Farmers Facing Risk: Evidence From Ethanol Plant Expansion in the Midwest

Connor Mulholland

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Abstract

A growing literature on the expansion of crop insurance in the United States attributes declining farm numbers and increases in average farm size to insurance provision itself. This paper hypothesizes that these interpretations may instead reflect the effects of price risk and heterogeneous price-risk aversion across farms. I develop a representative-farmer model in which the farmer faces stochastic input and output prices. The model predicts that increases in price risk exposure can disproportionately affect more risk-averse operators, typically smaller farms, leading them to reduce acreage and crop inputs and, in extreme cases, exit production. To test these predictions, I construct a county-level panel of agricultural farm sales in Wisconsin and Illinois from 2013 to 2024 and exploit plausibly exogenous variation in local corn prices generated by the expansion of ethanol production. The results indicate that greater exposure to ethanol production, thus increased local crop price volatility, increased farms sales and reduced the value of agricultural land, with effects strongest for farms closer to ethanol plants. These findings suggest that (1) price risk drives structural change in agriculture and (2) the relationship between crop insurance and consolidation may operate through risk-mediated channels. The results point to the potential for insurance design to mitigate, rather than amplify, consolidation pressures in agriculture.

1 Introduction

Over the past century, the structure of agriculture in the U.S has undergone enormous transformation. Since the end of World War II, the number of farms has steadily declined, while average farm size has increased, resulting in an increasingly consolidated agricultural sector. As 2023, large-scale operations with annual gross cash farm income exceeding one million dollars account for less than 10 percent of farms but produce over 70 percent of total agricultural output, with the largest four percent of farms producing more than half of the agricultural output in the U.S. (USDA ERS, 2023).

A range of economic and social consequences has accompanied this structural shift, particularly for rural communities. Rural areas continue to lag behind metropolitan regions in employment opportunities, income growth, and access to essential services (Farrigan et al. 2025). These disparities are reflected in persistently higher poverty rates, declining local economic activity, and increased dependence on public transfer programs (Lobao and Schulman, 1991; Lyson, Torres, and Welsh, 2001). More broadly, a substantial literature on agricultural restructuring finds that increasing industrialization and consolidation are associated with population decline, aging demographics, weakened civic engagement, the disappearance of locally owned businesses, and the erosion of community well-being (Lyson and Welsh, 2005; Lobao and Stofferahn, 2008).

Consolidation in agriculture raises environmental concerns on top of the direct human welfare consequences. Large-scale agricultural operations contribute significantly to rising greenhouse gas emissions, driven by fossil fuel sourced fertilizer use, mechanization and land-use change (Burney et al. 2010; Pereira et al. 2025). Although larger scale operations can generate a higher level of efficiency, it often comes at the cost of higher negative ecological externalities including nutrient runoff, soil degradation, and biodiversity loss (Stavins 2011; Shortle and Horan 2017). These dynamics suggest that understanding what drives agricultural consolidation is not only integral for agricultural policy but also to broader concerns surrounding rural development and environmental sustainability.

The downstream segments of the agricultural supply chain, particularly food processing and retail sectors, have become increasingly concentrated along with agricultural production. The four firm concentration ratio (CR4)[1], a standard measure of market concentration, currently exceeds 80 percent for beef packing and roughly 65 percent for pork processing, indicating a highly concentrated market structure for meatpacking in the U.S. (USDA ERS, 2024). This pattern extends to other key segments of agribusiness such as grain trading where four firms control 70 to 90 percent of international grain trade, the oilseed processing sector with a CR4 ratio of roughly 80 percent, and the food manufacturing sector with a CR4 ratio of 40 to 60 percent across major product categories (UNCTAD, 2012 ; USDA ERS, 2023).

At the retail level, through a series of mergers and expansion of large supermarket chains and big-box retailers, the sector has experienced increased buyer concentration and greater bargaining

[1] The four-firm concentration ratio (CR4) measures the combined market share of the four largest firms in an industry. Larger values indicate greater market concentration, with values exceeding 40 percent generally considered indicative of highly concentrated markets.

power over upstream suppliers. This trend of consolidation has led to the largest food retailers accounting for 30 to 50 percent of grocery sales nationally, with Walmart accounting for one quarter of the market themselves (Federal Trade Commission, 2020; Ellickson 2016). Taken together, these patterns bring additional concern for U.S consumers as agricultural consolidation increases along with an already consolidated food system.

A growing empirical literature attributes structural change to agricultural production, in part, to the expansions of the Federal Crop Insurance Program (FCIP). Several empirical studies conclude that increasing subsidies towards crop insurance encourages farm consolidation by reducing downside risk which enables larger operations to expand acreage and out-compete smaller, more risk constrained farms (Goodwin et al. 2003; Key and Roberts, 2007; Azzam et al. 2021; Yu et al. 2018). In this view, the FCIP is a primary driver of the continuing trend of declining farm numbers and increasing farm size in the U.S.

This paper challenges this prevailing explanation for the link between farm consolidation and insurance subsidies. I propose an alternative explanation that the observed relationship between the FCIP and consolidation may instead reflect a more fundamental mechanism: the role of price risk and heterogeneous risk aversion across farms. To demonstrate how this mechanism would work I develop a theoretical model of a representative farmer in which the risk averse producer faces stochastic output and input prices. The key insight of the model is that increases in price volatility disproportionately affect more risk-averse producers (likely smaller farms) leading them to reduce input use, contract acreage, and potentially exit production. This prediction implies that the less risk averse producers (typically large farms) remain in production and naturally will consolidate the properties of the farmers who exit as an equilibrium outcome of differential responses to risk rather than insurance provision. Most notably, increasing subsidies for crop insurance would help stave off consolidation in this model, as it helps shield the high risk averse farmer from price volatility.

To test the model's predictions, I construct a novel panel of agricultural land sales in Wisconsin and Illinois spanning 2013-2024. I exploit plausibly exogenous variation in local corn price exposure from the expansion of ethanol production. Localized demand shocks to corn markets from nearby ethanol production affects both corn price levels and volatility in local markets (Knittel and Smith, 2015; Du and Hayes, 2009). I measure exposure as the sum of ethanol plant capacitates within distance bins of farm sale locations. This approach captures both spatial and temporal variation in exposure to price risk induced by local corn demand by ethanol plants.

The empirical results show that increased exposure to corn-price volatility via increased exposure to local ethanol production leads to an increase in farm sales and a decline in agricultural land values, with effects strongest in the closest proximity bin to ethanol plants. These findings are consistent with the model's prediction that heightened price risk induces exit among more risk-averse producers. Importantly, the results suggest that the link between crop insurance and consolidation may operate through risk-mediated channels, rather than insurance provision alone.

This paper contributes to three strands of literature. First, it adds to the literature on agricultural structural change by highlighting the role of price risk as a fundamental driver of consolidation. Second, the paper contributes to the growing body of work on crop insurance by offering an alternative interpretation of its relationship with farm size and entry-exit dynamics. Third, it connects to a broader literature on risk, firm dynamics, and industry structure, highlighting how heterogeneity in risk preferences can shape equilibrium outcomes. Lastly, the results suggest there may be unintended consequences of ethanol production expansion in terms of farm selloffs.

The remainder of the paper proceeds as follows. Section 2 provides institutional background and places the analysis within the existing literature. Section 3 presents the theoretical model. Section 4 describes the data and empirical strategy, and Section 5 reports the main results. Section 6 concludes.

2 Background

2.1 Structural Change in U.S Agriculture

It has been well documented that the agricultural sector in the U.S has become increasingly consolidated as the number of farms has declined significantly. The number of farms decreased from almost seven million farms in 1935 to less than two million farms in 2024 (USDA, 2025). A considerable portion of this consolidation happened after World War II with the proliferation of industrial machinery, chemical inputs, and improved seed genetics leading to increased productivity and reduced labor requirements (Shultz, 1964). Technological innovations initially drove consolidation by allowing farms to grow larger and achieve lower average costs.

Consolidation has continued far past this post war period of innovation, even as technological progress has slowed. The persistence of consolidation suggests that factors beyond improved technological production capabilities play a central role in shaping agricultural structure to this day. Today, farmers across operation size generally have similar access to technology, seed and chemical inputs implying differential adoption alone cannot fully explain ongoing consolidation. Since farmers have access to similar production technologies, we observe that productivity differences from small farms to large-scale farms are marginal in magnitude (Key et al. 2018). With commodity crop growers sharing similar levels of market power, which is close to none, attention has turned to price dynamics as a potential driver of consolidation.

2.2 The Evolution of Agricultural Price Risk

Prominent in the early to mid-twentieth century the U.S federal government provided price stabilization to farmers in the form of direct price supports which reduced both the level and volatility of crop prices in the U.S. This price support system was dismantled in the beginning of the 1970s due to a combination of fiscal pressures and changing international trade policies (Gardner 2002; Alston and Martin 1996).

In the absence of the price supports, farmers faced greater market volatility, beyond the existing environmental uncertainties they historically faced. Along with the removal of direct price supports, the agricultural market began to globalize, introducing additional sources of uncertainty through international trade fluctuations, global supply or demand shocks, and exchange rate movements

(Wright 2011; Martin and Anderson 2012). Further, the increased reliance on synthetic fertilizers and the proliferation of bio-fuel production strengthened the relationship between agricultural and energy markets and amplified price volatility (Du et al. 2011; Serra et al. 2011).

In response to higher observed price volatility, the Federal Crop Insurance Program (FCIP) expanded and eventually restructured to provide income stabilization and risk management tools, especially for commodity crop producers (Goodwin and Smith 2013; Sumner 2014). Today the FCIP provides a number of subsidized insurance products designed to protect producers against both yield and price risk. While these products help producers mitigate downside risk, they do not fully replace the price stability provided by earlier price-support regimes, leaving modern producers more exposed to market-driven fluctuations (Sumner, 2014, Glauber, 2013).

2.3 Crop Insurance and Agricultural Sector Consolidation

A large empirical literature examines the impact of crop insurance expansion on agricultural market structure. Several studies find that insurance expansion and participation correlate with fewer number of farms and larger average farm size, suggesting insurance may facilitate consolidation by reducing financial constraints and encouraging expansion of farms (Goodwin et al, 2003; Key and Roberts, 2007; Azzam et al. 2021; Yu et al. 2018). Other work surrounding the effect of crop insurance documents shifts in crop choice towards better-insured commodities, consistent with induced distortions in production decisions (Babcock, 2015; Chavas and Holt 1990, Wu, 1999).

This link of crop insurance inducing sector consolidation is not universally accepted. Using farm-level data instead of county-level data, Jeremy Weber et al. shows the relationship between crop insurance is sensitive to specification and may not be as robust as previously thought (Weber et al, 2016). This study highlights the importance of underlying risk conditions and market environments and when properly controlled for they find that crop insurance has no effect on farm size.

This paper builds on the insight developed by Weber by explicitly modeling price risk as a central mechanism driving consolidation. Instead of viewing crop insurance as a primary casual factor, I take into account the broader risk environment in which producers operate. If farmers have differing levels of risk aversion, then price volatility may disproportionately affect the most averse farmers, suggesting that consolidation may arise even in the absence of insurance expansion. Using this framework, insurance has a secondary role, potentially mitigating but not fundamentally driving the structural changes observed in the data.

2.4 Ethanol Expansion as a Source of Price Risk

The expansion of ethanol production in the United States provides a useful empirical environment for studying the effects of price risk. Driven in part by the Renewable Fuel Standard implemented by the U.S. Environmental Protection Agency, ethanol production has increased substantially since the early 2000s (Glauber 2013; Knittel and Smith 2015). Ethanol plants generate localized demand for corn, increasing both price levels and volatility in nearby markets (Du and Hayes 2009; Teresa Serra et al 2011) Importantly, the spatial and temporal variation in ethanol plant location and production capacity generates variation in exposure to localized corn demand shocks that has been widely exploited in the literature to identify the effects of ethanol expansion on agricultural outcomes (Fatal and Thurman 2015; Miao 2016; Motamed et al. 2016). By constructing distance-based measures of exposure to ethanol capacity, this paper captures heterogeneity in risk exposure across counties and over time.

