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The Effect of a Cooperative Grain Alliance on Wheat Basis

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This study estimates the impact of joining a cooperative grain alliance on the wheat basis for elevators in Oklahoma. The study uses augmented difference-in-differences regressions to analyze the effects of joining the alliance on an elevator's grain basis. Entry is not randomly assigned across elevators, and an elevator's basis is codetermined with its neighboring elevators due to transport costs and other unobserved variables. Instrumental variable regression is used to address these issues. The main takeaway is that joining the alliance did not change the wheat basis.

Key words: cohorts, differences-in-differences, elevators, spatial dependence, staggered entry

Introduction

Grain elevators occasionally combine their commodity marketing activities under a separate cooperative entity or an alliance, a structure officially called a "marketing agency in common." The Capper Volstead Act of 1922 recognizes these structures as a permitted activity. Most local cooperatives refer to this structure as a grain marketing alliance. The Equity Marketing Alliance (EMA) was formed in 2001 by six grain cooperatives in Oklahoma. CoMark Grain was formed in 2008 by ten grain cooperatives in Kansas. In 2017, EMA and CoMark joined to create CoMark Equity Alliance, LLC (CEA). CoMark Equity Alliance, LLC comprises 25 cooperatives in Kansas, Oklahoma, and Texas, with 155 locations (CoMark Equity Alliance, 2021).

As defined by Subchapter T of the Internal Revenue Code, the CEA operates as a cooperative. Subchapter T recognizes that the objective of business conducted by a cooperative is not to generate earnings for the cooperative but to increase member income (US Department of Agriculture, 1995). Its members wholly own the CEA. The CEA distributes profits as patronage refunds to members in proportion to business volume with the alliance. Because of that organizational structure and taxation status, the CEA aims to maximize grain merchandising and storage profits, which are returned to the local member cooperatives.

Royer (2014a,b) discusses this scenario for input supply cooperatives. Royer does not explicitly address the case of a marketing cooperative operating in perfectly competitive markets. Still, it is easy to see that when the cooperative is a price taker and has no impact on market prices, member returns are maximized by the cooperative maximizing its profits and patronage. In terms of marketing the grain purchased by the alliance, it is obvious that the CEA, like other grain marketing cooperatives, is a price taker and does not face a downward-sloping demand curve. As a simple

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example, the CEA often sells wheat to the Gulf export facilities. The price of wheat at the Gulf changes based on how much wheat CEA decides to market through the Gulf. The alliance can sell as little or as much as it likes at the posted bid price on any given day. For these reasons, the CEA's only objective is to create and distribute the maximum benefit to its member-owners, including the prices paid and the patronage distributed. In the case of the CEA, as is the case for most agricultural cooperatives, the cooperative's market situation has little or no impact on market prices, resulting in the objective of maximizing member benefits being identical to maximizing the profits distributed to the member-owners.

One way to measure the impact of a cooperative alliance on the market price is by examining the area's grain basis. The basis is the difference between a commodity's local cash price and the comparable futures price for the same commodity. The grain basis reflects local supply and demand conditions. It affects where producers deliver and store their grain to maximize profits. The basis and expected basis also impact the producer's marketing decisions and influence how they evaluate cash forward contracts, forecast the profitability of storage, calculate expected hedge prices, and calculate the maximum and minimum prices when using puts and calls (Qasmi, 1992). The basis separates those effects from movement in the overall market. The basis at Oklahoma elevators is often negative (i.e., the posted price is below the futures price). The two terms commonly used to describe changes in the basis are "strengthening" and "weakening." When the basis becomes less negative, it is said to be strengthening. When the basis becomes more negative, it is said to be weakening. If the futures price is constant, the basis will strengthen when a local elevator increases the cash price paid to producers.

Profitable outcomes may arise from formal agreements among cooperatives when they coordinate transportation and realize the benefits of size economies (Fulton, Popp, and Gray, 1998). Cooperative members would be interested in information on any price effects an alliance might engender because it would affect their total benefit from the cooperative and their assessment of the cooperative's performance. Producers who are not cooperative members would also be interested in any price effect since it could positively or negatively affect their profits.

This research aims to estimate the impact of joining a cooperative grain alliance on the wheat basis for 129 elevators in Oklahoma over 4,236 days. The study uses augmented two-way fixed effect (TWFE) difference-in-differences (DiD) regressions to determine the effects of joining the alliance on the grain basis. The augmented regressions address two sources of potential endogeneity. First, an elevator's basis is codetermined with those reported at neighboring elevators due to similar transportation costs, distance between end users, and other unobserved spatially correlated variables. Omitting the spatial lag of the basis in a regression introduces omitted variable bias. Second, alliance membership is not randomly assigned across elevators. Instead, elevator managers and patrons vote on whether to join the alliance. Therefore, the treatment effect—entry into the alliance—is a potential source of endogeneity because elevators self-select into the alliance. Instrumental variable (IV) regression is used to address these issues. Elevator entry into the alliance was staggered during the study period. We use an extended TWFE-DiD estimator to test for treatment heterogeneity among the entry cohorts.

