Subsidy Capture and Monopsony Power in U.S. Grain Markets*

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Abstract

We study whether grain elevator buyers capture government subsidy payments intended for farmers through strategic bid suppression. Using a proprietary panel of daily cash bids posted by more than 3,000 grain elevators — a direct, buyer-level measure of farm-gate prices for a physically homogeneous commodity —and a local event-study design based on the Agricultural Risk Coverage-County (ARC-CO) subsidy scheme, we find that elevators lower corn cash bids following the October announcement of subsidy payments. A negative bid response could arise either because additional grain deliveries raise the elevators' marginal costs of grain handling and storage, or because payments reduce farmers' sensitivity to posted bids, allowing elevators with monopsony power to widen their markdowns. We distinguish the two mechanisms by testing whether the bid response varies with local buyer competition. ARC-CO-induced decreases in bids are concentrated in markets with few nearby elevators and are absent in spatially dense markets, a pattern that is difficult to reconcile with a pure increasing marginal costs explanation. A simple incidence-based calibration maps these estimates into a residual supply elasticity facing grain elevators of approximately 22, consistent with a spatially differentiated procurement market in which transportation costs limit farmers' outside options.

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1 Introduction

Government support to agriculture is intended to stabilize farm income and protect producers from adverse price and yield shocks. Whether these payments ultimately remain with farmers, however, depends on the markets through which farmers rent inputs and sell their output. Existing work shows that landowners capture part of agricultural subsidies through higher rents. This paper studies a different margin of subsidy incidence: whether grain buyers capture part of government payments by lowering their cash bids for grain.

We study this question using the Agricultural Risk Coverage-County program (ARC-CO), a U.S. Farm Bill commodity program that makes payments to producers when county-level crop revenue falls below a predetermined benchmark. Farm-level payments are based on a county per-hectare rate multiplied by farm-level historical base acres. Whether payments will be made is announced in October of the year following the eligibility-determining harvest, by which point farmers have harvested a new crop and a new marketing season has begun. We combine the universe of county-level ARC-CO payment determinations with a proprietary panel of daily cash bids posted by more than 3,000 grain elevators. We measure the price offered by an elevator using the basis, defined as its cash bid minus the front-month futures price. Netting out the futures price removes national price movements and isolates local grain-market conditions.

To estimate the incidence of ARC-CO payments, we combine cross-sectional variation in payments exposure with the timing of the October announcement. Because transporting grain is costly, farmers generally choose among a limited number of nearby buyers.[1] We therefore define local catchment areas around each elevator. We focus on elevators serving counties with realized revenue near the ARC-CO payment threshold and estimate whether their bids diverge after October as exposure to ARC-CO payments increases. Intuitively, the design compares markets just below the payment threshold, where farmers receive ARC-CO payments, with otherwise similar markets just above it, where they do not. The approximately one-year delay between the growing-season shock that determines payment eligibility and the October announcement reduces concerns that

1. A USDA Agricultural Marketing Service survey of Central Plains grain farms found that farmers haul grain an average of approximately 15 miles to their first-choice delivery point and 21 miles to their second-choice (Dybing, Vachal, and Rahman 2023).

our estimates reflect contemporaneous agricultural conditions. Our baseline specification exploits continuous variation in payment exposure, with a binary treated-versus-untreated specification yielding similar results. Elevator fixed effects absorb persistent differences across locations, while state-by-year-by-month fixed effects flexibly control for regional supply, demand, transportation, and storage conditions.

We find that cash bids decline after October in markets with greater ARC-CO exposure relative to those with lower exposure. The differential is negligible before October, turns negative and statistically significant following the announcement, and persists throughout the subsequent marketing months. In our preferred specification, a one-unit increase in the elevator-level payment-threshold index reduces the corn basis by approximately 8.2 cents per bushel. At the average exposure among treated elevator-years, this corresponds to approximately 1.2 cents per bushel, or 4.4 percent of the average ARC-CO payment per bushel. The result is robust to measuring exposure using a binary threshold indicator, the share of the elevator's 50-mile buffer area lying in counties that receive a payment, or the area-weighted ARC-CO payment rate. It is also robust to using the elevator's home-county threshold variable rather than its spatially averaged catchment measure and to replacing the basis with the absolute cash bid. Finally, results persist when we control for contemporaneous local weather and harvest conditions to address concerns of persistence in agro-climatic shocks.

To interpret this response, we develop a simple model in which ARC-CO payments can lower bids through two channels: by raising elevators' marginal handling and storage costs or by increasing their monopsony markdowns. The first mechanism arises if an ARC-CO payment induces farmers to front-load grain sales. While this response runs counter to the conventional liquidity channel, that channel may be less salient in our setting than in the subsistence agricultural markets studied in much of the existing literature. U.S. corn producers operate in a well-developed agricultural credit market, where severe liquidity constraints may be less central to farmers' marketing decisions. An ARC-CO payment may instead reduce farmers' willingness to incur the storage, transaction, and monitoring costs required to delay sales. With convex handling and storage costs, the resulting increase in current deliveries raises marginal costs and causes elevators to reduce their bids.

The second channel arises when elevators have market power. ARC-CO payments may reduce farmers' sensitivity to variation in posted bids, for example, because farmers solicit fewer competing offers, pay less attention to small price differences, or become less willing to incur the costs of switching elevators. More generally, search effort—and hence price responsiveness—may decline with income. Strategic elevators can then respond to the resulting decrease in their residual supply elasticity by lowering bids and widening their markdowns.

We use variation in local buyer competition to distinguish between the two mechanisms. As the number of nearby elevators increases, farmers can more readily redirect grain when a buyer increases its markdown, so the monopsony component of the bid response should attenuate. Convex handling and storage costs, by contrast, need not diminish with buyer density. Thus, under the maintained assumption that neither the payment-induced front-loading nor the convexity of elevator costs systematically disappears as local competition increases, a pure convex-cost mechanism predicts that some negative bid response should persist even in dense markets.

The evidence favors the monopsony mechanism. Among elevators with few nearby competitors, ARC-CO exposure reduces the basis by approximately 10 cents per bushel per unit of the payment-threshold index. Among elevators in dense markets, we find no significant response to ARC-CO payments. A pooled triple-difference specification confirms that bid suppression is concentrated in isolated markets and is significantly stronger there than in dense markets. The result holds when we replace buyer density measured from our price data with an independently constructed measure based on grain-handling establishments in the Quarterly Census of Employment and Wages. The absence of a bid response in dense markets is difficult to reconcile with a pure convex-cost explanation and instead indicates that local buyer power is necessary to explain the observed subsidy pass-through.

We use these estimates to benchmark the magnitude of buyer power. The average ARC-CO payment in the benchmark sample is approximately \$0.27 per bushel, while the estimates imply average bid suppression of approximately \$0.012 per bushel. Under a simple incidence-based calibration, this capture rate corresponds to a residual supply elasticity facing elevators of approximately 22, or a buyer-side markdown of about 4.4 percent. This magnitude lies within the range estimated

for other agricultural procurement markets, including corn processing, cattle procurement, and poultry contracting (Jung, Sesmero, and Siebert 2022; Moschini and Smith 2026; MacDonald and Key 2012).

The paper contributes to three strands of literature. First, it identifies a new margin of agricultural subsidy incidence. Existing work has studied incidence primarily through land markets. Because subsidies increase the return to operating an acre of land, they are partly capitalized into rental rates and shared with landowners rather than accruing fully to farmers. Kirwan (2009) estimates that tenant farmers retain roughly three quarters of agricultural subsidies, with the landowner share varying with local rental-market conditions; subsequent field-level and panel evidence confirms that landowners capture a meaningful portion of government support (Hendricks, Janzen, and Dhuyvetter 2012; Kirwan and Roberts 2016). We document a second capture margin operating through output markets. Grain intermediaries capture part of the transfer not by increasing the price at which farmers rent land, but by reducing the price at which farmers sell their crop. The two mechanisms share a common incidence logic: how much of a transfer remains with its intended recipient depends on the competitiveness of the market through which that recipient must transact. Our findings also connect to work outside agriculture showing that firms can capture transfers directed to households through adjustments in wages, rents, insurance premiums, and retail prices (Rothstein 2010; Cabral, Geruso, and Mahoney 2018; Collinson and Ganong 2018).

Second, the paper contributes to the literature on buyer power in agricultural markets. Much of the recent reduced-form evidence comes from developing countries, where thin markets and transportation costs give local intermediaries substantial leverage over farmers. Chatterjee (2023) shows that spatial competition among intermediaries affects farmgate prices in India, Rubens (2023) finds that consolidation among Chinese cigarette manufacturers increased markdowns paid to tobacco farmers, and Domínguez-Iino (2026) studies how market power along South American agricultural supply chains shapes the incidence of policy. The magnitude of buyer power is not uniform across settings: Casaburi and Reed (2022), for example, estimate highly elastic farmer supply and a competitive first stage in Sierra Leonean cocoa markets. Evidence from the United States has relied more heavily on structural models of processor competition and survey evidence on procurement arrangements (Jung, Sesmero, and Siebert 2022; Moschini and Smith 2026; MacDonald and

Key 2012). We contribute reduced-form evidence of buyer power in a large and comparatively well-integrated U.S. commodity market. Rather than exploiting consolidation, processor entry, or changes in downstream demand, we use a transfer that changes farmers' supply behavior without directly changing the downstream value of grain. The dissipation of the response in markets with many nearby buyers provides evidence that local monopsony power shapes the incidence of the transfer.

This result also speaks to the literature on spatial market integration. Transportation costs and infrastructure frictions create persistent barriers to arbitrage across locations (Anderson and Wincoop 2004; Donaldson 2013). This literature typically measures integration indirectly, from the co-movement of aggregated regional price series. Our data allow dispersion to be measured directly, across individual buyers, at the frequency at which bids are actually posted. Spatial frictions are particularly important in agricultural commodity markets, where products must be transported, stored, and aggregated before reaching terminal markets or processors (Fackler and Goodwin 2001; Atkin and Donaldson 2015). We show that spatial segmentation has distributional consequences beyond generating geographic price dispersion. By restricting farmers' outside options, it determines how government transfers are divided between farmers and the intermediaries purchasing their output.

Finally, our findings qualify the conventional view of liquidity and agricultural marketing. A substantial literature, largely focused on subsistence farmers facing severe credit constraints, shows that liquidity-constrained farmers sell near harvest, when prices are seasonally low, and that access to cash or credit allows them to delay sales and obtain higher prices (Stephens and Barrett 2011; Aggarwal, Francis, and Robinson 2018; Burke, Bergquist, and Miguel 2019; Fink, Jack, and Masiye 2020). Our setting differs: U.S. corn producers operate in a comparatively well-developed agricultural credit market, so this liquidity channel may be less dominant. Viewed solely through this channel, however, an ARC-CO payment should still increase the prices farmers receive. We find the opposite. This need not be contradictory because existing work generally studies farmers' timing decisions while taking buyer behavior as given. An ARC-CO payment may both affect farmers' ability to shift sales across time and change the elasticity of supply facing local buyers. Where those buyers possess market power, they can respond to a reduction in supply elasticity

by widening their markdowns. The buyer-side response can therefore offset—and in concentrated markets reverse—the price gains ordinarily associated with relaxing farmers' liquidity constraints.

2 Background and Data

2.1 The ARC-CO program

ARC-CO is a farm income support program established under the Agricultural Act of 2014 and reauthorized under both the 2018 Farm Bill and 2025 One Big Beautiful Bill Act. The program makes annual payments to enrolled farmers when county-level revenues fall below a historical benchmark. It constitutes one of the most significant direct subsidies to farmers. Payments reached $10 billion for corn and $1.5 billion for soybeans over 2014–2016,[2] on par with crop insurance subsidies paid by the U.S. Federal Crop Insurance Program.

We collect annual county-level ARC-CO payments for corn and soybeans from 2014 to 2024 from the USDA Farm Service Agency (FSA). Figure A1 summarizes payment variation over time and space. Panel (A) shows that payment incidence varies sharply across years, from near zero to more than 60 percent of counties. Panel (B) shows the corresponding mean payment rate across enrolled counties. Panels (C) and (D) map average payment rates over 2014–2024 for corn and soybeans.

The remainder of the paper focuses on corn, which accounts for substantially larger ARC-CO payments and is the crop for which our empirical results are strongest. We apply the same data construction and empirical design to soybeans as a secondary replication, with results reported in Appendix C.[3]

Enrollment and coverage. Participation in ARC-CO is voluntary. Under the 2014 Farm Bill, producers made a one-time election that remained in effect through the 2018 crop year. Under the 2018 Farm Bill, elections were initially fixed for the 2019 and 2020 crop years; beginning in 2021, producers could revise their election annually before the spring enrollment deadline.