A potential concern is that ethanol plants may locate in areas already experiencing structural changes in agriculture. Existing evidence, however, indicates that plant siting is primarily determined by persistent comparative advantages—including access to feedstock, transportation infrastructure, proximity to major waterways, and state policy incentives—rather than short-run changes in farm structure (Lambert et al. 2008). Consequently, after accounting for county fixed effects, changes in nearby ethanol production capacity are plausibly orthogonal to contemporaneous determinants of farm consolidation. The staggered expansion of ethanol capacity therefore provides a credible source of variation in local corn demand, allowing this paper to identify the causal effects of increased price risk exposure on farm turnover and consolidation.

3 The Optimal Allocation Facing Stochastic Prices

In this section I formalize the concept of optimal land use decisions of a farmer facing stochastic prices and explain the fundamental role risk aversion plays. A full model with greater detail is in Appendix A. To keep our terminology consistent with the empirical strategy, I label the insured crop C which can represent any combination of crops that have revenue protection products offered by the FCIP, and the uninsured crop O representing any combination of cultivars that have no revenue protection products available. However, the model applies to any production setting where firms are price takers facing stochastic input and output prices and the revenue for some outputs can be insured and others not.

A representative price taking farmer has the choice of two crops: insured C and uninsured O such that the total allocation of their land for cultivation L equals the acreage of C plus the acreage of O. The farmer also has the choice of inputs for each crop type: x_C and x_O respectively and the level of insurance coverage m for the insured crop C, where $m \in [0,1]$ is a choice variable. Allocations across crop specific acreage, inputs, total land, and coverage level must all be non-negative.

$$\{L, a_C, a_O, x_C, x_O, m\}, \qquad a_C + a_O = L, \qquad L, a_i, x_i \geq 0.$$

The output for each crop follows a production technology that is strictly concave in acreage and inputs. A total factor productivity for each crop A_i is a part of the production equation along with a production augmenting factor M_i, derived from suitability of the land for each crop. M_i is a concave transformation of ψ_i, where ψ_i measures how far off the share of the crop acreage allocation is from the share of the land that is suitable for each crop respectively. In total, the production technology follows as so:

$$Y_i = a_i M_i A_i x_i^{\alpha_i}, \qquad 0 < \alpha_i < 1.$$

where

$$\psi_i = 1 - (\theta_i - s_i)^2, \qquad M_i(\psi_i) = \psi_i^{\gamma}, \qquad 0 < \gamma < 1,$$

and

$$\theta_i = \frac{a_i}{L}.$$

Input prices w_C and w_O along with output prices p_C and p_O follow stochastic processes with means and second moments known to the farmer:

$$p_C = \bar{p}_C + \tilde{p}_C, \qquad p_O = \bar{p}_O + \tilde{p}_O,$$

$$w_C = \bar{w}_C + \tilde{w}_C, \qquad w_O = \bar{w}_O + \tilde{w}_O.$$

To reflect how only a small number of commodity crops have revenue protection insurance products with the FCIP, insurance is only available for the insured crop C where coverage level $m \in [0, 1]$ is a choice variable with a residual-risk floor of ω where $0 < \omega < 1$. Insurance reduces the variance of the output price of crop C using the variance reduction parameter $\phi(m)$:

$$\phi : [0, 1] \to [\omega, 1], \qquad \phi'(m) < 0, \qquad \phi(0) = 1, \qquad \phi(1) = \omega.$$

Premium per insured acre $r(m)$ is a strictly increasing function of coverage level. Total premium payout and price structure are as follows:

$$\Pi(a_C, m) = r(m)\bar{p}_C a_C, \qquad r'(m) > 0.$$

Taking prices, insurance framework and crop suitability as given the farmer chooses the allocation of crop acreages and inputs to maximize the certainty equivalent of profits. Following the literature, λ is the level of absolute risk aversion and this is incorporated into the variance side of the certainty equivalent. Below is the full specification of the constrained optimization:

$$\begin{aligned} \mathrm{CE} = {} & \bar{p}_C Y_C + \bar{p}_O Y_O - \bar{w}_C a_C x_C - \bar{w}_O a_O x_O - r(m)\bar{p}_C a_C \\ & - \frac{\lambda}{2}\Big(Y^\top \Sigma_{pp}(m) Y + (a \odot x)^\top \Sigma_{ww}(a \odot x) - 2Y^\top \Sigma_{pw}(a \odot x)\Big) \end{aligned} \tag{1}$$

subject to

$$a_C + a_O = L.$$

Problem:

$$\max \mathrm{CE} \quad s.t.\ a_C + a_O = L \quad L, a_i, x_i \geq 0.$$

$$\mathcal{L} = \mathrm{CE} + \mu\,(L - a_C - a_O).$$

A nonnegative optimal acreage level, input intensity, insurance coverage level and total land acreage is guaranteed to exist and to be a strict local maximum of the certainty equivalent. This is due to five assumptions of the model that induce the certainty equivalent to be strictly concave in (L, a_C, a_O, x_C, x_O) and the optimality constraint being linear in nature. The five main assumptions are rooted in the "real world" production process of farming, the framework of revenue insurance products from the FCIP, and the risk behavior of farmers. The assumptions are as follows: diminishing marginal products in inputs and acreage, the insurance premium schedule is weakly convex in coverage level m, the level of risk aversion λ is positive, the covariance price matrices are positive semidefinite, and existence of specialization effects i.e. reallocating acreage between crops reduces the marginal product of the other crop.

Proposition 1. The optimal acreage and total inputs across crop type decrease as the respective output crop price variance increases.

The proposition comes from the comparative statistics of the derivative of a_i^*/σ_i and x_i^*/σ_i being negative. This result naturally extends to optimal total acreage L. With a positive level of risk aversion, farmers decrease their exposure to higher levels of price risk by participating less in the production process associated with the risk. As acreage and inputs decrease the total farm acres decrease to minimize risk exposure accordingly.

Proposition 2. A decrease in the per acre insurance premium or an increase in the residual-risk floor of the insurance product increases the acreage and total inputs of the insured crop.

The comparative statistics of the derivative a_C^* with respect to the per acre insurance premium is negative and the derivative of a_C^* with respect to the residual-risk floor is positive. Decreasing the risk premium and increasing the residual-risk floor both fundamentally make the insured crop more attractive. Farmers allocate more acreage towards the insured crop as the per acre cost of insurance goes down and/or the insurance becomes more protective of revenues. This result has been empirically suggested in the literature.

Proposition 3. The level of risk aversion amplifies the effect output price variance has on optimal acreage and total inputs across crop type.

Sensitivity analysis of the comparative statics of the derivatives of a_i^*/σ_i and x_i^*/σ_i with respect to the level of risk aversion λ are positive. In combination with Proposition 1 this gives the main result of the paper: increased price variance causes more risk averse farmers to decrease acreage and inputs compared to less risk averse farmers. As output price variances increase a farmer with a level of risk aversion close to one allocates zero to a_C^*, a_O^* and subsequently L^* essentially exiting production all together, while a farmer with a risk aversion parameter close to zero is marginally affected.

Differing levels of risk aversion across farms can explain the continued consolidation of the agricultural sector as price variances continue to rise. Small farms typically exhibit behavior indicative of higher levels of risk aversion compared to large farms, and if given similar price variance shocks small farms would not be able to "weather" the risk as effectively as large scale farms. In an increasing price variance environment this model suggests that ultimately farms with higher levels of risk aversion exit the market, leaving the unaffected large farms to consolidate land and assets.

4 Empirical Approach

4.1 Data

4.1.1 Wisconsin and Illinois Department of Revenue

The Historical Data tool from the Wisconsin Department of Revenue provides arm's length real estate transfer data. The State of Illinois Data Portal from the Illinois Department of revenue provides real estate transfer data for all PTAX-203, PTAX 203-A, and PTAX-203-B filings. Both data sources are at the transaction level and are available for download going back to 2013. Among other pertinent real estate variables, the data includes the county, the address, the total sale amount, the designated use, the acreage, and the date of each real estate transfer. I filter out the real estate transfer associated with agricultural use to identify farm-level sales, and I use the data spanning 2013 to 2024. Table 1 in the Appendix shows the summary statistics aggregated at the county level.

4.1.2 U.S Fuel Ethanol Plant Production Capacity Report

The U.S Energy Information Administration provides an annual report on all ethanol plants and their capacities via the U.S Fuel Ethanol Plant Production Capacity report. The report is at the plant level providing data on the capacity in MMgal/yr and Mb/day, the company name, the state, the city and the Petroleum Administration for Defense District (PADD). Corroborating longitude and latitude data provided for each ethanol plant in 2022 from Emily McRaeEach of the New Mexico Community Data Collaborative and my own geocoding I collected precise longitude and latitude measures for every ethanol plant in the sample. Each yearly report is as of January 1st of the respective year, estimating the capacity of each plant over the previous 365 day cycle. Reports available for download start in 2014, so I use the data from 2014 to 2025.

4.1.3 PRISM Time Series Data

The PRISM Group at Oregon State University gathers weather observation from a wide range of monitoring networks, applies sophisticated quality control measures and mapping methods to develop spatial datasets to reveal short and long-term weather patterns. I collect annual precipitation and temperature weather for Illinois and Wisconsin at the 800m spatial resolution level. In order to track weather variables before the first farm sales, I use the data from 2012 to 2025.

4.1.4 USDA Census of Agriculture

The Census of Agriculture provided by the USDA National Agricultural Statistics Service is a quinquennial representative survey of agricultural producers at the county level. In this empirical approach the county level of existing farms and average farm size every five years are necessary to ensure an unbiased estimate. I use the data spanning 2012 to the most recent census of 2022.

4.1.5 Petroleum and Other Liquids Report

The U.S Energy Information Administration provides daily, weekly, monthly and annual prices for the Europe Brent Spot Price FOB in their Petroleum and Other Liquids report. I collect the annual price spanning the sample of farm sales from 2013 to 2025.

4.1.6 USDA Cropland Data Layer

The Cropland Data Layer provided by the USDA National Agricultural Statistics Service is an annual raster, geo-referenced, crop-specific land cover data layer produced using satellite imagery and extensive agricultural ground reference data. The Cropland Data Layer (CDL) has a spatial resolution of 30 meters and for major crop classifications, such as corn, there is an 85% to 95% level of accuracy. In this empirical approach the data is used to estimate the pre-sale crop choice of the observed farmland transactions, such that observations are either classified as predominately corn or non-corn operations. In order to be classified as a predominately corn operation the area of the land transfer the year previous to sale must consist of at least 50% corn. [2]

4.2 Empirical Framework

4.2.1 Identification Strategy

Estimating the effect of ethanol-driven price exposure on agricultural structural change, particularly farm exit is the main empirical objective of the paper. Ethanol production distorts local corn demand conditions inducing higher levels of price variance and thereby changes the price environment faced by local agricultural producers. Since ethanol is directly tied to gasoline through its primary use, the intensity of ethanol demand is expected to vary with gasoline and subsequently crude oil prices. In periods of high oil prices, ethanol becomes relatively more valuable as a fuel substitute and blending input, increasing the demand pressure generated by nearby ethanol plants on farms.

The empirical strategy exploits spatial and temporal variation in exposure to ethanol production generated by the location and operating capacity of ethanol plants. Ethanol plants exert stronger effects on nearby agricultural producers than on producers located farther away due to transportation costs and localized grain procurement markets (McNew and Griffith 2005; Keeney

[2] The exact shape and location of the parcel is not included within the real estate transfer data. In order to estimate the crop type the corn pixels inside of a circle centered around the latitude and longitude of each farm sale are summed. The size of the circle is the acreage of the transaction

and Hertel 2009). Counties with farms with greater proximity to ethanol production capacity therefore experience larger local demand shocks than counties with farms distant from plants.