Background

Bekkerman et al. (2014) documented the impact of shuttle-loading facilities on the local grain basis. Their research found that the basis strengthened when the elevator was closer to shuttle loaders than conventional elevators. O'Brien (2009) estimated price models for wheat and corn in Kansas and found that geographic proximity to grain ethanol plants in Kansas did not affect the local corn price. However, corn prices were affected by livestock feed usage, elevator storage capacity, and railroad access. Kansas wheat prices were also affected by similar factors, including local wheat production, elevator storage capacity, the number of competitors in the market, and proximity to flour mills

(O'Brien, 2009). This research measures the change in the grain basis for hard red winter wheat in Oklahoma for elevators after they joined a grain marketing alliance.

Cooperatives and other grain handlers set basis levels to cover the shipping cost between the receiving point and market outlet, influencing the grain flows into and out of their facilities (Hart and Olson, 2017). During harvest, cooperatives may set the grain basis to entice producers to deliver grain to a specific location. After harvest, cooperatives and other grain handlers can set the basis to influence whether producers storing grain at a facility decide to sell the grain and thus make it available for shipment to an end market. Historically, local cooperatives merchandised their grain. Each cooperative independently managed the basis at its location(s). Under the grain alliance structure, all the alliance members' grain is merchandised by the alliance (in our case, the CEA), and the alliance's grain merchandiser determines the grain basis for all member locations.

Many factors influence the grain basis at the overall market level, including transportation costs, quality, supply, and demand (Wilson and Dahl, 2011). Merchandisers set a basis to influence the number of bushels transported to their location. Proximity to other markets influences the grain basis (Bekkerman, Taylor, and Ridder, 2018), and spatial competition can increase grain cash prices (Grashuis, 2019). Managers of local grain cooperatives are typically responsible for setting the grain basis and merchandising their member's grain. Individual coop managers consider transportation costs and terminal market prices when establishing the basis. The basis affects the grain margin and profits of the local cooperative. Absent competition, a cooperative manager might want to weaken the basis and improve the cooperative's profits.

Managers consider the grain basis of nearby competitors. A cooperative manager could use the grain basis to encourage producers at the perimeter of their trade territory to deliver to the cooperative rather than to a competing firm. The manager would also have to consider the revenue lost from offering the basis to all customers and possible competitor's reactions. After the grain is in storage (but still owned by the producer), one would expect the cooperative manager to set the basis according to transportation costs and terminal market prices. Occasionally, a local cooperative manager might adjust their basis bids to encourage producers to sell grain and allow the cooperative to take advantage of a specific merchandising opportunity. However, this can be difficult to measure accurately because some aggressive bidding may not appear in published cash or basis bids.

Cooperative grain handlers often offer lower cash prices than those offered by corporate handlers, potentially offset by year-end refunds and dividends (Grashuis, 2020). However, their presence increases competitors' prices nearby, demonstrating a procompetitive effect (Grashuis, 2020; Sexton, 1990). Fousekis (2011) showed that cooperatives can intensify market competition by influencing pricing strategies and spatial positioning, leading to more competitive outcomes in agricultural markets. The basis of nearby competitors could influence a manager's decisions during the entire storage and marketing period. In many cases, the manager merchandises the grain. So, the alliance could increase the basis for alliance members and customers of nearby elevators.

The CEA has a specialized staff to oversee all 155 elevator locations and determine the basis for each commodity at each location. It aims to maximize grain merchandising and storage profits, which flow to cooperative members. Like a local cooperative, the CEA considers transportation and logistics costs when setting the grain basis at each location. The CEA could also use the basis to incentivize producers to bring their grain to a CEA location. Because of the CEA's size and scope and the fact that some alliance members are adjacent, one might expect the wheat basis of a cooperative to change after it joins the CEA. The primary hypothesis of this research is that there is no change in an elevator's basis after it joins the alliance.

Conceptual Framework

We start with the presumption that elevators joining the alliance benefit from doing so. By joining a grain marketing alliance, cooperatives can leverage economies of size (Jessup et al., 2011), reducing transportation and marketing costs, which may be reflected in a more favorable grain basis for the

cooperative members. The alliance could enhance the bargaining power of the cooperative members in the market. This increased market power might allow the alliance to secure better prices, leading to a stronger, less negative basis. However, increased competition among local elevators could diminish or eliminate this effect.

Cooperatives could reflect the benefits more favorably as patronage dividends or subsidize losing enterprises. The alliance, not individual elevators, sets the basis for elevators that join the alliance. The distribution of alliance members suggests that elevators in competitive areas where the distance between cooperatives is small have almost all joined the alliance. Elevators in less competitive areas or with a competitive advantage have not joined the alliance.

If the alliance chooses not to change the basis, then there is less to discuss since the only effect of joining the alliance would be a change in the merchandising efficiency of the participants with no effect on the basis received by members and nonmembers. Instead, we begin with the assumption that the alliance does offer a stronger basis. Elevators near an alliance elevator can offer a stronger basis or accept a lower volume. Suppose an elevator not in the alliance chooses to compete by offering a stronger basis. In that case, the alliance's existence will increase prices paid to producers (members and nonmembers) and decrease the profitability of the nonalliance elevators. The impact on the alliance elevators depends on whether the merchandising economies were greater or less than the decreased grain margin.

On the other hand, consider the case where the alliance uses its greater market power to weaken the basis and reduce cash prices to producers. Suppose we assume that nonalliance elevators follow suit. In that case, the effect of the alliance will be lower prices for producers and higher profits at the elevator level. Producers delivering to elevators within and outside the alliance would recapture the price decrease through increased patronage payments. However, the alliance's existence would negatively impact producers delivering to independent elevators. Thus, the theory is ambiguous about the expected impact of the alliance on the grain basis. Nonetheless, analyzing that potential effect is important for estimating the benefit of the alliance to its members (a topic that is not the focus of this paper) and determining the effect of the alliance on unaffiliated producers.