2. (https://farmdocdaily.illinois.edu/2018/05/comparing-arc-co-and-plc-payment-profiles.html)

3. ARC-CO payments are also available for other crops, including wheat. We do not extend the analysis to wheat because the harvest and marketing calendar varies substantially across winter and spring varieties, complicating the event-study design around the October announcement, and because USDA FSA payment records do not distinguish between wheat classes, making it impossible to assign a single exposure measure to an elevator's supply catchment.

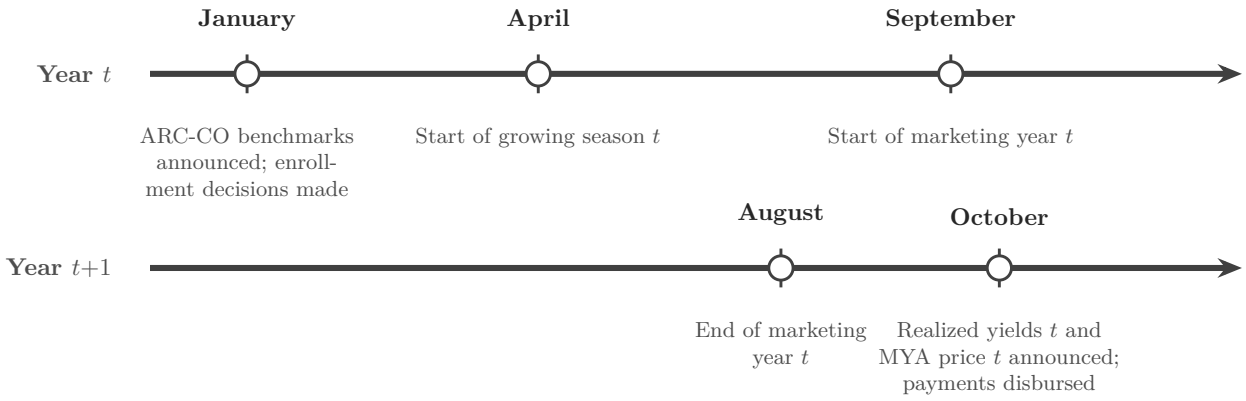


Figure 1. Timeline of the ARC-CO program for crop year t.

ARC-CO coverage is tied to a farm's commodity-specific *base acres*. Base acres are an administrative measure of the acreage historically associated with production of a particular crop on the farm. They remain attached to the farm and need not correspond to the crop or acreage currently planted. ARC-CO payments are therefore based on historical rather than current production.

Payment timing. Producers enroll before planting, around January of crop year t, and the growing season runs approximately from April through August. The marketing year then runs from September of year t through August of year $t+1$ (see Figure A3), during which USDA calculates the national average price received by producers, or the Marketing Year Average (MYA) price. Because this price is not finalized until the marketing year ends, ARC-CO payment rates are announced and payments are generally disbursed in October of year $t+1$ (Figure 1).

Payments. The program guarantees 86 percent of county-level benchmark revenue. All farms enrolled in ARC-CO for the same crop and county therefore receive the same payment rate per base acre.[4] Conditional on payment, the payment rate is

$$\text{PaymentRate}_{ct} = \max\left\{0,\ 0.86\,\bar{P}_t\bar{Y}_{ct} - P_tY_{ct}\right\}. \tag{1}$$

Payments are made on base acres and are capped at the smaller of 10 percent of benchmark revenue times base acres or $125,000 per person.

4. Economically, ARC-CO resembles publicly provided county-revenue index insurance with no producer-paid premium.

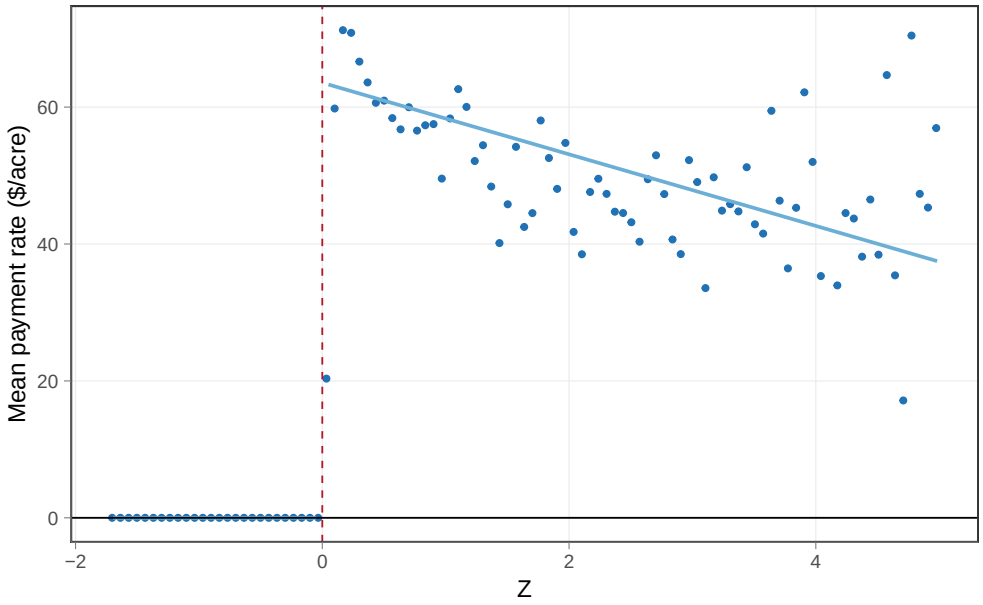


Figure 2. Corn ARC-CO payment rate and county-level payment threshold variable. An observation is a county-year. An ARC-CO payment is triggered when $Z_{ct} = \bar{Y}_c/Y_{ct} - P_t/0.86\bar{P}_t > 0$. Data are from USDA FSA Summary of Business and USDA NASS county yields.

A payment is triggered when realized county revenue falls below this guarantee. Equivalently, farmers in county c receive a payment in year t when

$$Z_{ct} = \underbrace{\frac{\bar{Y}_{ct}}{Y_{ct}}}_{\text{yield ratio}} - \underbrace{\frac{P_t}{0.86\,\bar{P}_t}}_{\text{price ratio}} > 0, \tag{2}$$

where $\bar{Y}_{ct}$ is the county benchmark yield, Y_{ct} is realized county yield, $\bar{P}_t$ is the benchmark price, and P_t is the national marketing-year average price.[5]

Figure 2 plots ARC-CO payment rates against the county-level payment-threshold index. Counties with $Z_{ct} \leq 0$ receive no payment, while payment rates are positive when $Z_{ct} > 0$. Payment rates eventually flatten because the payment cap becomes binding at high values of Z_{ct}.[6]

5. $\bar{Y}_{ct}$ is five-year Olympic average county yield, i.e. it excludes the highest and lowest observations. $\bar{P}_t$ is the crop price Olympic average with a one year lag. For each year, the price entering this average is the maximum of the statutory reference price and 85 percent of the five-year Olympic average market price.

6. Figure A4 illustrates two regimes. In high-price years (panel (A)), when $P_t > 0.86\,\bar{P}_t$, a payment is triggered only when realized county yield falls below benchmark, so Z_{ct} is determined entirely by local weather. In low-price years (panel (B)), the national price decline shifts the price-ratio term below one, so many counties receive payments even without a yield shortfall; cross-sectional variation in Z_{ct} then combines local yield shocks with a national price shock common to all counties. In our preferred specification, year fixed effects (or state-by-year-by-month fixed effects) absorb the national price component, and identification comes from within-year cross-sectional yield variation in both regimes. We show robustness to restricting the sample to high-price years only in Appendix A.

2.2 The U.S. Corn Market

Corn farmers in the Midwest sell the majority of their output through local grain elevators, which aggregate grain and forward it to terminal markets, domestic processors, and exporters. Transportation costs constrain farmer choice: a USDA Agricultural Marketing Service survey of Central Plains grain farms found that farmers haul their crop an average of approximately 15 miles to their first-choice delivery point and 21 miles to their second-choice (Dybing, Vachal, and Rahman 2023).[7] This limited travel radius restricts each farmer's effective buyer set to a handful of nearby facilities. The industry has simultaneously undergone substantial consolidation: the number of commercial off-farm grain storage facilities in the United States declined from 10,000 in 1999 to approximately 8,000 by 2022, as independent local elevators were absorbed by regional cooperatives and investor-owned firms (USDA National Agricultural Statistics Service 2000, 2023). Many farmers therefore face limited local competition, particularly outside the core of the Corn Belt. Grain is sold primarily through spot cash sales and short-horizon forward contracts set at or near the time of harvest; multi-year price or volume agreements remain uncommon. These features—high transport costs, industry consolidation, and spot-market trading—restrict farmers' outside options and give local elevators bargaining power over the cash prices they offer.

DTN price data. Our primary outcome data come from the Data Transmission Network (DTN), a commodity information service that collects and disseminates daily cash price quotes from grain elevators, river terminals, and processing plants across the contiguous United States. The main outcome of interest is the *basis*: the difference between the cash bid price and the front-month futures price on the Chicago Board of Trade (CBOT). A negative basis indicates that the elevator is offering a price below the futures benchmark. DTN covers approximately 3,100 corn-quoting locations over our sample period (crop years 2014–2023). We aggregate daily quotes to the elevator-month level, yielding an elevator-month-year panel. The panel is largely balanced: 2,308 of 3,082 elevators report prices in every year of the sample, and no elevator exits once it enters, consistent with DTN gradually expanding its coverage over time. Figure 3 shows the spatial distribution of the elevators in our data. We focus the analysis on twelve Midwest states—Iowa, Illinois, Indiana, Ohio, Missouri, Nebraska, Kansas, Minnesota, South Dakota, North Dakota, Wisconsin, and Michigan—

7. The survey covered Illinois, Indiana, Iowa, Kansas, and Nebraska for the 2019 crop.

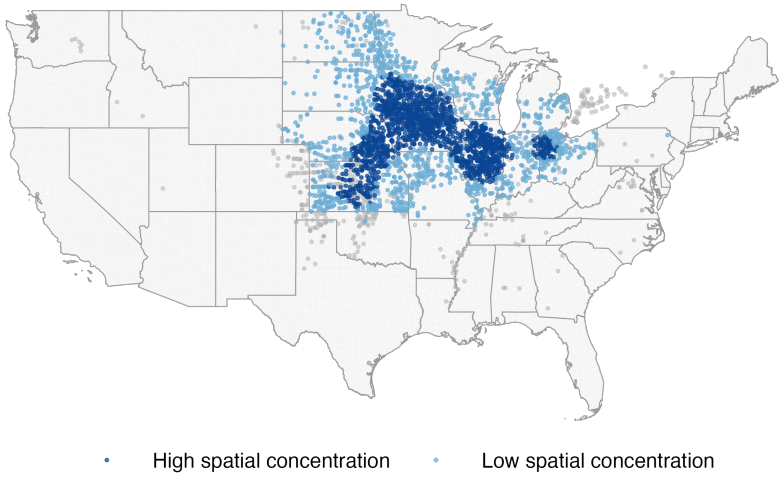
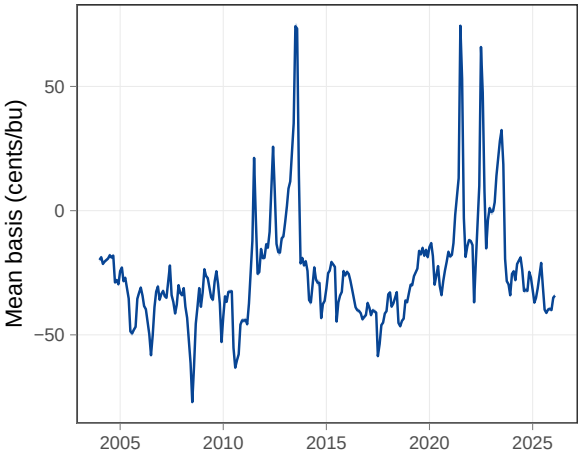


Figure 3. Elevator market concentration. Dark blue elevators have many local competitors (above the 66th percentile of the within-Midwest distribution of DTN-reporting elevator counts within 50 miles); light blue elevators have few local competitors (at or below the 66th percentile). Grey elevators are outside the Midwest sample. Data from DTN.