In order to capture this mechanism, the analysis combines a distance-based ethanol exposure measure with annual variation in Brent crude oil prices. Crude oil prices proxy for the strength of ethanol demand conditions in a given year, while ethanol exposure is constructed using the geographic proximity between farm sales and ethanol plants. The interaction between local ethanol exposure and oil prices identifies the marginal effect of ethanol exposure given the price of oil in a specific year. Larger effects on agricultural outcomes are to be expected during periods in which ethanol production is more economically valuable.

The identifying assumption is that, conditional on county fixed effects, year fixed effects, and time varying weather controls, variation in nearby ethanol production is plausibly exogenous to contemporaneous county-level structural changes in agriculture. The observed determinants of where ethanol plants locate, mainly related to ease of transportation, gives confidence that the identifying assumption is likely plausible. County fixed effects absorb time-invariant differences in agricultural suitability, soil productivity, and historical production patterns, while year fixed effects absorb aggregate national shocks affecting all counties simultaneously. The interaction specification further isolates whether counties more exposed to ethanol production respond differentially during periods of elevated energy prices.

4.2.2 Construction of Ethanol Exposure Measures

Let p index ethanol plants, i index farm sales, c index counties and t index years. Define Cap_{pt} as the annual production capacity of ethanol plant p in year t, and let d_{ip} denote the geographic distance between farm sale i and ethanol plant p in miles.

For each farm sale, ethanol exposure within distance bin b is defined as:

$$E_{ibt} = \sum_{p} Cap_{pt} \cdot \mathbf{1}(d_{ip} \in b),$$

where $\mathbf{1}(\cdot)$ is an indicator equal to one if ethanol plant p lies within distance bin b of farm sale i.

Distance bins are defined as: 0-50 miles, 50-100 miles, 100-150 miles, 150-200 miles, and 200-300 miles. This bin construction allows ethanol exposure to vary discreetly with distance, capturing the localized nature of ethanol procurement markets.

The preferred measures for County-level exposure are constructed by averaging farm-level exposure across all farm sales occurring within county c in year t:

$$\bar{E}_{cbt} = \frac{1}{N_{ct}} \sum_{i \in c,t} E_{ibt},$$

where N_{ct} denotes the number of farm sales observed in county c during year t.

These exposure measures are interacted with the annual Brent crude oil, denoted Oil_t, to capture time-varying ethanol demand conditions. Serving as a proxy for demand intensity of ethanol production, higher Brent crude oil prices increase the relative competitive of ethanol producers in crop markets.

The resulting interaction term,

$$\bar{E}_{cbt} \times Oil_t$$

captures the exposure to nearby ethanol plants on agricultural outcomes given the price environment of energy markets. Because the Brent crude oil price varies over time, while ethanol exposure varies across time and space, the interaction isolates heterogeneous local farm responses to price risk exposure.

As a robustness check, I also construct an alternative exposure measure using the geographic centroid of each county rather than the location of individual farm sales. Let d_{cp} denote the distance between the geographic centroid of county c and ethanol plant c. County-centroid exposure is defined as

$$\sum_p Cap_{pt}\mathbf{1}(d_{cp} \in b).]$$

Different to the preferred specification, this measure is independent of the spatial distribution and number of observed farm sales within each county. Although county-centroid exposure is less spatially precise, particularly in geographically large counties, it provides a useful robustness check by eliminating any concern that the preferred exposure measure is influenced by the locations or the number of observed land transactions themselves.

The primary data consists of county aggregated farm sale records from Wisconsin and Illinois spanning 2013-2024, combined with annual ethanol plant capacity data, historical Brent crude oil prices, weather covariates and county-level agricultural structure variables.

4.2.3 Primary Econometric Specification

The primary estimating equation is:

$$Y_{ct} = \sum_b \beta_b \bar{E}_{cbt} + \sum_b \delta_b(\bar{E}_{cbt} \times Oil_t) + X'_{ct}\gamma + \alpha_c + \lambda_t + \varepsilon_{ct}.$$

where Y_{ct} denotes an agricultural outcome in county c and year t, $\bar{E}_{cbt}$ is ethanol exposure in distance bin b, and Oil_t is the annual Brent crude oil price. County fixed effects, α_c, absorb time-invariant county characteristics. Year fixed effects, λ_t, absorb national shocks common to all counties. X_{ct} is a vector of county year covariates including precipitation, lagged precipitation, temperature, lagged temperature, existing county level agricultural acres and existing number of farms.

The coefficients β_b and δ_b are the primary parameters of interest. δ_b measures the marginal effect of ethanol exposure given the crude price of oil, while β_b measures the level effect of ethanol exposure when oil prices are 0. Oil_t in this specification varies only by year, its direct effect is absorbed by the year fixed effects. The model therefore identirfies the interaction term from differences in exposure across counties and distance bins, interacted with the global year-to-year variation in crude oil prices.

The marginal effect of ethanol exposure in distance bin b is:

$$\frac{\partial Y_{ct}}{\partial \bar{E}_{cbt}} = \beta_b + \delta_b Oil_t.$$

The total effect of ethanol exposure depends jointly on local exposure intensity and prevailing energy market conditions. For the number of farm sales in a county, a positive marginal effect implies that greater exposure to nearby ethanol production increases the rate of farm sales and possibly exit. If $\delta_b > 0$, this effect becomes larger during periods of elevated oil prices, consistent with stronger ethanol demand amplifying local agricultural adjustment. The same holds true for the other outcome of interest, the value per acre of farms sales within a county. The interaction structure therefore allows the effect of ethanol exposure to vary endogenously with energy market conditions rather than imposing a constant treatment effect across years.

4.2.4 Census-based Specification

The previous annual farm-sale based specifications identify the short-run effects of ethanol exposure on land transaction outcomes. These outcomes provide evidence of agricultural restructuring, they do not directly provide evidence of longer-run changes in agricultural structure. To test whether incremental land-market adjustments accumulate into persistent market consolidation, I estimate a second specification using successive USDA Censuses of Agriculture.

The Census specification examines changes in the number of farm operations, total operated acreage, and average farm size between Census periods. The Census of Agriculture is collected every five years and ethanol capacity data is available from 2013 on, the estimating sample consists of observations for 2013 (using the census of 2012), 2017, and 2022. For each county, the dependent variables are measured as the log change between consecutive Census observations.

To align with the nature of the dependent variables, ethanol exposure is measured as the cumulative change in county-centroid exposure between Census periods.

$$[C_{cb,\tau} - C_{cb,\tau-1},]$$

where τ denotes successive Census years. County-centroid exposure is used rather than farm-sale exposure because the Census outcomes describe county-level agricultural structure rather than individual land transactions and requires an exposure measure defined independently of observed farm sales.

The estimating equation is

$$\Delta \ln(Y_{c\tau}) = \sum_b \beta_b \Delta \ln(C_{cb}) + X'_{c\tau}\gamma + \alpha_c + \lambda_\tau + \varepsilon_{c\tau}$$

where $\Delta \ln(Y_{c\tau})$ denotes the log change in the number of farms, total agricultural acreage, or average farm size between Census periods. The vector $X_{c\tau}$ includes average precipitation and average temperature over each Census interval together with controls for the initial number of farms and initial operated acreage. County fixed effects absorb persistent differences in agricultural productivity and land suitability, while Census-period fixed effects account for common national trends between Census intervals.

Unlike the annual farm-sale specifications, this regression does not include interactions with Brent crude oil prices. The Census outcomes measure cumulative structural change over approximately five-year intervals rather than annual market responses, making the interaction with Brent crude oil prices less interesting. Consequently, the specification relates long-run changes in agricultural structure directly to cumulative changes in nearby ethanol exposure.

5 Results

This section tests the core prediction of the theoretical model: increased exposure to price risk induces structural change through heterogeneous risk responses across producers. *Proposition 1 and Proposition 3* in combination give us the prediction that greater price volatility disproportionately affects more risk-averse producers, leading them to reduce acreage, sell farmland and ultimately exit the market entirely. If ethanol expansion increases local corn price volatility, counties with greater exposure to ethanol production should therefore experience greater farm turnover, lower farmland values, larger land transactions and over longer horizons, fewer farms and larger average farm sizes.

Tables 2 through 7 show the results of evaluating these predictions. Tables 2-6 examine annual county-level outcomes using real estate transaction data, while Table 7 investigates longer-run structural adjustment at the county-level using Census of Agriculture data. Tables 2-4 measure ethanol exposure at the farm sale level described in Section 4.2.2 interacted with annual Brent crude oil prices to capture time-varying demand conditions in grain markets. Tables 5 and 6 measure ethanol exposure using distance bins from the county centroid interacted with annual Brent crude oil prices. Table 7 also measures the change ethanol exposure over census periods using distance bins from the county centroid. County and year (census period for Table 7) fixed effects absorb permanent differences across counties and aggregate national shocks, while weather and county agricultural characteristics account for time-varying local conditions.

Across the first four specifications, three consistent patterns emerge. First, the effects of ethanol exposure are concentrated among counties located closest to ethanol plants, with estimated effects declining as distance increases. Second, the relationship between ethanol exposure and agricultural outcomes depends importantly on prevailing energy market conditions, indicating that ethanol production affects agriculture primarily through changes in price incentives and volatility rather than through a constant local demand effect. Third, counties experiencing larger increases in ethanol exposure exhibit greater evidence of agricultural restructuring, including more farm sales, larger transactions, fewer farms, and larger average farm size.

5.1 Sale-Point Ethanol Exposure and Farm Sale Values

Column (1) of Table 2 reports estimates using farmland value per acre as the dependent variable for all types of farm operations. Column (2) and column (3) report estimates on the effect of farmland value for corn and non corn farms respectively. Farmland value per acre is simply calculated by dividing the sale price of the farm sale by the acreage of the farm sale. Conventional intuition suggests that the expansion of ethanol production should increase nearby farmland values by raising local demand for corn and improving expected crop revenues. Under this view, greater ethanol production should be capitalized into agricultural land values through higher expected future returns to production. The estimates presented in Table 2 provide little evidence supporting this prediction.

Across all three specifications, the estimated effects of nearby ethanol exposure on farmland values are generally negative or statistically indistinguishable from zero. While the point estimates for the closest distance bin for all farm sales suggest that greater exposure to nearby ethanol production is associated with lower sale values per acre, these effects are only significant at the 10% level. Likewise, the interaction terms between ethanol exposure and Brent crude oil prices are individually insignificant and are jointly insignificant according to a Wald test ($p = 0.272$). Consequently, the data provides little evidence that the relationship between ethanol exposure and farmland values varies systematically across different energy market conditions.

The absence of a positive capitalization effect is notable. If changes in expected returns were the dominant force affecting farmland values, one would expect land values to increase as nearby ethanol production expands. Instead, the estimates of Table 2 suggest that the increase in expected profitability is offset by the increased risk exposure associated from local ethanol expansion. This finding is consistent with the framework developed in Section 3. Since ethanol expansion simultaneously increases both expected returns and price risk, it likely the case for sufficiently risk-averse producers the increased variance of returns negates the possibly higher future discounted value of farmland close to ethanol expansion.

The comparison between predominantly corn-producing and non-corn-producing farms provides additional insight into the mechanism at play. Although the estimated responses for corn farms are generally larger in magnitude than those for non-corn farms, neither set of estimates provides strong statistical evidence of differential capitalization into land values. This pattern suggests that localized price-risk effects are not confined solely to farms currently producing corn (the main ingredient of ethanol) but instead influence expectations throughout local agricultural land markets. Farmland can be reallocated across crops over time, this leads prospective buyers to capitalize expectations about future production opportunities rather than current cropping patterns alone.

Taken together, Table 2 provides little evidence that ethanol expansion generated widespread appreciation in agricultural land values. Rather than increasing asset prices as expected, the results suggest that the opposing effects of higher expected returns and greater price risk largely offset one another. This finding foreshadows the subsequent results, which demonstrate that ethanol exposure influences agricultural structure primarily through increased farm turnover and consolidation rather than through higher farmland values.