Grain elevators offer a homogeneous service (handling, storing, and marketing grain). The basis setting by the alliance could influence the behavior of nonalliance elevators, which could respond by adjusting their basis to remain competitive. In that case, the effect of the alliance on the grain basis could be difficult to detect. Changes in an elevator's basis after entering the alliance and the effect of alliance and nonalliance competitors on the grain basis could still provide indirect evidence of an impact on the grain basis from the alliance formation.

The framework above suggests three hypotheses:

Hypothesis 1. *Joining a grain marketing alliance does not result in a stronger grain basis at the alliance member elevators relative to nonalliance elevators.*

Hypothesis 1 is rooted in the idea that the alliance can leverage economies of size and better market information to secure higher prices for its members.

Hypothesis 2. *An elevator's basis is independent of the basis reported by neighboring elevators.*

Hypothesis 2 suggests that proximity to end users and the number of competing elevators impact the basis and that an elevator's grain basis is codetermined with the basis reported by neighboring elevators. The effect of joining the alliance on the grain basis varies by the level of local market competition. In highly competitive areas, the increase in the basis might be less pronounced due to competitive pressure. In contrast, the effect might be more significant in less competitive areas. This second hypothesis posits that these spatial variables mediate the alliance's impact on the basis.

Hypothesis 3. *Elevator entry into the alliance is endogenous (i.e., not randomly assigned across elevators).*

Table 1. Alliance and Nonalliance Groups and Treated Cooperatives

		Cooperatives	Observations
Total coops (a)		141	200,855
Always treated (dropped from analysis) (b)		12	11,388
Sample (a − b)		129	189,467
Not in alliance (never treated)		71	105,493
In alliance		57	83,974
In alliance before 2009 (already treated) (1)		45	60,149
Joined alliance, post-2009		11	23,825
Treated Cohorts (t is entry day)	**No. of Cooperatives**	**Join Date**	**Observations**
hline $t = 1, 163$	3	12/11/14	6,785
$t = 2, 260$	2	9/13/17	7,527
$t = 2, 502$	3	1/2/18	4,392
$t = 3, 811$	1	9/23/20	1,952
$t = 4, 201$	2	11/25/20	3,169
Total:	11		23,825

Notes: The dataset covers the period from May 27, 2009, to December 31, 2020

Hypothesis 3 implies that elevator entry into the alliance is not randomly assigned. In other words, an elevator and its patrons self-select into the alliance. If the null is true, an estimate of the average treated effect on the treated is biased and inconsistent if the issue is ignored. We test these hypotheses using DiD instrumental variable regression.

Data

This study focuses on winter wheat in Oklahoma. Daily hard red winter wheat basis bids from 141 elevators across Oklahoma from May 27, 2009, to 31 December 2020, were purchased from Data Transmission Network (DTN). It is helpful to describe how "elevator" and "member" are used to minimize confusion. "Elevator" refers to a single location where grain is priced and received. The entities operating the elevator could be cooperatives (farmer-owned firms) or independent (investor-owned firms). Most cooperatives and independents operate multiple elevators, so the number of cooperative elevators is greater than that of cooperative firms. Because the grain basis reflects transportation costs, each elevator—even elevators owned by the same parent firm—reports its price and grain basis when the basis changes. That makes the elevator the logical unit of analysis.

Cooperatives are owned by farmers who are members of the cooperative. In this study, we use the term "member" to refer to a cooperative and its elevator locations as members of the grain alliance. There are no independent elevators in the grain alliance, so the nonmember elevators include both cooperative elevators and independent elevators not participating in the alliance.

Table 1 summarizes the data structure for 141 alliance and nonalliance elevators over 4,236 days. Gaps exist between days for all elevators because an elevator may not have any changes in the basis to report. After accounting for reporting gaps, there were 200,855 observations (2,924 reported periods, 69% of the 4,236 days) for the 141 elevators, 72 of which never joined the alliance ("never treated" group) and 69 of which joined the alliance either before the start of the data collection period or afterward. Some alliance elevators were "always treated" due to missing observations before the entry date (12 elevators, 11,388 observations). These elevators cannot be included in the DiD regressions and were dropped, reducing the number of elevators to 129 and the number of

Table 2. Summary Statistics (N = 189,467)

Variable	Label	Units	Mean	Std. Dev.	Min.	Max.
Wheat basis (dependent variable)	*basis*	$/bu	-0.51	0.36	-2.70	1.15
Spatial lag of wheat basis	*wbasis*	$/bu	-0.50	0.35	-1.65	0.58
Alliance member, before May 27, 2009	*exist*	1 = yes, 0 otherwise	0.32		0	1
New member after May 27, 2009	*entry*	1 = yes, 0 otherwise	0.06		0	1
Miles to shuttle	*miles*	miles	44.75	32.77	0	177
Alliance competitors, 10-mile radius	*compcea*	count	0.56	0.77	0	3
Alliance competitors, 10-mile radius	*compnoncea*	count	0.63	0.80	0	3
County wheat production (10,000s bu)	*prod*	bushels	42.85	31.97	0	120

observations to 189,467. Of these observations, there were 57 alliance elevators; 46 of these elevators formed or entered the alliance before May 27, 2009, and 11 joined the alliance between May 27, 2009, and December 31, 2020. These 11 elevators are the "treated" group (23,825 observations). There were five entry waves (Table 1). We labeled the cohorts using the days after May 27, 2009, until the elevator joined the CEA. We use these entry events in a staggered DiD cohort regression (discussed below). The models we consider include potentially endogenous regressors, entry into the alliance, and the grain basis's spatial lag. IV regression is used to estimate these models. A discussion of the candidate instruments follows.