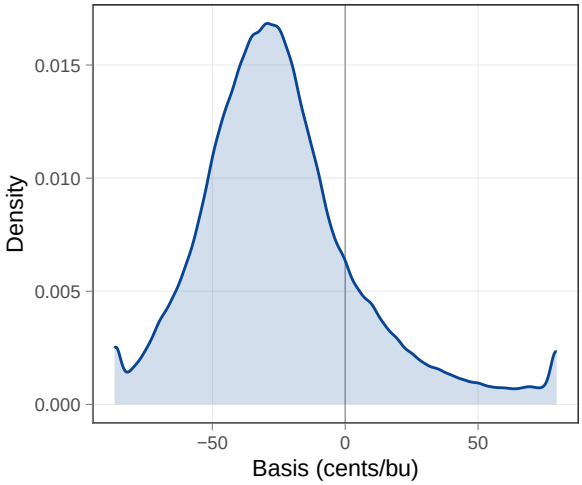
where ARC-CO exposure and DTN coverage are most complete. Light grey elevators in Figure 3 are excluded for this reason.

Figure 4 characterizes variation in corn basis prices in the DTN data. Panel (A) shows substantial variation over time in the mean basis across elevators, reflecting common changes in international, national and regional grain-market conditions. Panel (B) shows that, beyond these aggregate movements, basis prices also vary considerably across elevators. Panel (C) documents a clear spatial gradient: the mean absolute difference between two elevators' basis prices increases monotonically with the distance between them, from approximately 7 cents per bushel among elevators within 25 miles to 14–18 cents among elevators 100–200 miles apart. These patterns indicate that elevator bids respond to common market-wide shocks but remain locally differentiated, consistent with transportation costs limiting spatial arbitrage.

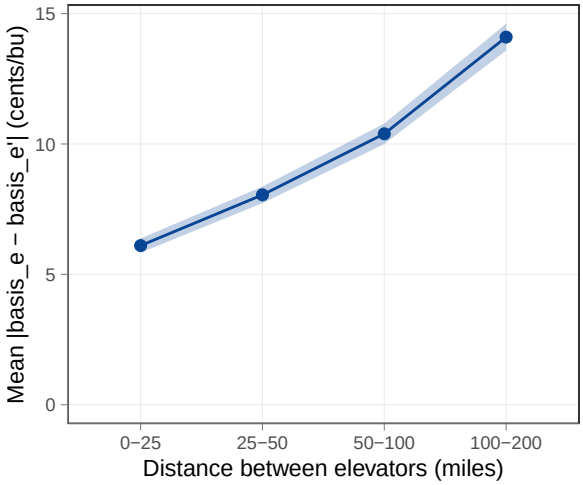
Market concentration. We use the DTN data to measure the competitive environment of each elevator. An elevator is in a high (low) spatial concentration if the number of other DTN-reporting elevators within a 50-mile radius falls above (below) the 66th percentile of the within-Midwest



(A) Mean basis over time



(B) All-elevator basis distribution



(C) Pairwise basis difference by distance (normalised)

Figure 4. Variation in corn basis. Panel (A) plots the monthly cross-elevator mean implied basis (cents/bu) with a ±1.96 standard-error ribbon. Panel (B) shows the cross-sectional distribution of the implied basis across all elevator-months. Panel (C) plots the mean absolute basis difference between elevator pairs against the distance separating them (miles), normalised by the mean cash price for that crop-month; ribbons show ±1.96 SE computed across months. Pairwise basis differences rise monotonically with distance, consistent with spatially segmented markets.

distribution.[8] Figure 3 shows that isolated elevators are located in the periphery of the Corn Belt and in the Great Plains, while the Corn Belt features denser networks of competing buyers. Because DTN only reports prices for a sample of elevators, we test the robustness of our results to using an alternative measure of concentration.

3 ARC-CO Payments and Elevator Bids

3.1 Empirical strategy

We estimate how the relationship between elevator bids and ARC-CO payment conditions changes following the October announcement. Counties with $Z_{ct} > 0$ receive an ARC-CO payment, whereas counties with $Z_{ct} \leq 0$ do not. We use the signed threshold variable Z_{ct} as our preferred measure because it preserves distance from the policy threshold on both sides and, for counties above the threshold, captures the severity of the revenue shortfall determining the uncapped payment amount. It therefore contains more information about local payment conditions than a binary eligibility indicator. To map these county-level conditions to individual elevators, we construct a monthly elevator-level panel and aggregate Z_{ct} over each elevator's geographic supply catchment:

$$\tilde{Z}_{et} = \sum_{c} w_{ec} Z_{ct},$$

where the weights w_{ec} are proportional to the share of elevator e's 50-mile buffer lying in county c. This spatial averaging converts county-level payment conditions into a continuous catchment-level measure. For elevators near county borders, $\tilde{Z}_{et}$ can be close to zero even when the catchment contains counties with both positive and negative values of Z_{ct} (see Figure A5 in the appendix). We therefore interpret $\tilde{Z}_{et}$ as a summary of payment-threshold conditions among an elevator's potential suppliers. Elevator fixed effects absorb any time-invariant correlation between catchment composition and local market structure, while measurement error in $\tilde{Z}_{et}$ may attenuate the estimated relationship between threshold exposure and bids.

8. This count is computed once from the full cross-section of all elevators ever observed in DTN pre-2014, yielding a time-invariant measure of local market structure that reflects the physical geography of grain infrastructure rather than year-to-year variation in DTN coverage. Elevators entering in 2014 or after do not have an associated market concentration.

Because averaging signed values can offset triggered and non-triggered counties within a catchment, and because $\tilde{Z}_{et}$ is not measured in dollars, we also assess robustness using a binary indicator for whether $\tilde{Z}_{et} > 0$, the share of the catchment lying in triggered counties, and the area-weighted actual ARC-CO payment rate.

Threshold-based event-study specification. We estimate an event-study specification that interacts the payment threshold variable with event-time dummies relative to the October announcement:

$$\text{Basis}_{emt} = \sum_{\tau \neq -1} \beta_\tau \, \mathbf{1}[\tau_{mt} = \tau] \cdot \tilde{Z}_{et} + \alpha_e + \alpha_{s(e),t,m} + \mathbf{X}'_{emt}\gamma + \varepsilon_{emt}, \tag{3}$$

where e indexes elevators, m months, and t crop years; τ_{mt} is the number of months relative to October of crop year t; α_e are elevator fixed effects; $\alpha_{s(e),t,m}$ are state-by-year-by-month fixed effects, absorbing aggregate and state-level commodity price movements; and $\mathbf{X}_{emt}$ includes cumulative growing-season precipitation, mean temperature, extreme degree days, and log corn harvested acres. September ($\tau = -1$) is the omitted reference period; the event window spans $\tau \in \{-4, \ldots, 6\}$. The coefficients β_τ measure how the relationship between basis prices and catchment-level payment-threshold exposure changes in month τ relative to September. Because the specification is linear in $\tilde{Z}_{et}$, it normalizes the differential event-time response to zero at $\tilde{Z}_{et} = 0$ and identifies the slope of the response with respect to threshold exposure. The reduced-form tables collapse the event study to a single post-period interaction with Post-Oct$_{mt} \equiv \mathbf{1}[\tau_{mt} \geq 0]$.

Identification. Our preferred sample includes all Midwest crop years within a symmetric local window around the payment threshold.[9] Identification comes from comparing the month-specific effects of elevators' catchment-level treatment exposures ($\tilde{Z}_{et}$), across markets with low treatment exposures that do not receive any ARC-CO payments, and markets with high treatment exposures that hence do receive ARC-CO payments. Our design focuses on the differential effect of having a higher chance of receiving an ARC-CO payment, before and after ARC-CO payments are realized. The causal interpretation of the $\{\beta_\tau\}_{\tau \geq 0}$ coefficients relies on the assumption that, for counties

9. We restrict to observations satisfying $|\tilde{Z}_{et}| \leq 0.2$. Table B4 in the appendix confirms robustness across local windows from 0.10 to 0.25.

whose treatment variable lies close to the threshold at which payments are realized, conditional variation in the intensity of ARC-CO exposure is not correlated with any underlying market-specific trends that can also impact the evolution of local cash bids. Our event study design provides a test for this assumption in the form of the $\{\beta_\tau\}_{\tau<0}$ coefficients, which should not be statistically different from zero.

Given our controls, the identifying assumption is more specifically that conditional on elevator fixed effects, state-by-year-by-month fixed effects, weather, and harvested acreage, markets with different threshold exposure would not have experienced systematically different changes in basis prices after October in the absence of ARC-CO payment announcements. The national price term $P_t/(0.86\bar{P}_t)$ is common to all counties in a given year and is therefore absorbed; conditional on these fixed effects, cross-sectional variation in $\tilde{Z}_{et}$ reflects local yield deviations. In high-price years ($P_t > 0.86\,\bar{P}_t$), the threshold variable is driven purely by local yield shortfalls. We show robustness to restricting the sample to those years only in Appendix A.

The one-year lag between the yield shock and the payment announcement provides an additional identification advantage (Figure 1). Any contemporaneous supply effect of the yield shortfall on basis has largely dissipated: a low yield in year t tightens local supply and pushes cash prices up during year t's marketing season, but those effects occur well before October $t+1$. Because grain elevators and farmers rarely hold grain for more than a season, we should not expect lagged variations in yields, for counties sitting near the payment threshold, to affect the $t+1$ marketing season, especially in a way that coincides with the October announcements. The timing of the event-study response therefore helps distinguish the payment announcement from the direct consequences of the underlying yield shortfall.

3.2 Evidence of Bid Suppression

Figure 5 plots the event-study coefficients $\hat{\beta}_\tau$ from equation (3) for corn across four progressively richer specifications. Specification (1) includes elevator and year-by-month fixed effects: elevator fixed effects remove permanent cross-sectional differences in basis levels (location, infrastructure, firm size), while year-by-month fixed effects absorb the national futures-cash spread common to all elevators in a given month. Specification (2) adds state-by-month fixed effects, which further remove

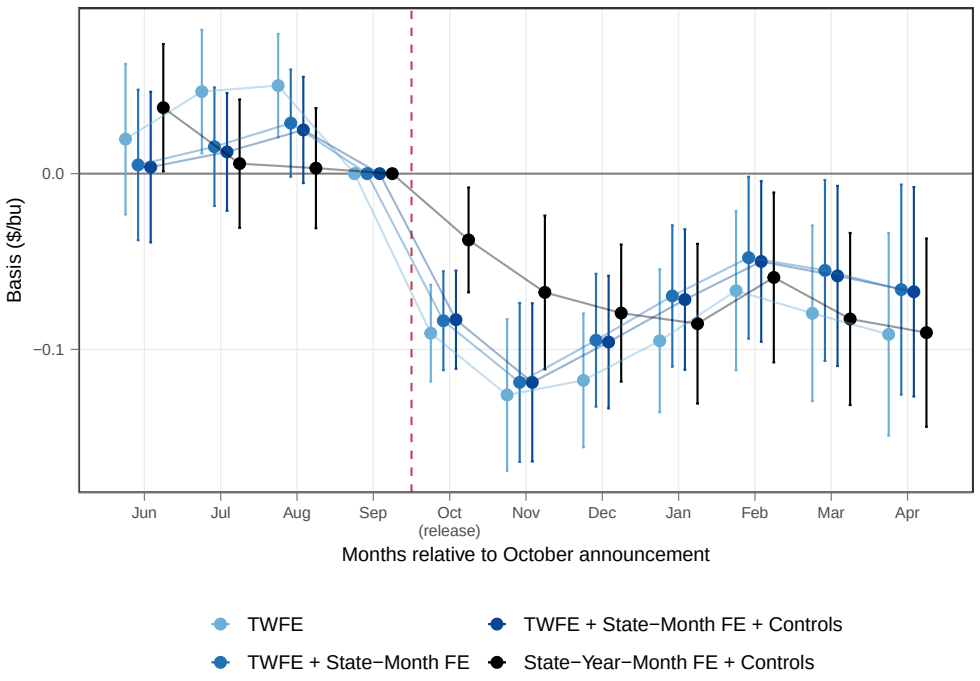


Figure 5. Event study across four specifications, corn. Each line shows the event-study estimate from a progressively richer specification: (1) elevator and year-by-month FE only; (2) adding state-by-month FE; (3) adding weather and acreage controls; (4) preferred specification with state-by-year-by-month FE. The x-axis is months relative to October of the crop year ($\tau = 0$). September ($\tau = -1$) is the reference period. The outcome is the basis (cash price minus CBOT front-month corn futures, dollars per bushel). The exposure variable is the continuous catchment-level payment-threshold measure $\tilde{Z}_{et}$. The sample is restricted to $|\tilde{Z}_{et}| \leq 0.2$. Shaded bands are 95% confidence intervals clustered at the county level.

seasonal basis patterns that vary by state—for instance, differential harvest timing or regional storage capacity constraints that shift basis at the state level each month. Specification (3) adds growing-season weather controls—cumulative precipitation, mean temperature, and extreme degree days above 29°C—and log corn harvested acres. These are measured during the growing season of year t (spring through summer), before the October announcement. Their purpose is to break the correlation between yield shortfalls and basis levels that is unrelated to the payment: a drought year triggers ARC-CO payments *and* tightens local cash supply, pushing basis up independently of any behavioral response by elevators. Controlling for weather isolates the payment announcement effect from this supply channel. Specification (4), our preferred specification, replaces state-by-month fixed effects with state-by-year-by-month fixed effects, controlling for any state-level factor that varies at the monthly frequency within a given crop year—including regional demand or supply shocks, local processor capacity utilization, and time-varying transportation costs.