5.2 Sale-Point Ethanol Exposure and Farm Sales

If increased exposure to nearby ethanol production doesn't significantly alter the value of agricultural land, as suggested by the results in Section 5.2.1, this begs the question of which margin do producers adjust along. The main prediction of the theoretical framework from Section 3 is that greater exposure to price risk disproportionately affects more risk-averse operators, increasing the likelihood that they shrink production or exit the market altogether. One way that this would manifest in the "real world" is through increased turnover in farmland markets rather than widespread appreciation of land value. Table 3 evaluates this prediction by estimating the effect of ethanol exposure on the annual number of farmland real estate transactions within each county. Although it is difficult to verify if a farmland sale is an operator exiting the market, it is almost certainly a reduction of production acreage if not a full market exit.

The estimates provide strong evidence that increased exposure to nearby ethanol production increases farm turnover. Across all specifications, the largest estimated effects occur within the 0–50 mile distance bin and generally decline with distance from ethanol plants. This spatial decay is consistent with the localized nature of grain procurement for ethanol plants and mirrors the geographic pattern expected if ethanol production influences restructuring through their effects on local commodity markets rather than broader statewide economic conditions.

Unlike the farmland value specification, the interaction terms between ethanol exposure and crude oil prices are positive and economically meaningful, indicating that the effect of nearby ethanol production on farm turnover becomes stronger during periods when ethanol production is more profitable. This result is consistent with the proposed mechanism linking energy markets to agricultural restructuring. Higher crude oil prices increase the competitiveness of ethanol relative to gasoline, strengthening local corn demand and increasing both price volatility and expected returns. Although higher expected returns may encourage some operators to expand, the increase in price risk appears to accelerate exit or shrinking of production among producers who are less willing or less able to bear additional uncertainty.

The comparison between predominantly corn-producing and non-corn-producing farms further supports this interpretation. Farm sales among operations classified as predominantly corn-producing respond more strongly to nearby ethanol production than sales among non-corn farms. If this was merely a demand effect from ethanol production one would expect a larger effect on non-corn producing farms than corn-producing farms from the expectation of higher returns from corn. Since corn producers are most directly exposed to higher level of price risk induced by ethanol production, the effect of ethanol exposure on predominantly corn farms is higher than non-corn farms. This pattern also provides evidence that the estimated effects operate through corn market conditions rather than general economic trends. Simultaneously, statistically significant positive responses among non-corn farms indicate that restructuring is not confined exclusively to corn producers as agricultural land markets are inherently interconnected. Changes in ownership among corn producers inevitability influence nearby producers through land markets and expectations around future land use.

The magnitude of these estimates suggests that the effects are substantial as a whole. Evaluated at observed Brent crude oil prices, the estimated marginal effects imply that the average increase in ethanol exposure experienced during the sample period increased annual farm sales by approximately 13 transactions per county, corresponding to roughly a 15% increase relative to average county-year turnover. The largest contribution arises from exposure within 50 miles of ethanol plants, with progressively smaller effects observed at greater distances. These estimates indicate that ethanol expansion has been an economically substantial source of agricultural restructuring throughout Wisconsin and Illinois.

Taken together, the results in Table 3 provide the first direct evidence supporting the theoretical mechanism developed in Section 3. Rather than primarily increasing the value of agricultural land, ethanol expansion appears to have little to no effect on the value of land, while accelerating ownership turnover. The expansion of ethanol production increases the incentives for more risk-averse producers to exit or shrink acreage while creating opportunities for less risk-averse operators to expand. The remaining analysis examines whether this increased turnover ultimately translates into larger land transactions and persistent changes in county-level agricultural structure.

5.3 Sale-Point Ethanol Exposure and Mean Farm Sale Size

The results presented in Table 3 provide evidence that increased exposure to nearby ethanol production increases the frequency of farmland transactions. However, increased turnover alone does not directly imply consolidation. Agricultural land could be changing ownership without altering the scale of production or the number of farm operations. To disentangle the effect of ethanol exposure on the size of operations, Table 4 examines the effect of ethanol exposure on the log average size of farmland sales.

Following the specification of Section 4.2.2, the estimates indicate that increased exposure to nearby ethanol production is generally associated with larger farm sales. The most economically meaningful estimates are concentrated within the smallest distance bin of 0-50 miles. Estimated effects become smaller and less significant at larger distance bins as the corn demand consequences of ethanol production weakens. Exposure to ethanol-induced price risk is associated with the transfer of progressively larger agricultural land parcels and, as suggested by the results of Table 3, at a higher rate.

Unlike the results from section 5.2, differences between predominantly corn-producing and non-corn-producing farms is flipped. Positive responses are observed for both groups, but in this specification there is a larger and more significant response from non-corn farms compared to corn farms. The relatively strong response among transactions involving land that was not predominantly in corn production the year prior to sale suggests that ethanol expansion influences broader agricultural land markets rather than only effecting the corn market. Since corn operations are typically larger than most other crops, one possible explanation is that some purchasers acquire non-corn land with the intention of converting it to corn production following the transaction, increasing the average farmland sale of non-corn operations. Because crop classification is based on land use prior to sale, the present analysis cannot distinguish between this mechanism and more general spillover effects within local land markets.

The interaction terms with Brent crude oil prices are generally estimated less precisely than those reported in Table 3, providing limited evidence that short-run fluctuations in energy markets substantially influence the size of agricultural land transactions. This result suggests that while changes in ethanol profitability may affect the timing of farm exits, the scale of land transferred reflects longer-run adjustments in farm structure rather than temporary movements in energy prices.

The economic magnitudes of the results reinforce this interpretation. Evaluated at observed oil prices, the estimated marginal effects imply that the average increase in ethanol exposure experienced during the sample period increased mean farm transaction size by approximately 1.3 percent, corresponding to roughly 0.9 additional acres for a representative agricultural land transaction. Although modest relative to the average size of a farmland sale, these estimates indicate that the increased turnover documented in Table 3 is accompanied by a systematic shift toward larger land transfers. Rather than reflecting isolated large acquisitions, the evidence suggests that consolidation occurs gradually through many relatively small increases in the acreage exchanged in each transaction.

Taken together, Tables 2, 3 and 4 provide complementary evidence regarding the mechanism through which ethanol induced price risk affects agricultural structure. Table 2 provides evidence that increased risk exposure from ethanol production negates the corn price premium in the form of unchanged land values. Table 3 demonstrates that greater exposure to ethanol production increases the frequency of farm sales, while Table 4 shows that those transactions also become modestly larger on average. The combination of more frequent and larger transactions without a price premium is precisely the pattern expected if relatively risk-averse producers exit agriculture and their land is absorbed by continuing operations. The following section investigates whether these repeated ownership changes accumulate into persistent changes in county-level agricultural structure as measured by the USDA Census of Agriculture.

5.4 County-level Agricultural Consolidation

The preceding analysis demonstrates that increased exposure to ethanol production increases both the frequency and average size of agricultural land transactions, while having no measurable effect on farmland values. These annual responses are consistent with increased restructuring, but they do not necessarily imply persistent changes in the organization of agricultural production. To evaluate whether the repeated land-market adjustments documented in Tables 3 and 4 accumulate into lasting structural change, Table 5 examines changes in the number of farm operations, total operated acreage, and average farm size using successive USDA Censuses of Agriculture.

The Census results follow the specification in Section 4.2.4 and provide evidence that counties experiencing larger increases in ethanol exposure experience a significant decline in the number of farm operations. This finding is particularly important because it connects the increase in annual farm sales, and increase in the size of annual farm sales to actual changes in the number of farms remaining in production. Rather than just representing temporary turnover in which land changes ownership, these estimates indicate that increased exposure to ethanol production is associated with a persistent reduction in the number of operations.

The estimated magnitudes suggest that these effects are economically substantial. Evaluated over the observed changes in ethanol exposure between Census periods, the results imply that the average county experienced approximately 293 fewer farm operations, corresponding to a 16.4% decline. The magnitude of this effect indicates that the restructuring associated with ethanol exposure accumulates into substantial changes in the number of producers operating within a county.

Changes in ethanol exposure have comparatively limited effects on the total acreage operated within a county relative to the substantial changes in the number of farm operations. Much of the land formerly operated by exiting producers appears to remain in agricultural production and is subsequently absorbed by continuing operators. This result is expected from the theoretical framework in Section 3. Ethanol induced price risk should not effect the total agricultural land operated, but the level of risk-aversion of producers willing to operate.

Consistent with this interpretation, increased ethanol exposure is also associated with substantial growth in average farm size. For the average county, the estimates imply that ethanol expansion increased average farm size by approximately 26.6 acres, equivalent to a 17.7 percent increase relative to an initial average farm size of approximately 152 acres. The simultaneous decline in farm numbers and increase in average farm size, combined with comparatively stable aggregate agricultural acreage, provides direct evidence of consolidation through the reallocation of existing farmland among fewer producers.

Taken together, the evidence from the Census specification substantially strengthens the interpretation of the annual farm-sale results as evidence of agricultural consolidation. Ethanol exposure does not appear to primarily remove land from agricultural production. Instead, it changes the distribution of that land across producers. More risk-averse operators exit, their land remains in agricultural use, and continuing operations become larger. This pattern closely matches the theoretical mechanism developed in Section 3, in which greater exposure to price risk generates differential exit and expansion across producers and ultimately leads to a more concentrated agricultural sector.

5.5 Robustness to County-Centroid Measures of Ethanol Exposure

The preceding analysis from real estate transfer data defines ethanol exposure in distance bins from the geograpahic location of each individual farm sale. This approach provides the most precise measure of the ethanol induced price conditions faced by the producers selling of their land. This specification although spatially accurate, does cause some concern since the RHS of the regression includes the number of farmland sales in the denominator of the main coefficients of interest. To evaluate the robustness of the results of Tables 2 through 4, Tables 6 through 8 repeat the primary specifications using an alternative measure of ethanol exposure based on the distance from the geographic centroid of each county. Measuring exposure from county centroids does substantially reduce the spatial accuracy of the main coefficients, but it does resolve possible exogeneity concerns of the previous specifications.

Table 6 examines the relationship between county-centroid ethanol exposure and farmland values. The conclusions of section 5.1 remain unchanged. As in the sale-point specifications, the estimates provide little evidence that greater ethanol exposure systematically increases agricultural land values. The point estimates and interaction terms between ethanol exposure and crude oil prices generally remain mostly negative and statistically insignificant. The overall pattern of results continues to suggest that any increase in expected profitability generated by nearby ethanol production is largely offset by the greater price uncertainty faced by agricultural producers. The absence of a meaningful capitalization effect under both exposure measures strengthens the conclusion that ethanol expansion influences agricultural structure through channels other than farmland appreciation.

Table 7 presents the corresponding estimates for annual farm turnover. The county-centroid specification confirms the results of the sale-point estimates to indicate that greater nearby ethanol exposure increases the number of agricultural land transactions. The estimated magnitudes are substantially smaller than those obtained using farm-sale locations. Evaluated at observed Brent crude oil prices and observed changes in ethanol exposure within 100 miles of the county centroid, the estimates imply that the average county experienced approximately 0.9 additional farm sales per year, corresponding to roughly a 1 percent increase in annual turnover relative to the average county-year. The attenuation in economic magnitude compared to the sale-point estimates is expected because county centroids provide a considerably noisier measure of producers' actual exposure to nearby ethanol production than the precise location of individual farm sales. Nevertheless, the positive relationship between localized ethanol exposure and farm turnover remains, indicating that the principal findings in section 5.2 are not driven solely by the number of sales being in the RHS of the regression.

Table 8 examines whether the increase in average farm transaction size documented in the previous specifications is also evident under the county-centroid measure of exposure. The results continue to indicate that greater ethanol exposure is associated with larger farmland transactions. Evaluated at observed changes in ethanol exposure, the estimates imply that the average county experienced approximately a 2.7 percent increase in mean farm sale size, equivalent to roughly 1.9 additional acres for the representative agricultural land transaction. This estimate is remarkably similar to the corresponding sale-point specification despite the substantially coarser measure of exposure, providing further evidence that ethanol expansion contributes to gradual consolidation through increasingly larger land transfers.