Candidate Instruments

Highway miles from each elevator to seven end users across Oklahoma, including flour mills, train shuttle shippers, and the Port of Catoosa, Oklahoma, were calculated using Google Maps. We expect the basis to decrease the further away an elevator is from an end user because the basis received will decrease as transportation costs increase.

The number of elevators within 10 miles of each location was also calculated using Google Maps to proxy local procompetitive effects between elevators. Two variables were made. The first counts the number of CEA elevators within a 10-mile radius. The second counts the number of non-CEA elevators in a 10-mile radius. Vachal and Tolliver (2001) found that 81% of grain in Oklahoma is sourced from within 14 miles of the elevator. We use a radius of 10 miles for this analysis based on Swanson, Bekkerman, and Taylor's (2019) study. We expect the basis to increase as the number of competitors within 10 miles increases.

Total wheat production in bushels by county was collected from 2009 to 2020 (US Department of Agriculture, 2023). We expect the basis to decrease as total county wheat production increases. We use the within-elevator variation of these variables to identify two potentially endogenous variables: entry into the alliance and cross-sectional codetermination of basis prices between elevators (discussed below). Table 2 reports summary statistics.

Methods and Procedures

Difference-in-differences (DiD) regression was used to estimate the effect of joining the alliance on the daily grain basis. The first model allows the impact of joining the alliance on the grain basis to vary across elevators. A second model examines the effect of staggered cohort entry on the treatment effect. We extend these models by relaxing the assumption that entry is exogenous and that the grain basis is not spatially correlated. In total, four regressions are estimated.

Two-Way Fixed Effects DiD

The two-way fixed effect (TWFE) regression follows Angrist and Pischke (2009, 2015) and Wooldridge (2020). Their DiD specifications relax the parallel trend assumption required to identify

a treatment effect by allowing each cooperative a unique daily trend. In other words, without joining the alliance, the basis for any elevator can deviate from common daily trends shared by all elevators according to its linear trend. The first DiD model is

$$basis_{it} = \tau_t + c_i + \gamma_i \cdot t + a \cdot entry_{it} + b \cdot prod_{i(year)} + u_{it}, \tag{1}$$

where $i = 1, \ldots, 129$ indexes elevators,

Estimation

Equation (1) (Model 1) was estimated using a multiway fixed effects (MWFE) estimator (Guimarães and Portugal, 2010). The Stata routine for the MWFE estimator is *reghdfe* ("hdfe" stands for "high-dimensional fixed effects," StataCorp, 2023; Correia, 2014). The MWFE procedure was used to absorb the daily fixed effects, elevator fixed effects, and the interaction between days and elevators using the Frish–Waugh (1933) partition theorem. Absorbing the fixed effects eliminates the computation time needed to estimate large numbers of fixed effects.

Standard errors were estimated using a two-way Driscoll–Kraay (1998) covariance estimator (Cameron, Gelbach, and Miller, 2011). The procedure produces consistent standard errors in the presence of arbitrary correlation within elevators across reported days (within-panel autocorrelation of the error terms) and arbitrary correlation across elevators within reported days (contemporaneous cross-sectional correlation of the error terms). Controlling for two-way clustering reduces the likelihood of understating the size of standard errors and detecting a false-positive effect.

TWFE with Endogenous Basis and Entry

Two issues complicate the estimation of the average treatment effect on the treated (ATT) with the previous specification. First, the daily basis reported by each elevator is spatially correlated (Figure 1). Spatial correlation between the wheat basis occurs because the transport costs of shipping grain to end users would be similar for elevators closer to each other (Viergutz, Zubek, and Schulze-Ehlers, 2016). Elevators near each other are more likely to experience the same shock caused by variations in wheat production or wheat quality (Chen et al., 2022; Roberts et al., 2022). Elevators with similar storage and handling costs may adjust the wheat basis using similar calculations. Local elevators must keep their basis similar to that of their competitors to attract grain into their facilities (Grashuis, 2019). Both producers and buyers use the basis to determine when and where they will buy and sell grain. The fact that the daily basis reported by an elevator correlates with the reported basis of neighboring elevators suggests that the above model omits a crucial variable: the basis values at neighboring elevators. Omitting this variable, the spatial lag of the grain basis, from the regression could produce bias and inconsistent treatment effect estimates.

This issue is addressed by introducing the spatial lag of the basis into equation (1) (Model 2). The average of the inverse Euclidean distances between an elevator and its six nearest neighbors was used to construct a row-standardized weighted average of basis prices.[1] A total of 2,924 $n_t \times n_t$ spatial weight matrices were constructed, one for each reported day. Separate weight matrices were calculated for each available period because not all cooperatives reported a basis on the same day. Spatially weighted basis averages were calculated using the weight matrix corresponding with a reported day and elevator. IV regression was used to estimate the models that included the spatially lagged basis because it is codetermined with an elevator's basis (Kelejian and Prucha, 2007), as we discuss later.[2]

[1] LeSage and Pace's (2014) extensive Monte Carlo analysis concluded that the specification of the spatial weights mattered little in terms of inference.