Pre-trend coefficients ($\tau \in \{-4, -3, -2\}$) are small and indistinguishable from zero across all specifications, supporting the parallel-trends assumption. The effect emerges sharply at $\tau = 0$—the month of the October announcement—and accumulates over the following two to three months, consistent with basis suppression during the period when most of the harvest is marketed (Figure A3). It remains negative through the end of the marketing season. Point estimates are stable across all four specifications, indicating that the result is not driven by omitted seasonal patterns, weather shocks, or regional demand conditions.

Table 1 collapses the event study into a single post-period interaction. Column (1) includes elevator and year-by-month fixed effects; column (2) adds state-by-month fixed effects; column (3) adds weather controls and log corn acreage; column (4) further adds state-by-year-by-month fixed effects and is our preferred specification. Across all columns, the post-announcement interaction is negative and significant. In the preferred specification, a one-unit increase in the payment threshold variable reduces basis by approximately 8.2 cents per bushel following the October announcement.[10]

Robustness. We assess robustness along four dimensions; results are collected in Appendix B. First, we examine whether the result depends on using the signed mean threshold variable, $\tilde{Z}_{et}$, as the measure of catchment exposure. The three alternatives address distinct concerns about the baseline measure. A binary indicator, $\mathbf{1}[\tilde{Z}_{et} > 0]$, discards cardinal variation in $\tilde{Z}_{et}$ and tests whether the result survives a coarse, nonlinear classification of catchments according to whether their average threshold measure is positive. The share of the elevator's 50-mile catchment lying in counties that trigger a payment measures the spatial extent of local eligibility without allowing positive and negative county-level values of Z_{ct} to offset one another. Finally, the area-weighted ARC-CO payment rate measures realized transfer intensity directly in dollars per base acre and incorporates both the nonlinear payment formula and the payment cap. All three specifications retain the baseline estimation sample and change only the definition of ARC-CO exposure. Across all measures, the post-announcement coefficient remains negative and statistically significant (Appendix Tables B1, B2, and B3). Together, these results show that the baseline finding is not driven by the linear mean-Z parameterization, the offsetting of triggered and non-triggered counties within

10. Spatial averaging may introduce measurement error in $\tilde{Z}_{et}$ and attenuate the estimated response, so we interpret the exact magnitude cautiously.

Table 1. ARC-CO payment-threshold exposure and corn basis

Dependent Variable:	Corn Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct × $\tilde{Z}$	-0.120***	-0.086***	-0.085***	-0.082***
	(0.018)	(0.019)	(0.019)	(0.018)
Observations	108,803	108,803	108,803	108,803
R^2	0.851	0.900	0.903	0.924
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Dependent variable is the basis (cash corn price minus CBOT front-month futures, dollars per bushel). The main regressor is the continuous catchment-level payment-threshold index $\tilde{Z}_{et}$ interacted with Post-Oct. Post-Oct equals one for October through the following April ($\tau \geq 0$). Sample restricted to $|\tilde{Z}_{et}| \leq 0.2$; observations are at the elevator-month-year level. Columns (1)–(3) progressively add weather controls, log corn acreage, and state-by-month fixed effects; column (4) is the preferred specification with state-by-year-by-month fixed effects. Weather controls: cumulative growing-season precipitation, mean temperature, and extreme degree days (above 29°C). Standard errors are clustered at the county level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

a catchment, or the use of a threshold-based rather than dollar-denominated exposure measure.

Second, we vary the width of the local window around the payment threshold from 0.10 to 0.25 (Appendix Table B4). Narrower windows compare markets with more similar threshold conditions but reduce precision, whereas wider windows increase precision while including observations farther from the threshold. The estimates remain stable across the reported windows.

Third, our baseline measure averages county-level payment-threshold conditions within an assumed 50-mile supply catchment. If the true geographic market differs from this radius, the resulting measurement error may attenuate the estimated response. We therefore replicate the analysis using only the threshold variable of the elevator's home county (Appendix Table B5). This measure is less dependent on assumptions about catchment boundaries but is likely noisier because elevators can procure grain across county borders. The estimate remains negative, although it is smaller and less precise in the preferred specification.

Fourth, because the basis is defined as the cash bid minus the front-month futures price, we verify that the result reflects changes in elevator cash bids rather than movements in futures prices. Replacing the basis with the log cash price yields a negative and statistically significant coefficient of -0.020 in the preferred specification (Appendix Table B6). At the sample mean cash price of approximately \$4.50 per bushel, this corresponds to a decline of about 9 cents per bushel per unit of $\tilde{Z}_{et}$, close to the magnitude of the baseline basis estimate.

Soybeans. Appendix C replicates the analysis for soybeans (Table C1 and Figure C1). The estimated effect is negative and significant in specifications (1)–(3), but attenuates once state-by-year-by-month fixed effects are included. The between-within decomposition in Appendix Table C2 clarifies why. We decompose Post-Oct $\times$ $\tilde{Z}$ into its state-by-year-by-month cell mean (the between-cell component) and the elevator-level deviation from that mean (the within-cell component). For soybeans, identification comes almost entirely from variation across cells ($\hat{\beta}_B = -0.35$, $\hat{\beta}_W \approx 0$), which is absorbed by the state-by-year-by-month fixed effects. For corn, the pattern is reversed: the within-cell component drives the estimate ($\hat{\beta}_B \approx 0$, $\hat{\beta}_W = -0.18$), so the effect survives the inclusion of these fixed effects. The attenuation for soybeans is not attributable to weaker local price segmentation: Appendix Figure C2 documents spatial price patterns comparable to those for corn. Because the soybean estimate is identified primarily from variation across state-by-year-by-month cells, it may also capture state-level consequences of the yield shocks underlying ARC-CO exposure—such as differences in grain availability, inventories, crop quality, storage utilization, or weather-related transportation conditions—rather than the payment announcement alone. We therefore treat the within-state corn results as primary.

4 Interpreting Bid Suppression

The preceding section establishes that ARC-CO payment exposure lowers the bids posted by grain elevators. A negative bid response, however, is not sufficient to establish monopsony. In this section, we develop a simple model that provides two possible explanations. The first operates through convex handling and storage costs and can arise in competitive grain markets. The second operates through an increase in the monopsony markdown. We then derive a test that distinguishes

the mechanisms using local buyer competition.

4.1 A Simple Model of Elevator Pricing

Let $\overline{Q}$ denote the grain available in an elevator's catchment, and let $s(p^b, n, W) \in [0, 1]$ denote the share of that grain purchased by the elevator during the relevant portion of the marketing season. Here, p^b is the elevator's posted cash bid, n is the number of nearby competing elevators, and W indexes farmer wealth. We assume that:

$$\frac{\partial s}{\partial p^b} > 0, \qquad \frac{\partial s}{\partial n} < 0, \qquad \frac{\partial^2 s}{\partial p^b \partial n} > 0. \tag{4}$$

Respectively, these assumptions imply that a higher bid allows the elevator to increase its market share, that an increase in the number of local competitors reduces the market share of a given elevator, and that an increase in the number of local elevators makes the elevator's market share more responsive to its own bid.

The elevator chooses p^b to maximize profits:

$$\pi = \left(p^d - p^b\right) s(p^b, n, W)\overline{Q} - c\left(s(p^b, n, W)\overline{Q}\right), \tag{5}$$

where p^d is the downstream price and $c(\cdot)$ captures handling and storage costs. We assume that profit is concave, and that second order conditions are met. The first-order condition writes as follows:

$$\left[p^d - p^b - c'\left(s\overline{Q}\right)\right] \frac{\partial s}{\partial p^b} = s. \tag{6}$$

Rearranging gives the optimal bid:

$$p^b = p^d - c'\left(s\overline{Q}\right) - \frac{s}{\partial s / \partial p^b}. \tag{7}$$

The optimal bid is therefore the marginal revenue product of grain, $p^d - c'(s\overline{Q})$, minus a monopsony markdown $s/(\partial s/\partial p^b)$. We show next how an ARC-CO payment can lower bids by changing either of these components of the optimal bid.

4.2 Two Mechanisms

Convex handling and storage costs. First consider a competitive market, in which the monopsony markdown converges to zero and elevators bid the marginal revenue product of grain:

$$p^b = p^d - c'\left(s\overline{Q}\right). \tag{8}$$

Because the quantity purchased depends on both the bid and farmer wealth, implicitly differentiating equation (8) with respect to W gives

$$\frac{dp^b}{dW} = -\frac{c''\left(s\overline{Q}\right)\overline{Q}\dfrac{\partial s}{\partial W}}{1 + c''\left(s\overline{Q}\right)\overline{Q}\dfrac{\partial s}{\partial p^b}}. \tag{9}$$

If costs are convex and ARC-CO payments increase the quantity of grain delivered during the current marketing period, bids decline even in a competitive market. This mechanism requires for ARC-CO payments to lead farmers to front-load their grain sales. Such a response could arise if the transfer reduces farmers' willingness to incur the storage, price-monitoring, and transaction costs required to delay sales—for example, because the payment helps them reach a revenue target and lowers the marginal value of continued intertemporal price arbitrage. The mechanism therefore requires a farmer response opposite to the conventional liquidity channel through which transfers allow farmers to delay sales.

Monopsony markdowns. The second mechanism operates through farmers' responsiveness to posted bids. To isolate the monopsony channel, we assume for an instant that marginal handling costs are locally constant and that payments do not directly shift the quantity supplied at a given bid.[11]. Instead, assume that ARC-CO payments reduce the responsiveness of the elevator's market share to its own bid:

$$c''\left(s\overline{Q}\right) = 0, \qquad \frac{\partial s}{\partial W} = 0, \qquad \frac{\partial^2 s}{\partial p^b \partial W} < 0. \tag{10}$$

11. This allows us to obtain an expression where bid decreases stem only from monopsony power. An expression that combines both channels can be obtained with similar derivations.

Following an increase in farmer wealth, deliveries to an elevator become less sensitive to variation in its cash bid. This effect might for example arise from costly search.[12] Farmers receiving a payment may solicit fewer competing offers, pay less attention to small differences across bids, or become less willing to incur the transportation and transaction costs of switching elevators. The sign in equation (10) is not specific to search; the model requires only that additional wealth softens farmers' responsiveness to differences across bids.

To characterize the bid response, define the elevator's first-order condition as

$$F(p^b, W) = \left[p^d - p^b - c'\left(s\overline{Q}\right)\right]\frac{\partial s}{\partial p^b} - s = 0. \tag{11}$$

The implicit function theorem gives

$$\frac{dp^b}{dW} = -\frac{\partial F/\partial W}{\partial F/\partial p^b}. \tag{12}$$

The second-order condition implies that $\partial F/\partial p^b < 0$. Under the assumptions in equation (10), we get

$$\frac{\partial F}{\partial W} = \left[p^d - p^b - c'\left(s\overline{Q}\right)\right]\frac{\partial^2 s}{\partial p^b \partial W} < 0, \tag{13}$$

where the inequality follows because the elevator charges a positive markdown and $\partial^2 s/(\partial p^b \partial W) < 0$. It follows that $dp^b/dW < 0$: the decline in farmers' bid responsiveness lowers the residual supply elasticity facing the elevator, allowing a buyer with market power to widen its markdown and capture part of the transfer. This mechanism disappears under perfect competition because a buyer facing perfectly elastic residual supply cannot profitably lower its bid, this corresponds to the previously stated assumption: $\frac{\partial^2 s}{\partial p^b \partial n} > 0$.