Taken together, the county-centroid specifications provide strong support for the robustness of the empirical results of Sections 5.1 through 5.3. Although measuring exposure from county centroids introduces additional measurement error and attenuates several estimated effects, the qualitative patterns remain unchanged from the previous specifications. Ethanol exposure continues to exhibit little relationship with farmland values while remaining significantly positively associated with both farm turnover and the size of agricultural land transactions. These findings suggest that the previous results are not an artifact of the construction of the ethanol exposure variable but instead reflect broader local market conditions generated by nearby ethanol production.

The combined evidence presented throughout Section 5 paints a consistent picture of how ethanol expansion has reshaped agricultural structure in Wisconsin and Illinois. Increased local demand for corn from ethanol expansion does not appear to generate widespread appreciation in farmland values. Instead via the effect of increased price risk, increased exposure to ethanol production increases farm turnover, modestly increases the size of agricultural land transactions, and ultimately contributes to fewer farms operating larger agricultural enterprises over time. The consistency of these findings across both the sale-point specifications and the alternative county-centroid measures substantially strengthens the interpretation that ethanol-induced price risk has been an important driver of agricultural consolidation.

6 Conclusion

This paper examines the role of price risk in driving agricultural structural change in the United States. Although a growing literature attributes declining farm numbers and increasing farm size to the expansion of the Federal Crop Insurance Program, I hypothesize that these patterns may instead reflect heterogeneous responses to price volatility among farmers with differing levels of risk aversion or the ability to handle risk. In this framework, crop insurance does not fundamentally create consolidation as it functions as a price volatility mitigation device. Rather, consolidation appears because increases in the volatility of crop prices affect more risk-averse producers, causing them to reduce acreage, sell farmland, and eventually exit the market.

To formalize this mechanism, I develop a representative-farmer model in which a farmer optimizes their amount of acreage, input intensity, total farm size, and insurance coverage over two crop choices (insured and uninsured) while facing stochastic output and input prices. The model demonstrates three major results in relation to the response to output price volatility; (1) optimal acreage and inputs decrease as the respective output crop price variance increases, (2) increasing the risk floor or decreasing the per acre premium of insurance increases optimal allocation of inputs and acreage towards to insured crop, (3) the level of risk aversion amplifies the affect of output price variance on optimal acreage and inputs. Consequently, sufficiently volatile price environments generate differential exit among producers, allowing less risk-averse farms to expand through the acquisition of land from exiting operators.

I test these predictions by constructing a novel county-level panel of agricultural land transactions in Wisconsin and Illinois spanning 2013 through 2024. Exploiting plausibly exogenous variation generated by the expansion of ethanol production, I construct measures of localized exposure to ethanol induced corn price volatility based on the ethanol production capacity surrounding individual farm sales and county centroids. Since ethanol demand is linked to energy markets, the empirical framework also allows the effects of local ethanol exposure to vary with prevailing Brent crude oil prices.

The empirical evidence consistently supports the theoretical mechanism. First, increased ethanol exposure has little systematic effect on agricultural land values, suggesting that any increase in expected profitability associated with the corn price premium of nearby ethanol production is largely offset by the greater price uncertainty facing farmers. Second, greater ethanol exposure substantially increases annual farm turnover. Evaluated at observed Brent crude oil prices, the average increase in ethanol exposure experienced during the sample period increased annual farm sales by approximately 13 transactions per county, representing roughly a 15 percent increase in annual turnover. Third, increased exposure is associated with larger agricultural land transactions, increasing the average farm sale by approximately 1.3 percent, or nearly one additional acre per transaction. Although modest in any single year, these changes indicate that farmland is gradually being transferred in increasingly larger parcels.

Most importantly, the Census of Agriculture demonstrates that these annual adjustments accumulate into substantial longer-run structural changes. Counties experiencing larger increases in ethanol exposure experienced significantly fewer surviving farm operations while total agricultural acreage remained relatively unchanged. Evaluated over observed changes in ethanol exposure between Census periods, the estimates imply that the average county lost approximately 293 farm operations associated withe ethanol expansion, a decline of 16.4 percent, while average farm size increased by approximately 26.6 acres, or 17.7 percent. Together, these findings indicate that ethanol-induced price risk does not primarily remove land from agricultural production. Instead, it reallocates existing farmland across fewer, larger, and less risk-averse operations through repeated ownership turnover.

The robustness exercises reinforce these conclusions. Re-estimating the principal specifications using county-centroid measures of ethanol exposure in place of farm-sale-point measures produces the same qualitative pattern of results despite the substantially coarser measure of local exposure. The estimated effects on farm turnover are attenuated, as expected, but ethanol exposure continued to exhibit little relationship with farmland values while remained statistically significantly positively associated with both farm turnover and the size of agricultural land transactions. The consistency of these findings across alternative exposure measures strengthens the interpretation that the estimated relationships reflect effect of ethanol expansion on local corn market conditions rather than the construction of the exposure variable itself.

These findings contribute to several strands of literature. First, the paper contributes to the literature on agricultural structural change by identifying price risk as an important mechanism generating consolidation. Second, it offers an alternative interpretation of the relationship between crop insurance and farm structure. Rather than viewing insurance as the primary cause of consolidation, the results suggest that previous empirical estimates may partly capture the effects of underlying price-risk environments that simultaneously increase demand for insurance and accelerate the exit of smaller, more risk-averse producers. Thirdly, the paper contributes to a broader literature examining how heterogeneous responses to uncertainty shape firm dynamics, market selection, and industry concentration. Finally, the paper contributes to a growing literature on the unintended consequences of ethanol expansion in the U.S, building upon the evidence that ethanol production is not only associated with changes in surrounding crop choices, but with nearby land tenure and ownership decisions as well.

The policy implications of the results of the paper differ significantly from those implied by the existing crop insurance literature. If consolidation is fundamentally driven by heterogeneous exposure and aversion to price risk, reducing insurance support could unintentionally accelerate structural change by increasing the vulnerability of smaller and more risk-averse producers. Well-designed crop insurance products may serve not as a catalyst for consolidation but as a mechanism for preserving producer participation in volatile agricultural price environments. As agricultural and energy markets continue to become more intertwined along with increased climate risk across the world, creating insurance products that can help shield the smaller, more risk-averse producers becomes ever more crucial to combat consolidation. At the same time, policies promoting biofuel production should be constructed within the context that localized increases in commodity price volatility may generate unintended structural consequences beyond their intended effects on energy security or environmental objectives.

Several pathways for future research remain. Future work could examine producer-level entry and exit decisions directly with the appropriate data, incorporate credit constraints and land rental markets into the theoretical framework, and test whether Proposition 2 is reflected in real world data at the individual farm level.

Overall, the evidence presented in this paper suggests that volatility itself—not simply technological progress, economies of scale, or crop insurance expansion—is an important determinant of the continuing consolidation of U.S. agriculture. As agricultural and energy markets become increasingly interconnected, understanding how producers with heterogeneous risk preferences respond to changing price environments will become increasingly important for designing agricultural policies that promote both economic efficiency and the long-run resilience of rural communities.

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7 Tables

Table 1: Summary Statistics by State

	IL (N=1415)		WI (N=1006)	
	Mean	Std. Dev.	Mean	Std. Dev.
Exposure 0-50 Miles	129.11	230.31	53.08	76.42
Exposure 50-100 Miles	382.61	499.54	204.34	298.44
Exposure 100-150 Miles	509.17	603.24	477.76	577.02
Exposure 150-200 Miles	580.95	667.36	833.04	819.89
Exposure 200-300 Miles	1474.90	1665.74	2454.20	1913.12
Existing Acres	263 050.05	134 696.68	175 431.71	115 058.17
Mean Temperature	11.98	1.67	7.10	1.72
Existing Farms	1309.86	573.28	1942.76	1292.60
Farm Sales	47.74	55.06	156.13	94.42
Precipitation	1089.46	210.17	932.13	151.55
Total Acres Sold	2 043 926.16	57 728 960.90	12 587.59	8980.30
Total Sale Value	28 851 555.63	44 783 321.93	43 441 164.85	60 149 486.96
Value Per Acre	14 215.79	51 942.98	4096.84	10 306.84

Table 2: Sale-Point Ethanol Exposure and Farm Sale Values

Model:	All sales (1)	Corn sales (2)	Non-corn sales (3)
Variables			
Capacity: 0–50 miles	-15.1*	-37.7	-11.5
	(8.82)	(31.5)	(8.85)
Capacity: 50–100 miles	4.92	31.2*	2.07
	(5.19)	(16.9)	(4.91)
Capacity: 100–150 miles	-2.42	1.31	0.542
	(4.87)	(14.5)	(4.17)
Capacity: 150–200 miles	-9.17*	-24.8	-8.88*
	(5.02)	(20.9)	(5.11)
Capacity: 200–300 miles	-2.57	5.24	-2.63
	(4.56)	(12.2)	(4.45)
Capacity: 0–50 × oil price	0.152	0.511	0.096
	(0.106)	(0.423)	(0.111)
Capacity: 50–100 × oil price	-0.027	-0.570*	0.021
	(0.067)	(0.301)	(0.062)
Capacity: 100–150 × oil price	-0.022	0.139	-0.045
	(0.061)	(0.222)	(0.059)
Capacity: 150–200 × oil price	0.056	0.080	0.056
	(0.045)	(0.270)	(0.045)
Capacity: 200–300 × oil price	-0.040	-0.019	-0.036
	(0.029)	(0.149)	(0.029)
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,693	1,313	1,684
R^2	0.25640	0.16737	0.25654
Within R^2	0.01293	0.02097	0.01153

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is farm sale value per acre.
All specifications include weather and county agricultural-structure controls.
Standard errors clustered by county are reported in parentheses.

Table 3: Sale-Point Ethanol Exposure and Farm Sales

Model:	All sales (1)	Corn sales (2)	Non-corn sales (3)
Variables			
Capacity: 0–50 miles	0.0009***	0.001***	0.0007***
	(0.0002)	(0.0003)	(0.0002)
Capacity: 50–100 miles	0.0009***	0.0007***	0.0010***
	(0.0001)	(0.0002)	(0.0001)
Capacity: 100–150 miles	0.0005***	0.0009***	0.0005***
	(0.0002)	(0.0002)	(0.0002)
Capacity: 150–200 miles	0.0004***	0.0009***	0.0004***
	(0.0002)	(0.0002)	(0.0002)
Capacity: 200–300 miles	0.0006***	0.0009***	0.0006***
	(6.98×10^{-5})	(9.57×10^{-5})	(6.94×10^{-5})
Capacity: 0–50 $\times$ oil price	7.15×10^{-6}***	3.93×10^{-6}	7.62×10^{-6}***
	(2.09×10^{-6})	(3.55×10^{-6})	(2.3×10^{-6})
Capacity: 50–100 $\times$ oil price	3.42×10^{-6}**	5.71×10^{-6}**	3.02×10^{-6}**
	(1.33×10^{-6})	(2.35×10^{-6})	(1.41×10^{-6})
Capacity: 100–150 $\times$ oil price	-6.58×10^{-7}	-4.17×10^{-6}*	-1.79×10^{-7}
	(1.29×10^{-6})	(2.3×10^{-6})	(1.32×10^{-6})
Capacity: 150–200 $\times$ oil price	-2.32×10^{-6}**	-4.02×10^{-6}**	-2.27×10^{-6}*
	(1.18×10^{-6})	(1.74×10^{-6})	(1.18×10^{-6})
Capacity: 200–300 $\times$ oil price	-4.69×10^{-6}***	-6.23×10^{-6}***	-4.47×10^{-6}***
	(6.58×10^{-7})	(1.02×10^{-6})	(6.73×10^{-7})
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,870	1,760	1,870
Log-Likelihood	-15,138.4	-3,837.5	-14,012.3
Pseudo R^2	0.79993	0.67831	0.80094

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is the number of farm sales.
Models are estimated using Poisson pseudo-maximum likelihood.
All specifications include weather and county agricultural-structure controls.
Standard errors clustered by county are reported in parentheses.

