Δ*Stored Bushels*			-0.017***
			(0.003)
Constant	0.002	0.008	0.004
	(0.001)	(0.005)	(0.005)
Controls	X	X	X
N	74	73	72
R^2	0.221	0.282	0.338
Adj R^2	0.137	0.194	0.246

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. subsidy is the change in total payments to wheat farmers through the PLC/ARC programs. 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. Three asterisks denotes significance at the 99% level, two denotes the 95% level, and one denotes the 90% level.

Payments data is in billions, so the coefficient can be interpreted as a \$1 billion dollar increase in PLC/ARC payments to wheat farmers leads to around a 4.2% increase in crop loss. This is quite a large increase in payments but it confirms my finding in the main text that crop loss increases in subsidy payments.

G Agricultural Subsidies in the United States

Here I provide a summary of historical and current agricultural subsidies in the U.S. as an aid to putting the PLC and ARC programs into perspective.

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.