4.3 A Mechanism Test Using Local Spatial Buyer Density

The two mechanisms differ in how the bid response varies with local competition. As the number of nearby elevators increases, farmers can more readily redirect grain in response to an increase in

12. Lentz and Tranaes (2005) provides one micro-foundation for this behavior, by showing that an agent's search effort is monotonically decreasing in wealth when that agent's utility is separable in consumption and effort.

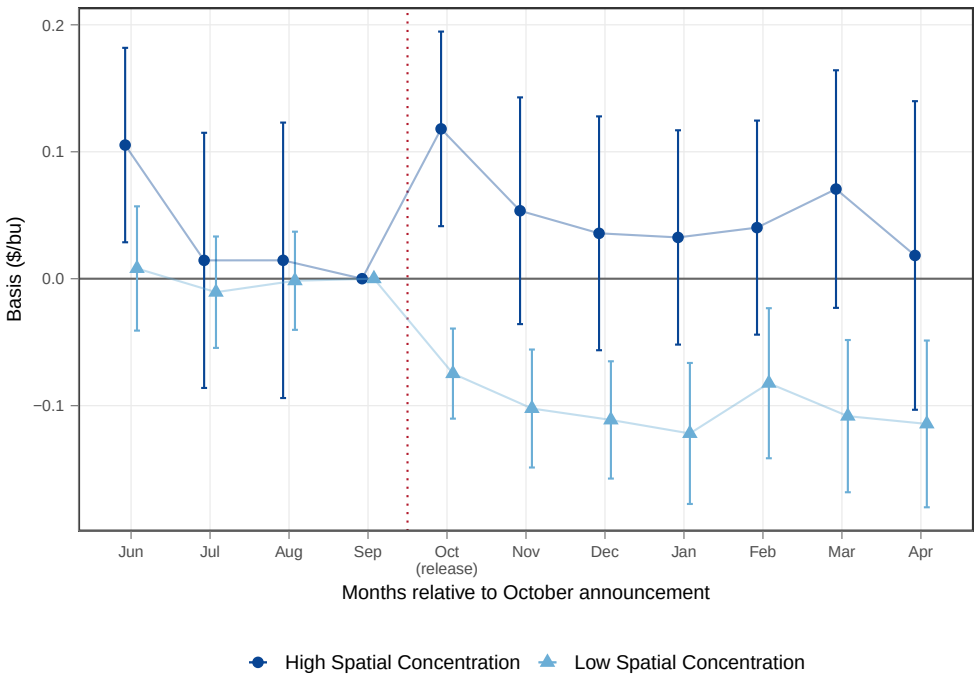


Figure 6. Heterogeneity event study by local buyer competition, corn. Event-study estimates from the preferred specification, estimated separately for elevators with few and many nearby competitors. The sample is restricted to Midwest states and observations satisfying $|\tilde{Z}_{et}| < 0.2$. Local buyer competition is measured using the number of DTN-reporting elevators within a 50-mile radius and is only defined for elevators present in the data pre-2014. Elevators entering in 2014 or after do not have an associated market concentration and drop from the sample (see Section 2.2). "Low spatial conc." elevators fall at or below the 66th percentile of this distribution and therefore have few nearby competitors; "High spatial conc." elevators exceed this threshold and have many nearby competitors. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Shaded bands are 95% confidence intervals clustered at the county level.

markdown. The residual supply elasticity facing an individual elevator therefore rises, the monopsony markdown converges toward zero, and the monopsony component of the ARC-CO response should disappear. Convex handling and storage costs, by contrast, need not disappear with buyer density. This comparison requires a maintained restriction. We require that neither the payment-induced front-loading of grain sales nor the convexity of handling costs systematically disappears as the number of nearby buyers increases. Under this restriction, a pure convex-cost mechanism predicts that some negative bid response should remain in markets with many nearby buyers, whereas the monopsony component should disappear as local competition increases.

We test this prediction using the spatial concentration measure defined in Section 2.2. Elevators with few nearby competitors operate in relatively isolated markets in which farmers have limited

outside options, whereas elevators with many nearby competitors operate in denser markets. The monopsony mechanism therefore predicts that basis suppression should be concentrated among elevators with few nearby competitors.

Figure 6 plots the monthly response separately for elevators in isolated and dense markets. Pre-announcement coefficients converge to zero for both groups by September. After the announcement, however, the groups diverge. Elevators with few nearby competitors suppress basis immediately, with the effect deepening through November–January to roughly 10–13 cents per bushel before partially recovering but remaining negative through April. Among elevators with many nearby competitors, the October coefficient is positive and significant, but it does not persist; subsequent post-announcement estimates are small and statistically indistinguishable from zero.

Table 2 formalizes the comparison. Among elevators with few nearby competitors, the post-announcement coefficient in column (3) is -0.098 (s.e. 0.021), or 9.8 cents per bushel per unit of the payment-threshold index. Among elevators with many nearby competitors, the estimate in column (2) is positive and statistically insignificant. Column (4) pools both groups. The coefficient on Post-Oct $\times \tilde{Z}$ is -0.030 and statistically insignificant, indicating no sustained ARC-CO-related bid suppression among elevators with many nearby competitors. The triple interaction, Post-Oct $\times \tilde{Z} \times$ Low spatial concentration, is -0.062 and significant at the 1 percent level, confirming that the response is significantly more negative in isolated markets.

Under the maintained restriction discussed above, the disappearance of the response in markets with many nearby buyers is difficult to reconcile with a pure convex-cost mechanism. Instead, the concentration gradient indicates that local buyer power is necessary to explain the observed bid suppression.

5 Benchmarking Monopsony Power in Grain Markets

The competition test indicates that local buyer power is necessary to explain the observed bid suppression. We now use the magnitude of the response to provide an order-of-magnitude benchmark for the residual supply elasticity facing grain elevators.

Table 2. ARC-CO payment effects by local buyer competition

Dependent Variable:	Corn Basis			
	Full sample	High spatial conc.	Low spatial conc.	Interaction test
Model:	(1)	(2)	(3)	(4)
Post-Oct × $\tilde{Z}$	-0.075***	0.018	-0.098***	-0.030
	(0.019)	(0.030)	(0.021)	(0.023)
Post-Oct × Low spatial conc.				-0.009***
				(0.003)
Post-Oct × $\tilde{Z}$ × Low spatial conc.				-0.062***
				(0.022)
Observations	85,311	28,794	56,517	85,311
R^2	0.925	0.952	0.920	0.925
Elevator FE	Yes	Yes	Yes	Yes
State-Year-Month FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Acreage control	Yes	Yes	Yes	Yes

Notes: The dependent variable is the corn basis. The sample is restricted to Midwest states and observations satisfying $|\tilde{Z}_{et}| \leq 0.2$. Local buyer competition is measured using the number of DTN-reporting elevators within a 50-mile radius and is only defined for elevators present in the data pre-2014. Elevators entering in 2014 or after do not have an associated market concentration and drop from the sample (see Section 2.2). "Low spatial conc." elevators fall at or below the 66th percentile of this distribution and therefore have few nearby competitors; "High spatial conc." elevators exceed this threshold and have many nearby competitors. Column (4) pools both groups and includes Post-Oct × $\tilde{Z}$ × Low spatial conc. and Post-Oct × Low spatial conc. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Incidence of the payment. We first calculate the share of the ARC-CO payment associated with lower elevator bids. We apply the preferred estimate to triggered elevator-years, excluding the top 5 percent of the $\tilde{Z}$ distribution to avoid extreme drought observations for which the payment cap binds and extrapolation far from the threshold is least reliable (see Figure A6). The mean payment-threshold index in this sample is $\bar{\tilde{Z}} = 0.144$. The average ARC-CO payment-per-bushel equivalent is \$0.27,[13] while the preferred estimate from column (4) of Table 1 implies average bid suppression of

$$|\Delta p^b| = 0.082 \times 0.144 \approx \$0.012/\text{bu}. \tag{14}$$

13. We construct the payment-per-bushel equivalent as the ARC-CO payment rate in dollars per base acre divided by realized corn yield in bushels per acre. Because payments are made on historical base acres rather than current production, this is a normalization rather than a subsidy literally paid on each bushel sold.

The corresponding reduced-form capture rate is therefore

$$\widehat{\kappa} = \frac{|\Delta p^b|}{\text{Payment per bushel equivalent}} = \frac{0.012}{0.27} \approx 0.044. \tag{15}$$

Thus, the estimates imply that lower bids capture approximately 4.4 percent of the average ARC-CO payment-per-bushel equivalent. The reduced-form relationship is also negative and statistically significant when exposure is measured using the area-weighted ARC-CO payment rate (Appendix Table B3). This confirms that bids decline more in catchments receiving larger realized transfers.[14]

Residual supply elasticity. The data identify the reduced-form capture rate in equation (15), rather than the residual supply elasticity directly. We use the model in Section 4 to map this capture rate into an implied residual supply elasticity. As derived in Appendix D, under locally iso-elastic residual supply and two benchmark normalizations, the model implies

$$\varepsilon = \frac{1}{\kappa} - 1. \tag{16}$$

At our estimated capture rate of 4.4 percent, this mapping implies a residual supply elasticity of approximately 22.[15] This elasticity lies within the range of estimates from other agricultural procurement markets. Jung, Sesmero, and Siebert (2022) estimate an inverse residual supply elasticity of 0.097 for corn processors in Indiana, corresponding to an elasticity of approximately 10 and a buyer-side markdown of 9.7 percent. Moschini and Smith (2026) estimate an average markdown of 2.6 percent in U.S. fed-cattle procurement. Consistent with the importance of local buyer competition, MacDonald and Key (2012) find that broiler growers facing a single integrator receive approximately 7–8 percent less compensation than growers facing four or more integrators.

Four considerations qualify this calibration. First, the mapping from the estimated capture rate to the residual supply elasticity relies on the proportionality assumption in equation (16). Second, cap-binding ARC-CO payments reduce the payment-per-bushel equivalent, tending to raise the implied

14. The payment-rate variable is measured in dollars per base acre, whereas bids are measured in dollars per bushel. Its coefficient is therefore not directly interpretable as the share of the subsidy captured by elevators. The incidence calculation instead compares the bid reduction implied by the baseline specification with a separately constructed payment-per-bushel equivalent.

15. For elasticities of this magnitude, $\kappa = 1/(1+\varepsilon)$ is well approximated by the familiar relationship $\kappa \simeq 1/\varepsilon$. Applying this approximation to $\widehat{\kappa} = 0.044$ yields $\widehat{\varepsilon} \simeq 23$.

capture rate and lower the calibrated elasticity. Third, spatial averaging of $\tilde{Z}_{et}$ may attenuate the estimated bid response, tending instead to lower the implied capture rate and raise the calibrated elasticity. Fourth, posted cash bids capture only one margin along which elevators may adjust. To the extent that elevators also respond through delivery scheduling, quality discounts, storage charges, or forward-contract terms, the observed bid response understates total buyer capture and correspondingly overstates the residual supply elasticity (Caldwell, Dube, and Naidu 2026). These considerations make the exact value of $\widehat{\varepsilon}$ an order-of-magnitude benchmark rather than a structural estimate. Nevertheless, the implied elasticity lies within the range documented in related agricultural procurement markets and indicates an economically meaningful degree of local buyer power.

6 Conclusion

This paper studies whether grain buyers capture part of government subsidies intended for farmers. We combine daily cash bids from grain elevators across the U.S. Midwest with a local event-study design using the ARC-CO payment-threshold index. Before October, basis prices exhibit little systematic relationship with threshold exposure. Beginning in the announcement month, however, bids decline more in markets with greater exposure and remain lower during the subsequent marketing months. In our preferred specification, a one-unit increase in the elevator-level payment-threshold index reduces the corn basis by approximately 8.2 cents per bushel. At the average exposure among triggered elevator-years, this corresponds to approximately 1.2 cents per bushel, or 4.4 percent of the average ARC-CO payment-per-bushel equivalent.

We develop a model in which bid suppression can arise either because payment-induced grain deliveries interact with convex elevator costs or because payments reduce farmers' responsiveness to posted bids, allowing elevators with market power to widen their markdowns. The two mechanisms differ in their predictions across local market structures. The monopsony component should disappear as the number of nearby buyers increases, whereas a pure convex-cost response need not. Consistent with the monopsony mechanism, bid suppression is concentrated among elevators with few nearby competitors and is absent in markets with many nearby buyers. This concentration gradient is robust to measuring local buyer density using grain-handling establishments from the

Quarterly Census of Employment and Wages. Under the maintained assumption that neither the payment-induced front-loading of sales nor cost convexity systematically disappears with buyer density, these results are difficult to reconcile with a pure convex-cost explanation.