Table 4: Sale-Point Ethanol Exposure and Mean Farm Sale Size

Model:	All sales (1)	Corn sales (2)	Non-corn sales (3)
Variables			
Capacity: 0–50 miles	0.001***	0.0004	0.0009**
	(0.0004)	(0.0005)	(0.0004)
Capacity: 50–100 miles	0.0004	0.0002	0.0006*
	(0.0003)	(0.0002)	(0.0003)
Capacity: 100–150 miles	0.0005	-0.0001	0.0004
	(0.0004)	(0.0002)	(0.0004)
Capacity: 150–200 miles	0.0004*	6.02×10^{-5}	0.0004**
	(0.0002)	(0.0002)	(0.0002)
Capacity: 200–300 miles	7.07×10^{-5}	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Capacity: 0–50 × oil price	-6.49×10^{-6}	9.9×10^{-7}	-5.04×10^{-6}
	(5.49×10^{-6})	(5.25×10^{-6})	(6.04×10^{-6})
Capacity: 50–100 × oil price	3.56×10^{-6}	5.1×10^{-6}	2.48×10^{-6}
	(4.29×10^{-6})	(3.14×10^{-6})	(4.42×10^{-6})
Capacity: 100–150 × oil price	-3.15×10^{-6}	-1.01×10^{-6}	-2.66×10^{-6}
	(2.98×10^{-6})	(2.98×10^{-6})	(3.09×10^{-6})
Capacity: 150–200 × oil price	5.16×10^{-7}	-1.1×10^{-6}	5.18×10^{-7}
	(2.11×10^{-6})	(2.71×10^{-6})	(2.14×10^{-6})
Capacity: 200–300 × oil price	$-3.75 \times 10^{-6***}$	$-3.8 \times 10^{-6**}$	$-3.65 \times 10^{-6***}$
	(1.37×10^{-6})	(1.87×10^{-6})	(1.35×10^{-6})
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,693	1,313	1,684
R^2	0.49776	0.31775	0.51968
Within R^2	0.02746	0.02886	0.02633

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is the log of mean acreage sold.
County-years without sales of the relevant type are excluded.
All specifications include weather and county agricultural-structure controls.
Standard errors clustered by county are reported in parentheses.

Table 5: Changes in Ethanol Exposure and County Agricultural Structure

Model:	Farm operations (1)	Operated acreage (2)	Average farm size (3)
Variables			
Log initial farm operations	-141.4***	-31.8*	109.6***
	(12.2)	(17.5)	(14.5)
Log initial operated acreage	-3.47	-67.7***	-64.2***
	(5.49)	(25.5)	(23.5)
Period-average precipitation	0.004	-0.016	-0.020
	(0.012)	(0.016)	(0.015)
Period-average temperature	-3.50	-10.1	-6.64
	(4.72)	(6.33)	(6.57)
Δ capacity: 0–50 miles	-0.022	0.007	0.028
	(0.015)	(0.017)	(0.018)
Δ capacity: 50–100 miles	-0.032**	-0.025	0.007
	(0.014)	(0.016)	(0.016)
Δ capacity: 100–150 miles	-0.040***	-0.018	0.023
	(0.014)	(0.013)	(0.014)
Δ capacity: 150–200 miles	-0.027***	0.0005	0.027***
	(0.008)	(0.009)	(0.010)
Δ capacity: 200–300 miles	-0.020***	-0.0007	0.020***
	(0.005)	(0.006)	(0.006)
Fixed-effects			
Census-period fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	344	344	344
R^2	0.80627	0.81388	0.82142
Within R^2	0.72319	0.48955	0.53228

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent variables equal 100 times the log change over each Census period.
Exposure variables are changes in ethanol capacity measured from county centroids.
The first period is 2013–2017 and the second period is 2017–2022.
Standard errors clustered by county are reported in parentheses.

Table 6: County-Centroid Ethanol Exposure and Farm Sale Values

	All sales	Corn sales	Non-corn sales
Model:	(1)	(2)	(3)
Variables			
Capacity: 0–50 miles	-12.0	-23.3	-9.41
	(7.75)	(21.1)	(7.90)
Capacity: 50–100 miles	1.09	-4.61	-1.10
	(3.62)	(22.8)	(3.34)
Capacity: 100–150 miles	-1.64	9.60	0.146
	(4.97)	(15.3)	(4.41)
Capacity: 150–200 miles	-10.1	-27.9	-9.30
	(7.81)	(19.3)	(8.03)
Capacity: 200–300 miles	0.844	-7.98	0.849
	(2.61)	(5.27)	(2.63)
Capacity: 0–50 × oil price	0.096	0.512	0.054
	(0.072)	(0.428)	(0.074)
Capacity: 50–100 × oil price	-0.007	-0.496*	0.025
	(0.042)	(0.261)	(0.033)
Capacity: 100–150 × oil price	-0.058	0.064	-0.069
	(0.072)	(0.209)	(0.070)
Capacity: 150–200 × oil price	0.069	0.117	0.068
	(0.049)	(0.222)	(0.049)
Capacity: 200–300 × oil price	-0.034	-0.006	-0.030
	(0.022)	(0.103)	(0.021)
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,693	1,313	1,684
R^2	0.25548	0.16637	0.25560
Within R^2	0.01170	0.01979	0.01028

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is farm sale value per acre.
Ethanol exposure is measured from each county centroid.
All specifications include weather and county agricultural-structure controls.
Standard errors clustered by county are reported in parentheses.

Table 7: County-Centroid Ethanol Exposure and Farm Sales

Model:	All sales (1)	Corn sales (2)	Non-corn sales (3)
Variables			
Capacity: 0–50 miles	0.0004**	0.001***	0.0004*
	(0.0002)	(0.0003)	(0.0002)
Capacity: 50–100 miles	0.0003*	0.0006**	0.0003*
	(0.0002)	(0.0003)	(0.0002)
Capacity: 100–150 miles	-3.41×10^{-5}	0.0005*	-7.07×10^{-5}
	(0.0002)	(0.0003)	(0.0002)
Capacity: 150–200 miles	-9×10^{-5}	0.0003	-0.0001
	(0.0002)	(0.0003)	(0.0002)
Capacity: 200–300 miles	-8.59×10^{-5}	1.51×10^{-6}	-0.0001
	(9.75×10^{-5})	(0.0002)	(9.53×10^{-5})
Capacity: 0–50 × oil price	6.29×10^{-6}***	6.48×10^{-6}*	5.98×10^{-6}***
	(1.91×10^{-6})	(3.45×10^{-6})	(1.9×10^{-6})
Capacity: 50–100 × oil price	1.91×10^{-6}	3.21×10^{-6}	1.72×10^{-6}
	(1.22×10^{-6})	(2.36×10^{-6})	(1.22×10^{-6})
Capacity: 100–150 × oil price	7.14×10^{-7}	-3.8×10^{-6}*	1.05×10^{-6}
	(1.06×10^{-6})	(2.17×10^{-6})	(1.07×10^{-6})
Capacity: 150–200 × oil price	-2.94×10^{-6}***	-5.18×10^{-6}***	-2.8×10^{-6}***
	(9.62×10^{-7})	(1.87×10^{-6})	(9.29×10^{-7})
Capacity: 200–300 × oil price	-3.25×10^{-6}***	-5.89×10^{-6}***	-3.07×10^{-6}***
	(6.78×10^{-7})	(1.21×10^{-6})	(6.77×10^{-7})
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,870	1,760	1,870
Log-Likelihood	-18,550.9	-4,865.8	-17,153.8
Pseudo R^2	0.75483	0.59210	0.75631

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is the number of farm sales.
Models are estimated using Poisson pseudo-maximum likelihood.
Ethanol exposure is measured from each county centroid.
Standard errors clustered by county are reported in parentheses.

Table 8: County-Centroid Ethanol Exposure and Mean Farm Sale Size

Model:	All sales (1)	Corn sales (2)	Non-corn sales (3)
Variables			
Capacity: 0–50 miles	0.0010^{**}	0.0006	0.0008^{**}
	(0.0004)	(0.0006)	(0.0004)
Capacity: 50–100 miles	0.0004	0.0001	0.0006^{*}
	(0.0003)	(0.0002)	(0.0003)
Capacity: 100–150 miles	0.0002	1.48×10^{-5}	0.0002
	(0.0004)	(0.0002)	(0.0004)
Capacity: 150–200 miles	0.0006^{**}	9.62×10^{-5}	0.0006^{**}
	(0.0002)	(0.0002)	(0.0002)
Capacity: 200–300 miles	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
Capacity: 0–50 × oil price	-5.96×10^{-6}	-4.89×10^{-6}	-3.64×10^{-6}
	(4.61×10^{-6})	(4.75×10^{-6})	(4.94×10^{-6})
Capacity: 50–100 × oil price	1.23×10^{-6}	$8.12 \times 10^{-6***}$	-8.94×10^{-8}
	(4.03×10^{-6})	(3×10^{-6})	(4.11×10^{-6})
Capacity: 100–150 × oil price	-3.45×10^{-7}	-2.82×10^{-6}	3.2×10^{-7}
	(2.78×10^{-6})	(2.51×10^{-6})	(2.81×10^{-6})
Capacity: 150–200 × oil price	-8.65×10^{-7}	-1.31×10^{-6}	-1.03×10^{-6}
	(1.7×10^{-6})	(2.25×10^{-6})	(1.7×10^{-6})
Capacity: 200–300 × oil price	$-3.36 \times 10^{-6***}$	$-3.22 \times 10^{-6*}$	$-3.29 \times 10^{-6***}$
	(1.22×10^{-6})	(1.85×10^{-6})	(1.22×10^{-6})
Fixed-effects			
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Fit statistics			
Observations	1,693	1,313	1,684
R^2	0.49644	0.31516	0.51858
Within R^2	0.02490	0.02519	0.02411

Clustered (county_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The dependent variable is the log of mean acreage sold.
Ethanol exposure is measured from the geographic centroid of each county.
All specifications include weather and county agricultural-structure controls.
Standard errors clustered by county are reported in parentheses.

8 Full Theoretical Model

8.1 Environment and Technology

Two crops $i \in \{C, O\}$ (insured C, uninsured O). Choices:

$$\{L,\ a_C,\ a_O,\ x_C,\ x_O,\ m\}, \qquad a_C + a_O = L, \quad L, a_i, x_i \geq 0, \quad m \in [0,1].$$

Acreage shares $\theta_i = a_i/L$. Crop-specific suitability:

$$\psi_i = 1 - (\theta_i - s_i)^2, \qquad M_i(\psi_i) = \psi_i^{\gamma}, \quad 0 < \gamma < 1.$$

Per-crop output :

$$Y_i = a_i\, M_i\, A_i\, x_i^{\alpha_i}, \qquad 0 < \alpha_i < 1.$$

Let $Y = (Y_C, Y_O)^\top$ and $a \odot x = (a_C x_C,\ a_O x_O)^\top$.