[2] The dataset did not include 14 alliance cooperatives in Kansas and Texas. We cannot model border effects. This is a data limitation that should be kept in mind.

A second issue complicating consistent estimation of the ATT is that CEA membership and nonmembership are not randomly assigned to elevators. The *entry* variable is potentially endogenous and may bias the ATT estimates because elevator operators and patrons collectively decide if they want to join the CEA. Model 3 extends Model 2 by presuming *entry* to be an endogenous variable. The exogeneity of entry is tested using IV regression.

Generated Instrumental Variables

The lack of temporal variation within elevators limits the choice of possible instruments. The candidate instruments are constant within elevators, except for wheat production, which varies by county and year. The primary source of variation is the daily basis reported by each elevator. The dataset is, therefore, essentially cross-sectional with a long time series. Lewbel's (2012) generated regressors are one approach for constructing instruments when the number of candidate instruments is limited.

Lewbel IVs leverage heteroskedasticity in the error terms from an initial regression of the purported endogenous variable on exogenous variables. Lewbel IVs are the product of the error terms from the regression of the endogenous variables on exogenous ones and the zero-centered exogenous variables. The variation of the IV due to the error terms provides the additional information needed to produce unbiased and consistent estimates of the ATT.

Two sets of Lewbel IVs are constructed: one for the situation where entry is potentially endogenous and the second for the spatially lagged basis, which is endogenous. For the first IV set, a linear probability model (LPM) is used to regress *entry*, a binary variable, on 1, *exist*, *compnoncea*, *compcea*, *miles*, *prod*, $dT_2 \dots dT_{2,924}$, with the dT_t daily dummy variables. A feasible generalized least squares estimation procedure was used to estimate the LPM because it is heteroskedastic (Wooldridge, 2020). The steps are

i. Regress *entry* on 1, *exist*, *compnoncea*, *compcea*, *miles*, *prod*, $dT_2 \dots dT_{2,924}$.
ii. Obtain the residuals ($\hat{u}$).
iii. Regress $\ln \hat{u}^2$ on 1, *exist*, *compnoncea*, *compcea*, *miles*, *prod*, $dT_2 \dots dT_{2,924}$.
iv. Obtain and exponentiate the predicted values, $\hat{h} = \exp(\widehat{\ln \hat{u}^2})$.
v. Use $1/\hat{h}$ as a weight in a second-stage regression of *entry* on 1, *exist*, *compnoncea*, *compcea*, *miles*, *prod*, $dT_2 \dots dT_{2,924}$.

The residuals from step v, $\hat{e}_{it}^A$, are used to generate the first set of Lewbel IVs as $\boldsymbol{z}_{it}^A = \hat{e}_{it}^A \cdot (\boldsymbol{x}_{it} - \bar{\boldsymbol{x}})$, where $\bar{\boldsymbol{x}}$ is a vector of the covariate sample averages (Table 2).

A second set of Lewbel IVs was constructed for the spatial lags of the basis. The spatial average of neighboring wheat basis was regressed on 1, $dT_2 \dots dT_{2,924}$, *exist*, *compnoncea*, *compcea*, *miles*, *prod*, $s \cdot$ *compnoncea*, $s \cdot$ *compcea*, $s \cdot$ *miles*, $s \cdot$ *prod*, where "*s*" indicates that the continuous variable is the spatial average of neighboring elevator variables calculated with a reported day's spatial weight matrix (Kelejian and Prucha, 2007). The residuals from this regression were used to construct the second Lewbel IV set, $\boldsymbol{z}_{it}^B$.

Estimation with Endogenous Wheat Basis and Entry

Models 2 and 3 were estimated using an MWFE instrumental variable (IV) procedure (*ivreghdfe*, Correia, 2014). The MWFE-IV models are estimated using Baum, Schaffer, and Stillman's (2007) generalized IV procedure. The efficacy of the excluded instruments in identifying a causal effect between an elevator's decision to join the CEA and a change in basis prices depends critically on the validity of the IV regression used here and the relevance and admissibility of the instruments (Wooldridge, 2010). Three statistical tests are conducted toward this end: underidentification, weak instrument, and overidentification tests. Failure to meet the thresholds of these tests means that a

causal link between entry into the CEA and member/nonmember differences in the wheat basis cannot be established.

Kleibergen and Paap's (2006) Lagrange multiplier (LM) statistic is used to test whether the estimating equation with endogenous variables is identified. The null hypothesis is that the equation is underidentified, which means that the excluded IVs are uncorrelated with the endogenous regressors. Failure to reject the null hypothesis indicates that the instruments cannot establish a causal effect between the endogenous variable (the decision to enter the CEA, the spatial correlation between the basis) and the outcome (member/nonmember differences in the wheat basis).

When instruments are weakly correlated with a potentially endogenous variable, the IVs lack the variation needed to identify a causal effect. The outcome is that the IV estimator's efficiency (precision) and accuracy (unbiasedness) are compromised (Stock and Wright, 2000). Weak identification is tested using Kleibergen and Paap's (2006) Wald statistic. Stock and Yogo's (2005) critical values determine the degree to which poorly performing instruments introduce bias, rendering estimates of the standard errors inefficient. There are no formal degrees of freedom for this test. Instead, the statistic is compared to a table of values produced by Stock and Yogo. A statistic larger than the values reported in the Stock–Yogo table suggests that the instruments are not weak.