The findings imply that the incidence of agricultural support depends on the structure of the markets through which farmers sell their output. Existing work shows that landowners capture part of farm subsidies through higher rents. We document a complementary product-market margin: local intermediaries capture part of a transfer through lower procurement prices. A simple incidence-based calibration maps the estimated capture rate into a residual supply elasticity of approximately 22. Because this mapping requires assumptions about how payments affect residual supply and about the margins along which elevators adjust procurement terms, we interpret the elasticity as an order-of-magnitude benchmark rather than a directly identified structural parameter.

The mechanism is not necessarily limited to ARC-CO, but neither does it imply that every agricultural transfer will be captured in the same way. Capture requires that a payment alter farmers' marketing behavior or their responsiveness to competing bids, and its magnitude should depend on local outside options. Whether crop-insurance indemnities and other forms of farm support generate similar buyer responses is therefore a natural direction for future work. More generally, the results show that evaluating a subsidy solely through its statutory recipient can miss an important part of its incidence when that recipient sells into a spatially segmented and imperfectly competitive market.

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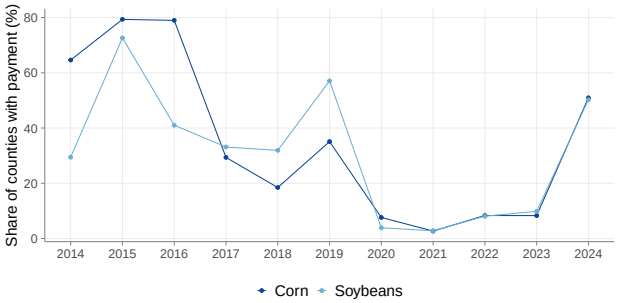
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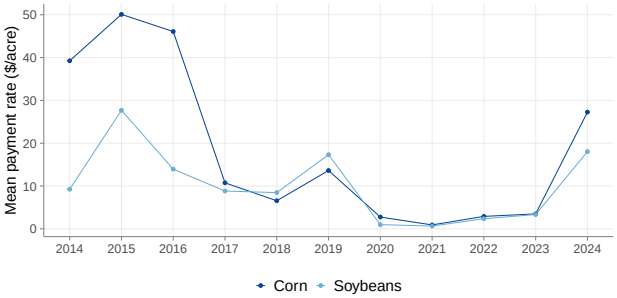
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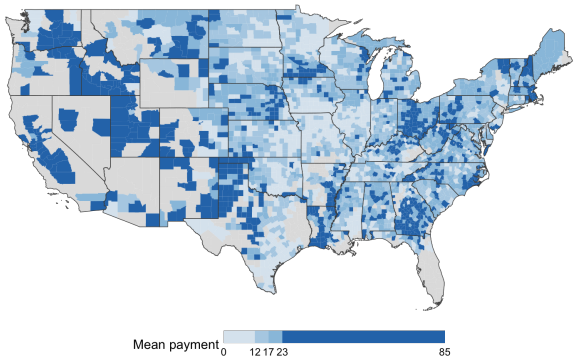
A Additional Figures and Tables



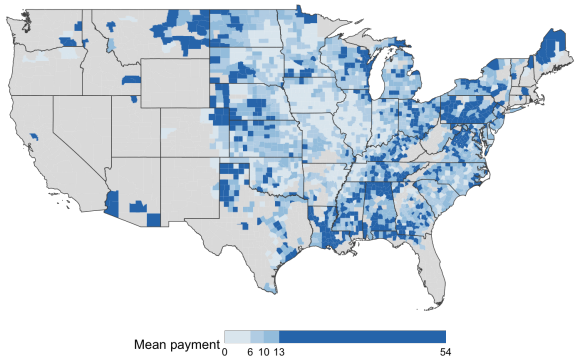
(A) Share of counties with a positive ARC-CO payment



(B) Mean payment rate ($/acre), all enrolled counties



(C) Corn



(D) Soybeans

Figure A1. ARC-CO payment activity over time and space. Panel (A) shows the fraction of counties receiving a positive payment each year. Panel (B) shows the mean payment rate per enrolled acre. Panel (C) and (D) show payment rates averaged over 2014–2024. Data from USDA FSA Summary of Business.

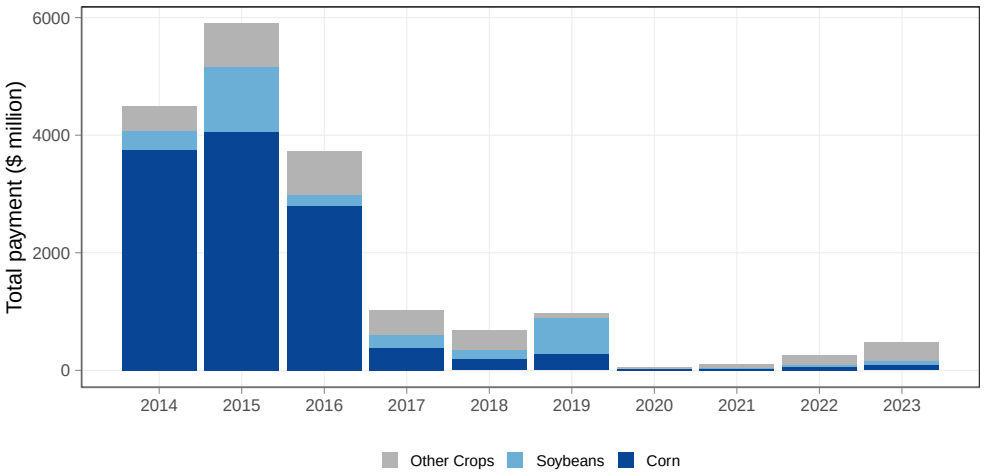


Figure A2. ARC-CO payment levels over time. Stacked bars report total ARC-CO payments ($ millions) by crop year, decomposed into corn, soybeans, and all other covered commodities. Data from USDA FSA Summary of Business.

Grain marketing timing. Figure A3 shows the cumulative fraction of the corn harvest sold by month. The October ARC-CO announcement coincides with the start of the peak marketing window, when most of the harvest is sold.

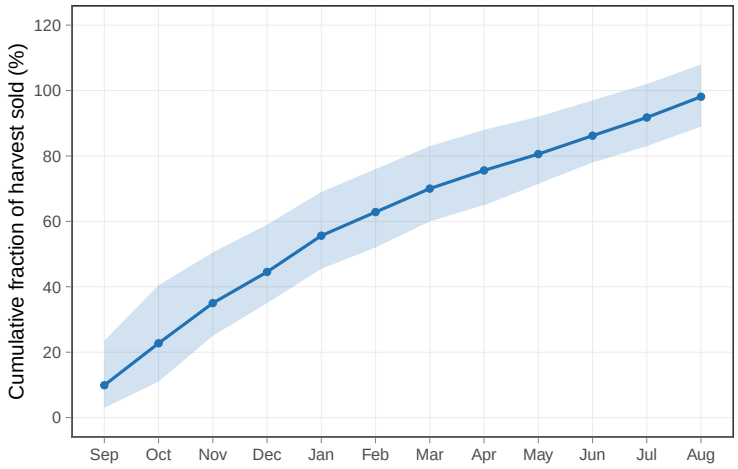
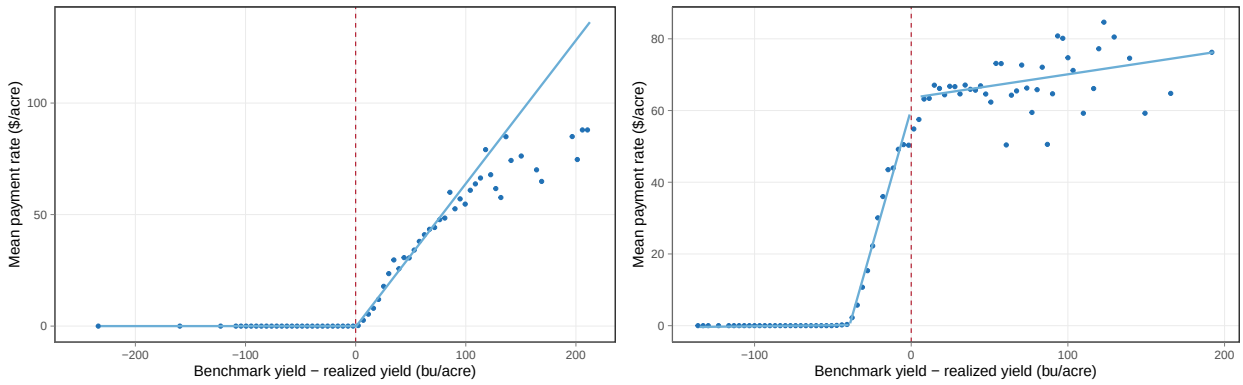


Figure A3. Cumulative fraction of corn harvest sold by month. Lines show the mean cumulative share of the annual harvest marketed through each month of the crop year (September–August); shaded bands are 95% confidence intervals across years. The vertical dashed line at October marks the ARC-CO announcement date. Data from USDA NASS monthly grain stocks reports.



(A) High-price ratio

(B) Low-price ratio

Figure A4. Corn ARC-CO payment rate and county-level yield shortfall (binscatter). An observation is a county-year. Data are from USDA FSA Summary of Business and USDA NASS county yields.

Elevator-level threshold exposure. Figure A5 plots average ARC-CO payment rates against the elevator-level payment-threshold index. Each elevator's $\tilde{Z}_{et}$ is a 50-mile area-weighted average of the county-level threshold variables within its supply catchment. Because catchments can span counties on both sides of the payment threshold, spatial averaging smooths the relationship between $\tilde{Z}_{et}$ and average payment exposure.

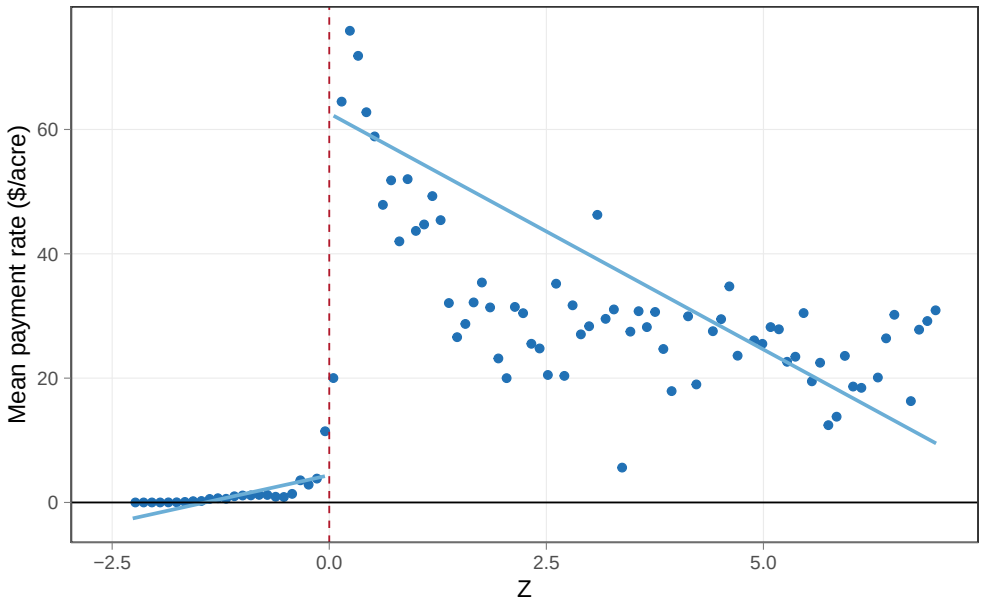


Figure A5. Corn ARC-CO payment exposure vs. elevator-level payment threshold variable. Each point is an elevator-year. The payment threshold variable $\tilde{Z}_{et}$ is the area-weighted average of county-level payment threshold variables within a 50-mile buffer. Spatial averaging across counties smooths the relationship between the elevator-level threshold measure and average payment exposure.

Distribution of $\tilde{Z}$ in the benchmark sample. Figure A6 shows the distribution of $\tilde{Z}$ among triggered elevator-years for corn and soybeans. Navy bars correspond to the benchmark sample used in Section 5; the dashed line marks the 95th-percentile cutoff above which observations are excluded.