Useful derivatives. With $\theta_i = a_i/L$:

$$\frac{\partial \psi_i}{\partial a_i} = -\frac{2}{L}(\theta_i - s_i), \qquad\qquad \frac{\partial \psi_i}{\partial L} = \frac{2\theta_i}{L}(\theta_i - s_i),$$
$$\frac{\partial M_i}{\partial a_i} = -\frac{2\gamma}{L}\psi_i^{\gamma-1}(\theta_i - s_i), \qquad\qquad \frac{\partial M_i}{\partial L} = \frac{2\gamma\theta_i}{L}\psi_i^{\gamma-1}(\theta_i - s_i).$$

Hence, defining $y_{x_i} := \partial Y_i/\partial x_i$,

$$\begin{aligned}
y_{x_i} &= a_i M_i A_i \alpha_i x_i^{\alpha_i - 1}, \\
Y_{a_i,i} := \frac{\partial Y_i}{\partial a_i} &= A_i x_i^{\alpha_i} \psi_i^{\gamma-1}\Big(\psi_i - 2\gamma\theta_i(\theta_i - s_i)\Big), \\
Y_{L,i} := \frac{\partial Y_i}{\partial L} &= \frac{2\gamma\theta_i}{L}\, \psi_i^{\gamma-1}(\theta_i - s_i)\, Y_i.
\end{aligned}$$

Jacobian notation b_i and y_L.

$$b_i := \frac{\partial Y}{\partial a_i} = \begin{pmatrix} \frac{\partial Y_C}{\partial a_i} \\ \frac{\partial Y_O}{\partial a_i} \end{pmatrix}, \qquad y_L := \frac{\partial Y}{\partial L} = \begin{pmatrix} Y_{L,C} \\ Y_{L,O} \end{pmatrix}.$$

8.2 Prices, Insurance, and Risk

Coverage $m \in [0,1]$ a choice variable with residual-risk floor $0 < \omega < 1$ and $\phi : [0,1] \to [\omega, 1]$, $\phi'(m) < 0$, $\phi(0) = 1$, $\phi(1) = \omega$. Premium per insured acre is a function of insured acreage a_C and coverage level m; total premium is

$$\Pi(a_C, m) = r(m)\, \bar{p}_C\, a_C, \qquad r'(m) > 0.$$

Prices are stochastic with known means and second moments. Let

$$p_C = \bar{p}_C + \tilde{p}_C, \qquad p_O = \bar{p}_O + \tilde{p}_O, \qquad w_C = \bar{w}_C + \tilde{w}_C, \qquad w_O = \bar{w}_O + \tilde{w}_O,$$

where $\mathbb{E}[\tilde{p}_C] = \mathbb{E}[\tilde{p}_O] = \mathbb{E}[\tilde{w}_C] = \mathbb{E}[\tilde{w}_O] = 0$ and the variances/covariances are given below.

$$\Sigma_{pp}(m) = \begin{pmatrix} \phi(m)\sigma^2_{p_C} & \sigma_{p_{CO}} \\ \sigma_{p_{CO}} & \sigma^2_{p_O} \end{pmatrix}, \quad \Sigma_{ww} = \begin{pmatrix} \sigma^2_{w_C} & \sigma_{w_{CO}} \\ \sigma_{w_{CO}} & \sigma^2_{w_O} \end{pmatrix}, \quad \Sigma_{pw} = \begin{pmatrix} \sigma_{p_C w_C} & \sigma_{p_C w_O} \\ \sigma_{p_O w_C} & \sigma_{p_O w_O} \end{pmatrix}.$$

8.3 Objective (Certainty Equivalent) and Lagrangian

$$\begin{aligned} \mathrm{CE} = {} & \underbrace{\bar{p}_C Y_C + \bar{p}_O Y_O - \bar{w}_C a_C x_C - \bar{w}_O a_O x_O - r(m)\,\bar{p}_C a_C}_{\mathbb{E}[\pi]} \\ & \underbrace{-\frac{\lambda}{2}\Big(Y^\top \Sigma_{pp}(m) Y + a\odot x^\top \Sigma_{ww} a\odot x - 2\,Y^\top \Sigma_{pw} a\odot x\Big)}_{\mathrm{Var}[\pi]}. \end{aligned} \tag{2}$$

Problem: $\max \mathrm{CE}$ s.t. $a_C + a_O = L$ and $L, a_i, x_i \geq 0$. Lagrangian (multiplier μ on $a_C + a_O - L = 0$):

$$\mathcal{L} = \mathrm{CE} + \mu\,(L - a_C - a_O).$$

8.4 First-Order Conditions (FOCs)

Inputs x_i ($i \in \{C, O\}$).

$$\begin{aligned} 0 \;=\; & \bar{p}_i\, y_{x_i} \;-\; a_i \bar{w}_i \\ & -\; \lambda\Big[y_{x_i}\,\big(\Sigma_{pp}(m)\,Y\big)_i \;+\; a_i x_i\,\big(\Sigma_{ww}\,a\odot x\big)_i \;-\; y_{x_i}\,\big(\Sigma_{pw}\,a\odot x\big)_i \;-\; a_i\,(\Sigma_{pw}^\top Y)_i \Big]. \end{aligned} \tag{3}$$

Acreage a_i ($i \in \{C, O\}$).

$$\begin{aligned} \mu \;=\; & \bar{p}^\top b_i \;-\; \bar{w}_i x_i \\ & -\; \mathbf{1}_{\{i=C\}}\,\bar{p}_C r(m) \\ & -\; \lambda\Big[b_i^\top \Sigma_{pp}(m) Y \;+\; x_i\,\big(\Sigma_{ww}\,a\odot x\big)_i \;-\; b_i^\top \Sigma_{pw} a\odot x \;-\; x_i\,(\Sigma_{pw}^\top Y)_i \Big]. \end{aligned} \tag{4}$$

Total acreage L.

$$0 \;=\; \bar{p}^\top y_L \;-\; \lambda\, y_L^\top\big(\Sigma_{pp}(m) Y - \Sigma_{pw} a\odot x\big) \;+\; \mu. \tag{5}$$

Curvatures used later.

$$f_{x_i} := \frac{\partial}{\partial x_i}\big(\text{RHS of (3)}\big) < 0, \quad G_{i,a_i} := \frac{\partial}{\partial a_i}\big(\text{RHS of (4)} - \mu\big) < 0, \quad H_{LL} := \frac{\partial}{\partial L}\big(\text{RHS of (5)}\big) < 0.$$

Define the own-variance factor $\kappa_i := \phi(m)$ if $i = C$, and $\kappa_i := 1$ if $i = O$.

8.5 Comparative Statics

All use the rule $S = -Q_\zeta/Q_q$ from implicit differentiation of $Q(q, \zeta) = 0$.

(i) w.r.t. output-price variance $\sigma^2_{p_i}$

Input x_i.

$$\frac{dx_i^*}{d\,\sigma^2_{p_i}} = -\frac{f_{\sigma^2_{p_i}}}{f_{x_i}} = -\frac{-\lambda\,\kappa_i\,Y_i\,y_{x_i}}{f_{x_i}} = \frac{\lambda\,\kappa_i\,Y_i\,y_{x_i}}{f_{x_i}} \;<\; 0.$$

Acreage a_i.

$$\frac{da_i^*}{d\,\sigma^2_{p_i}} = -\frac{G_{i,\sigma^2_{p_i}}}{G_{i,a_i}} = -\frac{-\lambda\,\kappa_i\,Y_i\,Y_{a_i,i}}{G_{i,a_i}} = \frac{\lambda\,\kappa_i\,Y_i\,Y_{a_i,i}}{G_{i,a_i}} \;<\; 0.$$

(ii) w.r.t. input-price variance $\sigma^2_{w_i}$

Input x_i.

$$\frac{dx_i^*}{d\,\sigma^2_{w_i}} = -\frac{f_{\sigma^2_{w_i}}}{f_{x_i}} = -\frac{-\lambda\,a_i^2 x_i}{f_{x_i}} = \frac{\lambda\,a_i^2 x_i}{f_{x_i}} \;<\; 0.$$

Acreage a_i.

$$\frac{da_i^*}{d\,\sigma^2_{w_i}} = -\frac{G_{i,\sigma^2_{w_i}}}{G_{i,a_i}} = -\frac{-\lambda\,a_i x_i^2}{G_{i,a_i}} = \frac{\lambda\,a_i x_i^2}{G_{i,a_i}} \;<\; 0.$$

(iii) w.r.t. coverage m (exogenous)

Input on insured crop C.

$$\frac{dx_C^*}{dm} = -\frac{f_m}{f_{x_C}} = -\frac{-\lambda\,\phi'(m)\sigma^2_{p_C}\,Y_C\,y_{x_C}}{f_{x_C}} \;>\; 0.$$

Acreage on insured crop C.

$$\frac{da_C^*}{dm} = -\frac{G_{C,m}}{G_{C,a_C}} = -\frac{-\,\bar{p}_C r'(m) - \lambda\,\phi'(m)\sigma^2_{p_C}\,Y_C\,Y_{a_C,C}}{G_{C,a_C}} \quad \text{(sign ambiguous in general).}$$

Acreage on uninsured crop O (sign claim).

$$\frac{da_O^*}{dm} = -\frac{G_{O,m}}{G_{O,a_O}} = -\frac{-\lambda\,\phi'(m)\sigma^2_{p_C}\,Y_C\,Y_{a_O,C}}{G_{O,a_O}} = \frac{\lambda\,\phi'(m)\sigma^2_{p_C}\,Y_C\,Y_{a_O,C}}{G_{O,a_O}}.$$

Assumption (standard): the cross derivative $Y_{a_O,C} < 0$ (allocating acres to O lowers C's output margin). With $\phi'(m) < 0$ and $G_{O,a_O} < 0$,

$$\boxed{\frac{da_O^*}{dm} \; < \; 0}.$$

Total acreage L.

$$\frac{dL^*}{dm} = -\frac{H_{L,m}}{H_{LL}} = -\frac{-\lambda\,\phi'(m)\sigma_{p_C}^2\,Y_C\,Y_{L,C}}{H_{LL}} \;>\; 0.$$

Implied sign for insured acreage a_C. Since $L = a_C + a_O$,

$$\frac{da_C^*}{dm} \;=\; \frac{dL^*}{dm} \;-\; \frac{da_O^*}{dm}.$$

With $\frac{dL^*}{dm} > 0$ and (by the assumption above) $\frac{da_O^*}{dm} < 0$, it follows that

$$\boxed{\frac{da_C^*}{dm} \; > \; 0}.$$

(Thus the ambiguous direct sign in the a_C–FOC is resolved when combined with these margins.)

(iv) Total acreage L w.r.t. variances

Output-price variance.

$$\frac{dL^*}{d\,\sigma_{p_i}^2} = -\frac{H_{L,\sigma_{p_i}^2}}{H_{LL}} = -\frac{-\lambda\,\kappa_i\,Y_i\,Y_{L,i}}{H_{LL}} = \frac{\lambda\,\kappa_i\,Y_i\,Y_{L,i}}{H_{LL}} \;<\; 0.$$

Input-price variance. (Under the local assumption L does not directly enter $a \odot x$ in H_L)

$$\frac{dL^*}{d\,\sigma_{w_i}^2} = 0.$$

8.6 Sensitivities w.r.t. λ

Let $Q(q, \zeta, \lambda) = 0$ be an FOC; the CS is $S = -Q_\zeta / Q_q$. Then

$$\frac{\partial S}{\partial \lambda} = -\frac{Q_{\zeta\lambda}\,Q_q - Q_\zeta\,Q_{q\lambda}}{Q_q^2}.$$

Below we also state the *likely sign* under the empirically common case of *no strong natural hedge* (i.e., risk penalization steepens the FOCs so $f_{x_i\lambda} \lesssim 0$ and $G_{i,a_i\lambda} \lesssim 0$).

$\partial\big(\frac{dx_i^*}{d\sigma_{p_i}^2}\big)/\partial\lambda$ **(likely >0).** Here $Q=f$ from (3), with $f_{\sigma_{p_i}^2}=-\lambda\,\kappa_i\,Y_i\,y_{x_i}$ and $f_{\sigma_{p_i}^2,\lambda}\approx-\kappa_i\,Y_i\,y_{x_i}$:

$$\frac{\partial}{\partial\lambda}\bigg(\frac{dx_i^*}{d\,\sigma_{p_i}^2}\bigg)=-\,\frac{\big(-\kappa_i Y_i y_{x_i}\big)\,f_{x_i}-\big(-\lambda\kappa_i Y_i y_{x_i}\big)\,f_{x_i\lambda}}{f_{x_i}^2}.$$

Explanation: with $f_{x_i}<0$ and $f_{x_i\lambda}\lesssim 0$, the numerator is positive, so the derivative is $\boxed{>0}$: as λ rises, the (negative) sensitivity becomes more negative in magnitude.