The third check to verify instrument validity is Hansen's J test (Hansen, Heaton, and Yaron, 1996). Under the null, the excluded instruments are uncorrelated with the model errors, and the excluded IVs do not belong in the estimating equation. Rejection of the null means the model is overidentified, and the IVs are correlated with the estimating model's errors. The degrees of freedom for this test is the number of instruments minus the number of exogenous variables included in the estimating equation.

We test the endogeneity of entry when it is included in the spatial model (Model 3) using a robust Hausman test (Wooldridge, 2020). The test statistic is a chi-square random variable with 1 degree of freedom. The critical value for this test is 3.84 at the 5% significance level. Failure to reject the null hypothesis indicates that *entry* is not statistically endogenous.

Staggered Cohort Entry

Equation (1) and Models 1–3 assume that the treatment effect is homogeneous among cohorts. The ATT is presumed to be biased if the effects of entry on the basis differ for each cohort (Baker, Larcker, and Wang, 2022). Wooldridge's extended TWFE (ETWFE) estimator allows for cohort heterogeneity in treatment effects when entry into the alliance is staggered (Wooldridge, 2021).[3] The ETWFE method is an alternative to other DiD estimators that admit heterogeneous cohort effects (e.g., Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The ETWFE with cohort heterogeneity is

$$basis_{it} = \tau_t + c_i + \gamma_i \cdot t + b \cdot prod_{i(year)} + \sum_{m=1}^{5} a_m \cdot h_{it} \cdot entry_{it} + u_{it}, \tag{2}$$

where $m = 1, \ldots, 5$ denotes cohorts, h_{im} is a dummy variable indicating which observations belong to a cohort, and a_m are treatment effects. Equation (2) (Model 4) is estimated using the *ivreghdfe* procedure.

We use Model 4 to test whether the cohort ATT are heterogeneous with a joint F-test. The null hypothesis of this test is $\alpha_1 = \cdots = \alpha_5$. We also test whether the cohort ATT are jointly significant with an F-test. The null of this test is $\alpha_1 = \cdots \alpha_5 = 0$. The combined effect of the ATT is estimated as the weighted average (the weights are the number of days post-entry) of the cohort ATT, with the weights the number of observations in each cohort (Table 1). A t-test is used to test the significance of the ATT averaged over the cohorts.

[3] Nagengast, Rios-Avila, and Yotov (2024) provide a user-written package, *jwdid*, to estimate the extended TWFE. This package cannot accommodate endogenous regressors. The authors wrote their code, which replicates *jwdid* results but accommodates endogenous regressors and multi-way covariance estimators with autocorrelation.

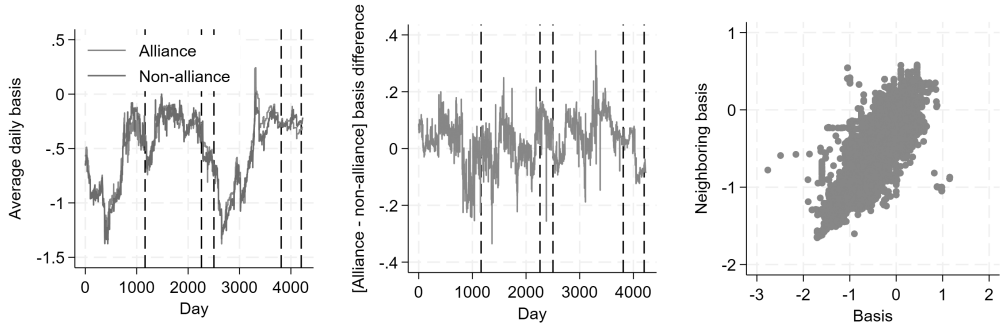

Figure 1. Daily Reported Alliance and Nonalliance Basis (panel a), the Difference (panel b), and Spatial Correlation Between the Basis of Neighboring Elevators (panel c)

Notes: The average daily basis is the mean over the number of alliance and nonalliance cooperatives. Reference lines indicate the day cohorts 1163, 2260, 2502, 3811, and 4201 joined the alliance. The number of cooperatives in a cohort is in Table 1.

Results

The daily averages of the basis for alliance and nonalliance elevator groups are plotted in Figure 1 (left panel), along with the difference between alliance/nonalliance basis (middle panel). The series overlap considerably but generally trend in the same direction. The lines in the figures indicate when an elevator cohort joined the alliance. A *t*-test of the raw difference (Figure 1, middle panel) suggests that the basis for alliance members was \$0.023 stronger (less negative) than nonmembers (*t*-statistic = 15.44).

When the difference was detrended, it was still significant at the 5% significance level (*t*-statistic, 2.49). The effect diminished to a basis difference of \$0.007/bu. The pooled group results are suggestive but ignore elevator-specific heterogeneity and do not answer the primary question: Does joining the alliance strengthen (or weaken) an elevator's wheat basis?

Two-Way Fixed Effect Regressions

Column 1 of Table 3 reports the TWFE-DiD estimates of Model 1. The ATT, −0.014, is not significant at any conventional level (*t*-statistic, −0.98). Entry into the alliance does not appear to affect the basis under this specification.