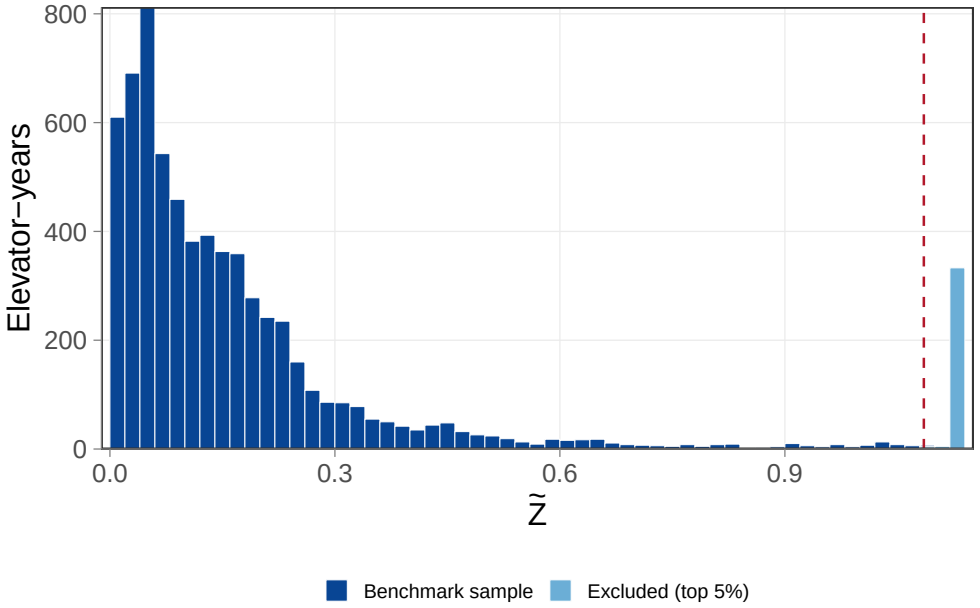


Figure A6. Distribution of $\tilde{Z}$ for corn among triggered elevator-years. Navy bars show the benchmark sample used in the supply elasticity calculation (triggered elevator-years below the 95th percentile of $\tilde{Z}$); light blue bars show excluded elevator-years, winsorized to the right of the dashed cutoff. The right-skewed tail reflects extreme drought years in which ARC-CO payments were large.

B Robustness

B.1 Alternative Measures of ARC-CO Exposure

The preferred specification uses the area-weighted mean of the signed county-level threshold variable within each elevator's 50-mile catchment. This measure retains distance from the payment threshold on both sides and the intensity of the underlying revenue shortfall, but it imposes a linear response in mean Z and allows positive and negative county values to offset one another. We therefore consider three alternative measures that progressively emphasize the extensive margin of eligibility and the realized intensity of the transfer. To isolate the role of exposure measurement, all three specifications retain the baseline Midwest local-window sample, fixed effects, and controls; only the measure of ARC-CO exposure changes.

Binary threshold indicator. Table B1 replaces the continuous catchment-level threshold variable with a binary indicator $D_{et} \equiv \mathbf{1}[\tilde{Z}_{et} > 0]$. This specification tests whether the result survives a coarse, nonlinear classification of catchments according to whether their average threshold measure is positive.

Table B1. Robustness: binary threshold indicator

Dependent Variable:	Corn Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct $\times$ $\tilde{Z} > 0$	-0.018***	-0.015***	-0.015***	-0.011***
	(0.004)	(0.004)	(0.004)	(0.003)
Observations	108,803	108,803	108,803	108,803
R^2	0.851	0.900	0.902	0.924
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Replicates Table 1 using a binary trigger indicator $D_{et} \equiv \mathbf{1}[\tilde{Z}_{et} > 0]$ as the exposure variable. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Area-weighted share triggered. Table B2 replaces $\tilde{Z}_{et}$ with the share of the elevator's 50-mile buffer area lying in counties for which $Z_{ct} > 0$. Unlike the signed mean threshold variable, this measure does not allow triggered and non-triggered counties to offset one another. It captures the extensive margin of local ARC-CO exposure but deliberately discards information about the size of the revenue shortfall within triggered counties.

Table B2. Robustness: share of the catchment area triggered

Dependent Variable:	Corn Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct × share_triggered_known	-0.034***	-0.023***	-0.022***	-0.016***
	(0.005)	(0.006)	(0.006)	(0.005)
Observations	108,803	108,803	108,803	108,803
R^2	0.852	0.900	0.902	0.924
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Replicates Table 1 replacing $\tilde{Z}_{et}$ with the share of the elevator's 50-mile buffer area lying in counties satisfying $Z_{ct} > 0$. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Area-weighted ARC-CO payment rate. Table B3 replaces $\tilde{Z}_{et}$ with the area-weighted mean ARC-CO payment rate in the elevator's 50-mile catchment. This is the most policy-proximate exposure measure: it is expressed in dollars per base acre and incorporates both the payment formula and the payment cap. The specification therefore tests directly whether bids decline more in catchments receiving larger ARC-CO transfers.

Table B3. Robustness: area-weighted ARC-CO payment rate

Dependent Variable:	Corn Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct × Payment Rate / 10	-0.004***	-0.002**	-0.002**	-0.003***
	(6.47×10^{-5})	(7.42×10^{-5})	(7.42×10^{-5})	(7.58×10^{-5})
Observations	108,803	108,803	108,803	108,803
R^2	0.853	0.900	0.902	0.924
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Replicates Table 1 replacing $\tilde{Z}_{et}$ with the area-weighted mean ARC-CO payment rate, measured in \$10 dollars per base acre, within the elevator's 50-mile catchment. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

B.2 Other Robustness Checks

Robustness to the local-window definition. Table B4 replicates the preferred specification (column 4 of Table 1) across local windows from 0.10 to 0.25. Results are stable across all windows.

Table B4. Robustness to alternative local windows

Dependent Variable:	Corn Basis			
	BW=0.10	BW=0.15	BW=0.20	BW=0.25
Model:	(1)	(2)	(3)	(4)
Post-Oct $\times$ $\tilde{Z}$	-0.071**	-0.067***	-0.082***	-0.091***
	(0.031)	(0.024)	(0.018)	(0.015)
Observations	63,023	89,463	108,803	122,595
R^2	0.942	0.930	0.924	0.921
Elevator FE	Yes	Yes	Yes	Yes
State-Year-Month FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Acreage controls	Yes	Yes	Yes	Yes

Notes: Each column replicates the preferred specification (column 4 of Table 1) at the indicated local window. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Home-county threshold measure. Table B5 replicates the preferred specification using the payment-threshold index of each elevator's home county rather than the 50-mile buffer average.

Table B5. Robustness: home-county threshold measure

Dependent Variable:	Corn Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct × $Z_{c(e)t}$	-0.084***	-0.062***	-0.062***	-0.029*
	(0.020)	(0.019)	(0.019)	(0.016)
Observations	107,903	107,903	107,903	107,903
R^2	0.845	0.897	0.899	0.922
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Replicates Table 1 using the payment threshold variable of the elevator's home county as the exposure variable rather than the 50-mile buffer-weighted average. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Log cash price. Table B6 replicates the preferred specification using the log cash price as the dependent variable in place of the implied basis. This addresses the concern that basis movements could reflect futures price changes rather than elevator bid changes; the negative and significant coefficient confirms that elevators are lowering their absolute cash bids.

Table B6. Robustness: log cash price

Dependent Variable:	Log Corn Cash Price			
Model:	(1)	(2)	(3)	(4)
Post-Oct $\times$ $\tilde{Z}$	-0.044***	-0.033***	-0.032***	-0.020***
	(0.006)	(0.005)	(0.005)	(0.005)
Observations	108,803	108,803	108,803	108,803
R^2	0.978	0.985	0.986	0.989
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

Notes: Replicates Table 1 using the log corn cash price as the dependent variable. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

B.3 Robustness of Local Market Power Analysis

Alternative concentration measure from QCEW. As an alternative to the DTN elevator count, we measure local buyer density using county grain-handling establishment counts (merchant wholesalers and farm-product storage) from the Quarterly Census of Employment and Wages (QCEW). Since QCEW reports only county totals, we assume establishments are uniformly distributed within a county and compute the expected count inside each elevator's 50-mile buffer as $\sum_c n_{c,t}\,(a_{ec}/A_c)$, where $n_{c,t}$ is county c's count in year t, a_{ec} is the area of county c inside elevator e's buffer, and A_c is the county's total area. This is the direct analogue of the DTN elevator count, and we split elevators at the 66th percentile as before. Table B7 and Figure B1 replicate our main results: the estimates are qualitatively unchanged, if anything larger, so the concentration heterogeneity is not an artifact of using the DTN sample to measure the competitive environment.

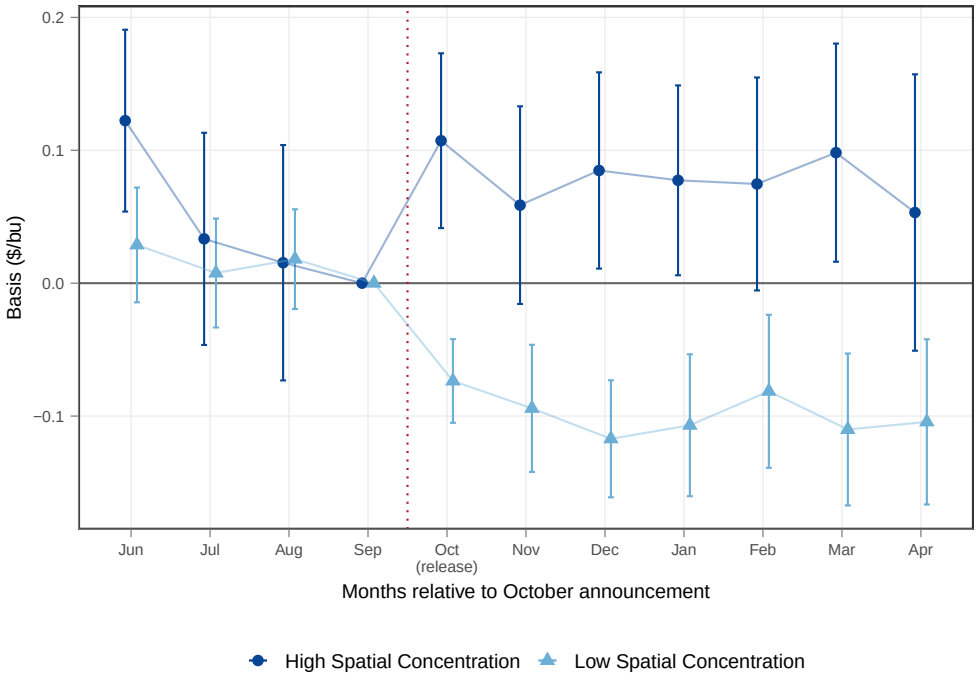


Figure B1. Heterogeneity event study by market concentration, corn. Replicates the event-study estimates from Figure 6 using an alternative concentration measure constructed from elevator counts in the QCEW. Low-spatial-concentration elevators fall at or below the 66th percentile of the within-Midwest distribution of elevator counts within 50 miles. Midwest states only. Shaded bands are 95% confidence intervals clustered at the county level.

Table B7. Robustness: Heterogeneity by market concentration

Dependent Variable:	Basis			
	Full sample	High spatial conc.	Low spatial conc.	Interaction test
Model:	(1)	(2)	(3)	(4)
Variables				
Post-Oct × Z	-0.082***	0.036	-0.112***	-0.018
	(0.018)	(0.026)	(0.020)	(0.022)
Post-Oct × Low estab. conc.				-0.010***
				(0.003)
Post-Oct × Z × Low estab. conc.				-0.088***
				(0.023)
Fixed-effects				
Elevator	Yes	Yes	Yes	Yes
State-Year-Month	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Acreage controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	108,803	36,986	71,817	108,803
R^2	0.92382	0.95186	0.92054	0.92407
Within R^2	0.02921	0.04999	0.03150	0.03236

Notes: Replicates Table 2 using an alternative concentration measure constructed from elevator counts in the QCEW. Low-spatial-concentration elevators fall at or below the 66th percentile of the within-Midwest distribution of elevator counts within 50 miles. Column (4) pools both groups and adds a triple interaction (Post-Oct × $\tilde{Z}$ × Low spatial conc.) and Post-Oct × Low spatial conc. as a control. All specifications include elevator and state-by-year-by-month fixed effects, weather controls, and log corn acreage. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C Soybeans

Table C1 replicates Table 1 for soybeans. Figure C1 shows the corresponding event study across four specifications. The post-announcement interaction is negative and significant in specifications (1)–(3). In specification (4), which adds state-by-year-by-month fixed effects, the estimated effect attenuates to near zero: soybean basis is more nationally integrated than corn basis, so the demanding FE absorb most of the cross-sectional variation.