$\partial\big(\frac{da_i^*}{d\sigma_{p_i}^2}\big)/\partial\lambda$ **(likely >0).** With $Q=G_i$ from (4), $G_{i,\sigma_{p_i}^2}=-\lambda\,\kappa_i\,Y_i\,Y_{a_i,i}$ and $G_{i,\sigma_{p_i}^2,\lambda}\approx-\kappa_i\,Y_i\,Y_{a_i,i}$:

$$\frac{\partial}{\partial\lambda}\bigg(\frac{da_i^*}{d\,\sigma_{p_i}^2}\bigg)=-\,\frac{\big(-\kappa_i Y_i Y_{a_i,i}\big)\,G_{i,a_i}-\big(-\lambda\kappa_i Y_i Y_{a_i,i}\big)\,G_{i,a_i\lambda}}{G_{i,a_i}^2}.$$

Explanation: with $G_{i,a_i}<0$ and $G_{i,a_i\lambda}\lesssim 0$, the derivative is $\boxed{>0}$: higher λ strengthens (makes more negative) the acreage response to $\sigma_{p_i}^2$.

$\partial\big(\frac{dx_i^*}{d\sigma_{w_i}^2}\big)/\partial\lambda$ **(likely >0).** Since $f_{\sigma_{w_i}^2}=-\lambda a_i^2 x_i$ and $f_{\sigma_{w_i}^2,\lambda}=-a_i^2 x_i$,

$$\frac{\partial}{\partial\lambda}\bigg(\frac{dx_i^*}{d\,\sigma_{w_i}^2}\bigg)=-\,\frac{\big(-a_i^2 x_i\big)\,f_{x_i}-\big(-\lambda a_i^2 x_i\big)\,f_{x_i\lambda}}{f_{x_i}^2}.$$

Explanation: again $f_{x_i}<0$ and $f_{x_i\lambda}\lesssim 0$ imply $\boxed{>0}$: greater risk aversion amplifies the (negative) input response to input-price risk.

$\partial\big(\frac{da_i^*}{d\sigma_{w_i}^2}\big)/\partial\lambda$ **(likely >0).** With $G_{i,\sigma_{w_i}^2}=-\lambda a_i x_i^2$ and $G_{i,\sigma_{w_i}^2,\lambda}=-a_i x_i^2$,

$$\frac{\partial}{\partial\lambda}\bigg(\frac{da_i^*}{d\,\sigma_{w_i}^2}\bigg)=-\,\frac{\big(-a_i x_i^2\big)\,G_{i,a_i}-\big(-\lambda a_i x_i^2\big)\,G_{i,a_i\lambda}}{G_{i,a_i}^2}.$$

Explanation: with $G_{i,a_i}<0$ and $G_{i,a_i\lambda}\lesssim 0$, we get $\boxed{>0}$: higher λ intensifies the (negative) acreage response to input-price risk.

For $dL^*/d\sigma_{p_i}^2$ (sign can be positive). Since $\dfrac{dL^*}{d\sigma_{p_i}^2}=\dfrac{\lambda\,\kappa_i\,Y_i\,Y_{L,i}}{H_{LL}}<0$, we have

$$\frac{\partial}{\partial\lambda}\bigg(\frac{dL^*}{d\sigma_{p_i}^2}\bigg)=\frac{Y_iY_{L,i}}{H_{LL}}-\frac{\lambda Y_iY_{L,i}\,H_{LL,\lambda}}{H_{LL}^2},\qquad H_{LL,\lambda}=-\,y_L^\top\Sigma_{pp}(m)\,y_L<0.$$

The first term is negative while the second is positive; without an *extreme* natural hedge the second dominates, so this derivative is $\boxed{\text{likely }>0}$: as λ increases, the negative impact of output-price risk on L^* strengthens in magnitude.

8.7 Second-Order Conditions and the Bordered Hessian

Let $v = (L, a_C, a_O, x_C, x_O)^\top$ collect the choice variables and recall the single linear constraint

$$g(v) = L - a_C - a_O = 0.$$

The Lagrangian is $\mathcal{L}(v, \mu) = \mathrm{CE}(v) + \mu\, g(v)$. Since g is linear, $\nabla^2_{vv}\mathcal{L} = \nabla^2_{vv}\mathrm{CE}$.

Hessian of the Certainty Equivalent

Write

$$H_{qr} := \frac{\partial^2 \mathrm{CE}}{\partial q\, \partial r}, \qquad q, r \in \{L, a_C, a_O, x_C, x_O\}.$$

Let

$$Y_q := \frac{\partial Y}{\partial q}, \quad Y_{qr} := \frac{\partial^2 Y}{\partial q\, \partial r}, \qquad (a\odot x)_q := \frac{\partial a\odot x}{\partial q}, \quad (a\odot x)_{qr} := \frac{\partial^2 a\odot x}{\partial q\, \partial r},$$

and denote the second derivatives of expected profit by

$$\mathrm{EP}_{qr} := \frac{\partial^2 \mathbb{E}[\pi]}{\partial q\, \partial r}.$$

From the matrix-calculus derivation,

$$\begin{aligned} H_{qr} = \mathrm{EP}_{qr} \\ - \lambda\Big[& Y_{qr}^\top \Sigma_{pp}(m) Y + Y_q^\top \Sigma_{pp}(m) Y_r + (a\odot x)_{qr}^\top \Sigma_{ww} a\odot x + (a\odot x)_q^\top \Sigma_{ww} (a\odot x)_r \\ & - Y_{qr}^\top \Sigma_{pw} a\odot x - Y_q^\top \Sigma_{pw} (a\odot x)_r - Y_r^\top \Sigma_{pw} (a\odot x)_q - Y^\top \Sigma_{pw} (a\odot x)_{qr} \Big]. \end{aligned} \tag{6}$$

This expression applies for every pair $q, r \in \{L, a_C, a_O, x_C, x_O\}$.

Derivatives of $a\odot x$ w.r.t. (L, a_C, a_O, x_C, x_O). Write standard basis vectors $e_C = (1, 0)^\top$, $e_O = (0, 1)^\top$. Since

$$a\odot x = (a_C x_C,\ a_O x_O)^\top,$$

we have

$$\begin{aligned} (a\odot x)_L &= 0, & (a\odot x)_{LL} &= 0, \\ (a\odot x)_{a_C} &= x_C e_C, & (a\odot x)_{a_C a_C} &= 0, \\ (a\odot x)_{a_O} &= x_O e_O, & (a\odot x)_{a_O a_O} &= 0, \\ (a\odot x)_{x_C} &= a_C e_C, & (a\odot x)_{x_C x_C} &= 0, \\ (a\odot x)_{x_O} &= a_O e_O, & (a\odot x)_{x_O x_O} &= 0, \\ (a\odot x)_{a_C x_C} &= e_C, & (a\odot x)_{a_O x_O} &= e_O, \end{aligned}$$

and all other mixed second derivatives $(a\odot x)_{qr}$ are zero.

Derivatives of Y used in H_{qr}. We already defined

$$Y_{x_i} = \frac{\partial Y}{\partial x_i}, \quad Y_{a_i} = b_i, \quad Y_L = y_L.$$

Second derivatives such as $Y_{x_i x_i}$, $Y_{a_i a_i}$, $Y_{a_i x_i}$, Y_{LL}, and Y_{La_i} are obtained by differentiating the expressions in the Environment and Technology section; they are negative along own directions under $0 < \alpha_i < 1$ and $0 < \gamma < 1$ and mild regularity.

Expected-profit curvature terms. Since

$$\mathbb{E}[\pi] = \bar{p}^\top Y - \bar{w}_C a_C x_C - \bar{w}_O a_O x_O - r(m)\, \bar{p}_C a_C,$$

we have, for example:

$$\begin{aligned}
\mathrm{EP}_{LL} &= \bar{p}^\top Y_{LL}, \\
\mathrm{EP}_{a_C a_C} &= \bar{p}^\top Y_{a_C a_C}, \\
\mathrm{EP}_{x_C x_C} &= \bar{p}_C Y_{x_C x_C}, \qquad \mathrm{EP}_{a_C x_C} = \bar{p}_C Y_{a_C x_C} - \bar{w}_C,
\end{aligned}$$

and analogously for a_O, x_O (without the premium term). Plugging these and the $Y_q, (a \odot x)_q$ into (6) yields the explicit H_{qr} for all pairs.

Bordered Hessian

The gradient of the constraint $g(v) = L - a_C - a_O$ is

$$\nabla g(v) = \begin{pmatrix} \partial g/\partial L \\ \partial g/\partial a_C \\ \partial g/\partial a_O \\ \partial g/\partial x_C \\ \partial g/\partial x_O \end{pmatrix} = \begin{pmatrix} 1 \\ -1 \\ -1 \\ 0 \\ 0 \end{pmatrix}.$$

With $v = (L, a_C, a_O, x_C, x_O)$, the bordered Hessian of $\mathcal{L}$ is

$$H_B = \begin{pmatrix}
0 & 1 & -1 & 0 & 0 & 0 \\
1 & H_{LL} & H_{La_C} & H_{La_O} & H_{Lx_C} & H_{Lx_O} \\
-1 & H_{a_C L} & H_{a_C a_C} & H_{a_C a_O} & H_{a_C x_C} & H_{a_C x_O} \\
-1 & H_{a_O L} & H_{a_O a_C} & H_{a_O a_O} & H_{a_O x_C} & H_{a_O x_O} \\
0 & H_{x_C L} & H_{x_C a_C} & H_{x_C a_O} & H_{x_C x_C} & H_{x_C x_O} \\
0 & H_{x_O L} & H_{x_O a_C} & H_{x_O a_O} & H_{x_O x_C} & H_{x_O x_O}
\end{pmatrix},$$

where the entries H_{qr} are given by (6) with the specific derivatives for Y and $a \odot x$ listed above; symmetry of the Hessian implies $H_{qr} = H_{rq}$.

Sufficient Second-Order Conditions and Parameter Assumptions

A sufficient condition for (v^*, μ^*) solving the FOCs to be a strict local maximum of CE subject to $g(v) = 0$ is that the bordered Hessian H_B be negative definite on the tangent space to the constraint. In the single-constraint case, this is ensured, for example, if:

- The certainty equivalent CE(v) is strictly concave in (L, a_C, a_O, x_C, x_O), so that the Hessian matrix $\big(H_{qr}\big)$ is negative definite.
- The constraint $g(v) = L - a_C - a_O$ is linear (which it is), so the usual bordered-Hessian conditions apply directly.

Economically transparent parameter restrictions that deliver (local) strict concavity of CE are:

1. **Diminishing marginal products in inputs and land:**
   - Cobb–Douglas exponents satisfy $0 < \alpha_i < 1$ so that $Y_{x_i x_i} < 0$;
   - Suitability curvature satisfies $0 < \gamma < 1$ and the suitability term $M_i(\psi_i) = \psi_i^{\gamma}$ is concave in ψ_i, ensuring $Y_{a_i a_i} < 0$ and $Y_{LL} < 0$ for economically relevant ranges of (L, a_i).
2. **Premium schedule convexity:** the per-acre premium $r(m)$ is nondecreasing and (weakly) convex, $r'(m) \geq 0$, $r''(m) \geq 0$.
3. **Risk aversion and well-behaved second moments:**
   - $\lambda > 0$, so that the variance penalty $-\frac{\lambda}{2}\text{Var}(\pi)$ is concave in $(Y, a \odot x)$;
   - Covariance matrices $\Sigma_{pp}(m)$, Σ_{ww} are positive semidefinite, and the cross-covariance Σ_{pw} does not generate an "extreme" natural hedge that would overturn the negative own-curvature terms in H_{qr}. Both are empirically supported.
4. **No pathological cross effects:** the cross derivatives Y_{qr} for $q \neq r$ (e.g. $Y_{a_C a_O}$, $Y_{L a_C}$, $Y_{a_i x_i}$) are not so large in magnitude as to dominate the negative diagonal terms in (6). Under standard agronomic responses—where reallocating acreage between crops reduces the marginal product of the other crop and suitability penalties are moderate—this holds naturally.

Under these assumptions, each diagonal element H_{qq} is negative and the off-diagonal elements H_{qr} $(q \neq r)$ are not large enough to overturn negative definiteness. Hence the Hessian $\big(H_{qr}\big)$ is negative definite on $\mathbb{R}^5$, and the bordered Hessian H_B is negative definite on the constraint-consistent subspace. This guarantees that any interior solution to the FOCs with $a_C + a_O = L$ is a unique, economically valid strict local maximum of the farmer's certainty equivalent.