Model 2 includes the spatial lag of the basis. The IV estimates are reported in column 2 of Table 3. Compared to Model 1, the Akaike information criterion (AIC) improved by 28%. The LM statistic of the weak identification test is 12.46, just above the Stock–Yogo 10% relative bias value of 11.16. The LM statistic for the underidentification test (20.14) is significant at the 5% level. The J statistic is 12.26 and insignificant. These results suggest that the instruments used to identify the spatially lagged basis are valid and relevant. The coefficient on the spatially lagged basis is interpreted as a first-order autoregressive parameter; it is 0.81 and significant at the 0.1% level, suggesting that an elevator's basis is codetermined with the basis of neighboring elevators (see Figure 1, right panel, as a reference). The findings support the studies by Viergutz, Zubek, and Schulze-Ehlers (2016), Roberts et al. (2022), and Chen et al. (2022) and suggest that elevators set their basis to levels similar to neighboring elevators due to similar transport costs to end users and possibly by word-of-mouth by operators or clients. The ATT of this regression (−0.015) is similar in magnitude to that of Model 1 and was also insignificant.

Model 3 tests whether entry into the alliance is statistically endogenous (column 3 of Table 3). The root mean squared error and AIC show that the fit is identical to Model 2. The LM statistic for underidentification is significant at the 1% level, suggesting this model is identified. The J statistic is not significant at any conventional level. Together, these results suggest that the instruments are

Table 3. Difference-in-Differences Grain Basis Regressions (N = 189,467)

Variable	Model 1	Model 2	Model 3	Model 4
entry	−0.0140 [−0.98]	−0.0146 [−1.86]	−0.0139 [−1.75]	
Cohort 1163 *entry*				−0.0183 [−1.83]
Cohort 2260 *entry*				−0.0113 [−1.13]
Cohort 2502 *entry*				−0.0227 [−1.01]
Cohort 3811 *entry*				−0.0109 [−0.56]
Cohort 4201 *entry*				0.0835*** [8.49]
prod (00,000s)	−1.41E-04 [−1.90]	−3.35E-05 [−1.15]	−3.40E-05 [−1.16]	−3.45E-05 [−1.14]
Spatial lag of basis[a]		0.8090*** [8.98]	0.8070*** [[9.01]	0.8080*** [[8.99]
Elevator fixed effects (= 129)	yes	yes	yes	yes
Elevator × daily trend (= 129)	yes	yes	yes	yes
Time (daily) fixed effects (= 2, 924)	yes	yes	yes	yes
Akaike's information criterion	−371,712	−476,169	−476,169	−476,219
Root mean squared error	0.0908	0.0689	0.0689	0.0689
Weak identification[b]		12.46	9.03	12.55
Underidentification[b]		20.14* (df=9)	25.84* (df=13)	21.19* (df=9)
J-test (overidentification)[c]		12.26 (df=8)	14.93 (df=12)	12.32 (df=8)
Endogeneity of *entry*[d]	n/a	n/a	0.76	n/a

Notes: Values in brackets are t statistics. Single, double, and triple asterisks (*,**,***) indicate significance at the 5%, 1%, and 0.1% level, respectively.

[a] Indicates instrumented variable.

Stock–Yogo 10% relative bias value is 11.46 and a maximal instrumental variable size of 11.07 at 25%.

[c] Degrees of freedom are in parentheses.

[d] Critical chi-square value is 3.84 at the 5% significance level.

performing as they should. The ATT of −0.014 was similar in magnitude to the previous two models and insignificant. The focus of this specification is on the exogeneity of *entry*. The null of "no endogeneity" could not be rejected.

Cohort Entry

Previous results suggest that entry into the alliance is statistically exogenous and that the basis's spatial lag explains most of the variation in the grain basis. We estimate the cohort DiD model with IV regression, instrumenting the basis's spatial lag.

The ATT of all but one cohort, 4201, are insignificant (Table 3, column 4). The ATT of cohort 4201 is \$0.08/bu and significant at the 0.1% level, suggesting a strengthening of the basis for this cohort after it joined the alliance. The joint F-statistic for the test that the ATT are 0 is 20.85, which

is significant at the 1% level. The ATT estimate for cohort 4201 caused the rejection of the null. The ATT are heterogeneous (F-statistic, 24.16, $p < 0.001$). Rejection of this null was also driven by cohort 4201. When cohort 4201 was excluded from the heterogeneity test, the null that the ATT for cohorts 1163, 2260, 2502, and 3811 were equal could not be rejected ($p = 0.98$). The weighted average of the five cohort ATTs was −0.003 and is not different from 0 (t-statistic = −0.44, $p = 0.66$). Overall, it appears that entering the alliance had no impact on the basis when the cohort ATT are weighted and pooled.

The positive and significant ATT of cohort 4201 is interesting. Two elevators joined cohort 4201 just 35 days before the end of the data series (Table 1). With a comparatively limited number of post-entry observations, the effect of temporal shocks on this cohort's ATT post-entry is limited relative to the others. For instance, cohort 1163 has 2,212 days between the entry date (November 12, 2014) and the last day in the data (December 31, 2020). While there appears to be a statistically positive effect for these two elevators, the short post-entry period gives pause to a definitive conclusion. An extended post-entry period is needed to determine whether this effect on this cohort's basis is robust.