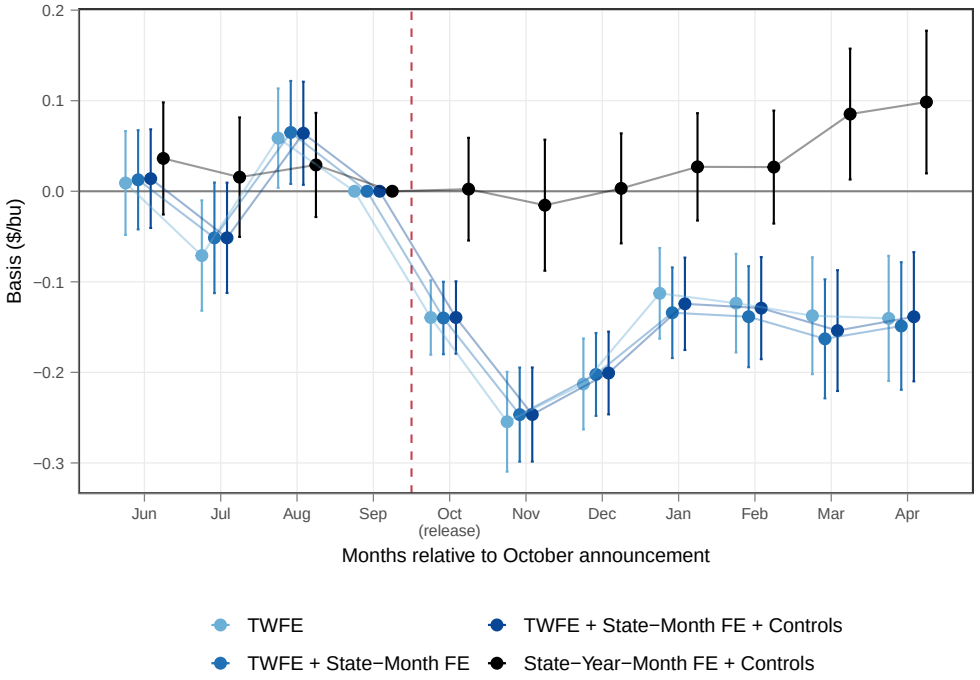
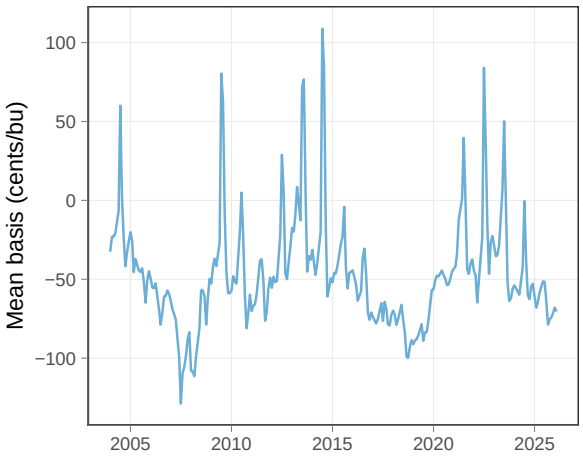


Figure C1. Event study across four specifications, soybeans. Replicates Figure 5 for soybeans. Each line shows the event-study estimate from a progressively richer specification: (1) elevator and year-by-month FE only; (2) adding state-by-month FE; (3) adding weather and acreage controls; (4) preferred specification with state-by-year-by-month FE. Pre-trends are flat across all specifications; the post-announcement effect is present in specifications (1)–(3) but attenuates under specification (4). Sample restricted to $|\tilde{Z}_{et}| \leq 0.2$. Shaded bands are 95% confidence intervals clustered at the county level.

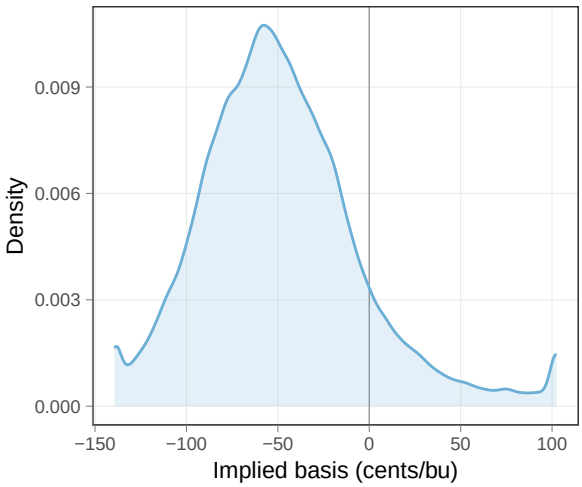
Table C1. ARC-CO payment trigger and soybean basis

Dependent Variable:	Soybean Basis			
Model:	(1)	(2)	(3)	(4)
Post-Oct $\times$ $\tilde{Z}$	-0.165***	-0.169***	-0.168***	0.012
	(0.022)	(0.022)	(0.022)	(0.024)
Observations	138,261	138,261	138,261	138,261
R^2	0.920	0.937	0.937	0.952
Elevator FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	
State-Year FE		Yes	Yes	
State-Month FE		Yes	Yes	
State-Year-Month FE				Yes
Weather controls			Yes	Yes
Acreage controls			Yes	Yes

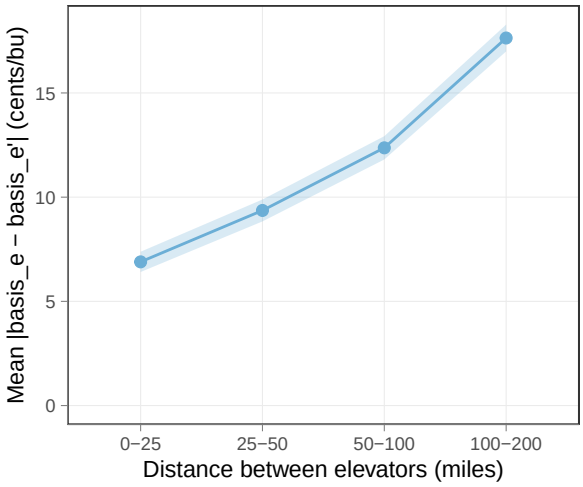
Notes: Replicates Table 1 for soybeans. Dependent variable is the implied basis (cash soybean price minus CME front-month futures, dollars per bushel). Sample restricted to $|\tilde{Z}_{et}| \leq 0.2$. All other notes as in Table 1.



(A) Mean implied basis over time



(B) All-elevator basis distribution



(C) Pairwise basis difference by distance

Figure C2. Soybean basis variation Same layout as Figure 4, for soybeans. The normalised pairwise differences are smaller in absolute terms than for corn (reflecting the higher cash price of soybeans), but the monotone relationship with distance is equally pronounced.

Between/within decomposition of Post-Oct $\times$ $\tilde{Z}$. Table C2 decomposes the interaction Post-Oct $\times$ $\tilde{Z}$ into its state-by-year-by-month mean (the component absorbed by the preferred state-by-year-by-month fixed effects) and the elevator-level deviation from that mean (the component that survives those fixed effects). For corn, the effect is entirely within-state: the within-state coefficient is -0.184^{***} and the between-state coefficient is indistinguishable from zero. For soybeans the pattern is reversed: the between-state coefficient is -0.347^{***} while the within-state coefficient is zero. This explains why state-by-year-by-month fixed effects absorb the soybean result but not the corn result.

Table C2. Between/within decomposition of Post-Oct $\times$ $\tilde{Z}$

Dependent Variable:	Implied basis ($/bu)	
	Corn	Soybeans
Model:	(1)	(2)
Post-Oct $\times$ $\tilde{Z}$ (between states)	-0.029	-0.347***
	(0.034)	(0.030)
Post-Oct $\times$ $\tilde{Z}$ (within state)	-0.184***	-0.020
	(0.024)	(0.024)
Observations	107,636	136,888
R^2	0.866	0.924
Elevator FE	Yes	Yes
Year $\times$ Month FE	Yes	Yes

Notes: Dependent variable is implied basis ($/bu). Post-Oct $\times$ $\tilde{Z}$ is decomposed into its state-by-year-by-month mean (*between states*) and the elevator-level deviation (*within state*). Both components enter simultaneously with elevator and year-by-month fixed effects and weather controls. The decomposition shows that the corn relationship is driven primarily by within-state-year-month variation, whereas the soybean relationship is driven primarily by variation across state-year-month cells. Standard errors clustered at the county level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

D Capture Rate and Residual Supply Elasticity

This appendix derives the mapping from the reduced-form capture rate estimated in Section 5 to the residual supply elasticity in the model of Section 4.

Define the residual supply elasticity facing the elevator as[16]

$$\varepsilon \equiv \frac{\partial s}{\partial p^b}\frac{p^b}{s} \tag{17}$$

and recall that the elevator first-order condition is given by

$$F(p^b, W) = \left[p^d - p^b - c'\left(s\overline{Q}\right)\right]\frac{\partial s}{\partial p^b} - s = 0. \tag{18}$$

Combining Equations (17) and (18) gives

$$p^d - p^b - c'\left(s\overline{Q}\right) = \frac{p^b}{\varepsilon}. \tag{19}$$

As in the monopsony mechanism in Section 4.2, suppose that marginal handling costs are locally constant, $c''(s\overline{Q}) = 0$, and that the payment does not directly shift the quantity supplied at a given bid, $\partial s/\partial W = 0$. We additionally assume that residual supply is locally iso-elastic in the elevator's bid, $\partial\varepsilon/\partial p^b = 0$.

Holding the elevator's bid fixed and differentiating ε with respect to W gives

$$\frac{\partial^2 s}{\partial p^b \partial W} = \frac{s}{p^b}\frac{\partial \varepsilon}{\partial W}, \tag{20}$$

while local iso-elasticity implies

$$\frac{\partial^2 s}{\partial (p^b)^2} = \varepsilon(\varepsilon - 1)\frac{s}{(p^b)^2}. \tag{21}$$

Under the maintained assumptions, the derivatives of the elevator's first-order condition simplify

16. Because $\overline{Q}$ is fixed at the time of the ARC-CO announcement, ε is also the elasticity of grain deliveries to the elevator with respect to its own bid.

to

$$\begin{aligned}\frac{\partial F}{\partial p^b} &= -2\frac{\partial s}{\partial p^b} - c''\left(s\overline{Q}\right)\overline{Q}\left(\frac{\partial s}{\partial p^b}\right)^2 + \left[p^d - p^b - c'\left(s\overline{Q}\right)\right]\frac{\partial^2 s}{\partial (p^b)^2} \\ &= -\frac{s}{p^b}(1+\varepsilon),\end{aligned} \tag{22}$$

and

$$\begin{aligned}\frac{\partial F}{\partial W} &= \left[p^d - p^b - c'\left(s\overline{Q}\right)\right]\frac{\partial^2 s}{\partial p^b \partial W} \\ &= \frac{s}{\varepsilon}\frac{\partial \varepsilon}{\partial W}.\end{aligned} \tag{23}$$

The implicit function theorem therefore gives

$$\frac{dp^b}{dW} = \frac{p^b}{W}\frac{\xi}{1+\varepsilon}, \qquad \xi \equiv -\frac{\partial \varepsilon}{\partial W}\frac{W}{\varepsilon} > 0, \tag{24}$$

where ξ is the wealth elasticity of farmers' bid responsiveness.

Equation (24) shows that mapping the reduced-form capture rate into ε requires two additional quantities: the response of bid responsiveness to farmer resources, ξ, and the scale of farmer resources relative to the cash bid, p^b/W. For the benchmark calibration, we measure W in farmer resources per bushel marketed and approximate these resources by cash revenue per bushel, so that $p^b/W \simeq 1$. We further set $\xi = 1$, corresponding to a payment reducing farmers' bid responsiveness in the same proportion that it raises their resources. Under these normalizations, the empirical capture rate κ satisfies

$$\kappa = \frac{1}{1+\varepsilon}, \qquad \text{or equivalently} \qquad \varepsilon = \frac{1}{\kappa} - 1. \tag{25}$$