Conclusions

This study estimated the impact of joining the CoMark Equity Alliance (CEA), a cooperative grain alliance, on the wheat basis for grain elevators in Oklahoma. The first hypothesis that joining a grain marketing alliance does not affect the wheat basis for alliance members could not be unequivocally rejected. This outcome may be unsurprising, as Thomsen and Eidman (2004) predicted. The findings suggest that CEA is a price taker with no market power regarding grain sales. It can market as little or as much grain as it wishes on a given day without impacting the market price. The CEA can only affect the quantity purchased by changing its price bids on the purchase side. Given those structures, we remain confident in our existing conclusion that the CEA's objective of maximizing benefit to its member cooperatives can be achieved by maximizing its profits and distributing those profits through patronage.

There may be some argument that the possibility of a higher basis after joining an alliance may not be, more broadly, realized. The findings have implications for cooperative boards that may consider the cost benefits of joining alliances in the future. Boards should concentrate on the major function of the alliance in enhancing grain handling margins without concern that changes in basis influence their farmer-member total returns. In addition to the alliance's potential to increase grain handling margins, which is a separate research question, grain marketing alliances have the potential to create cost savings and management efficiencies. The alliance structure eliminates the need for grain merchandising by the local cooperative. Before joining the alliance, most grain cooperative general managers were responsible for merchandising and management functions.

Alliance participation can free the local cooperative manager from grain merchandising responsibilities and allow them to manage better the cooperative's operational, human resource, and fiscal aspects. The grain alliance provides the grain accounting software, eliminating that expense at the local cooperative level and likely providing more sophisticated systems. The grain alliance can also create benefits for the local cooperative's grain producer members above and beyond their increased patronage from grain margins or any effect on the grain basis. For example, the CEA created a phone app that assisted producers with price discovery and grain marketing functions. Developing that app or similar products for producers would be cost-prohibitive for a local cooperative. Doing so is easily feasible when spread over the large volume of the alliance producers.

Including the spatial lag of the basis in the regression highlighted the importance of the relationship between an elevator's basis and those of neighboring elevators. The spatial lag of the basis explained most of the variation in the basis. The significant spatial autocorrelation suggests that local market conditions influence individual elevator pricing strategies. This finding supports the second hypothesis, which is that the spatial distribution of elevators influences the grain

basis member elevators receive. This codetermination of the basis among elevators underscores the competitive nature of the grain market, consistent with Grashuis (2019). Using instrumental variables to test for the endogeneity of the decision to join the CEA reinforced the initial findings. The regressions also confirmed that the entry decision is statistically exogenous.

The heterogeneity in treatment effects across elevator cohorts illustrates the complexity of the alliance's impact, or lack thereof, on the grain basis. Four of the five cohorts experienced no significant change in the basis after joining the CEA. Only two of the 11 elevators experienced a significantly stronger basis after joining the alliance, and these elevators joined the alliance days before the end of the data series. This variability suggests that the effects of entering the alliance on an elevator's basis are not uniformly distributed across periods and may depend more on specific local conditions and competitive pressures.

Several limitations should be considered when interpreting the study's findings. First, the data used in this study were from 2009 to 2020 and were restricted to daily basis bids from 141 elevators in Oklahoma. Any changes in market conditions, policies, or external factors before or beyond this period are omitted from the analysis. Additionally, gaps in reporting days and the exclusion of some elevators from the study due to incomplete data influence the results. However, the DiD procedures used here do not require a balanced panel. Second, despite using instrumental variables to address potential endogeneity, the instruments may not fully capture all unobserved factors affecting the decision to join the CEA and the wheat basis. This omission could lead to downward-biased estimates of the alliance's impact on the basis. However, the tests indicated that the IVs were valid for the three models with endogenous covariates. Third, although the study accounted for spatial correlation in the basis, other unmeasured spatial factors might influence the results. For instance, local infrastructure, weather patterns, and transportation networks could impact elevators differently. On the other hand, the elevator and daily fixed effects capture aspects of these time-invariant factors. Fourth, the findings are specific to elevators in Oklahoma and may not be generalizable to other regions or commodities with different market dynamics, cooperative structures, or agricultural practices.

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Online Supplement: The Effect of a Cooperative Grain Alliance on Wheat Basis

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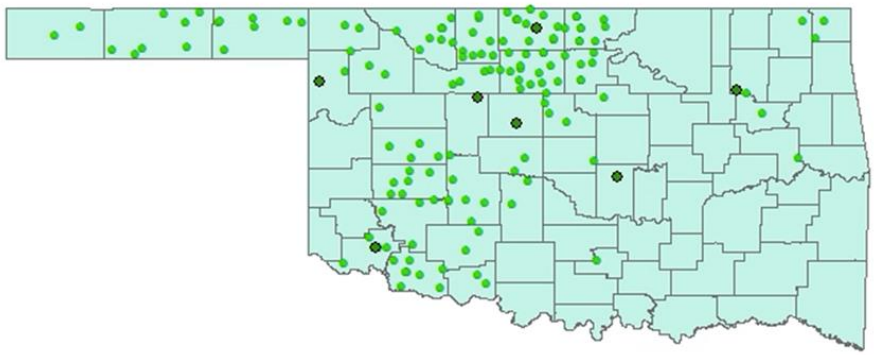

Figure S1. Distribution of Cooperatives Included in the Study
Notes: Darker-shaded points are end-users.

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

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