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Bekkerman, Anton, and Hernan A. Tejeda. "Revisiting the determinants of futures contracts success: the role of market participants." Agricultural Economics 48, no. 2 (March 2017): 175-185. DOI: 10.1111/agec.12324.

Revisiting the Determinants of Futures Contracts Success:
The Role of Market Participants

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Abstract: The Chicago Mercantile exchange introduced a futures contract for distillers' dried grains (DDGs) in early 2010, but the market became inactive only four months after its inception. While many new futures contracts do not develop into high-volume traders, interest from DDG cash market participants indicated that this contract could be successful. Prompted by the unexpected lack of trading activity in this new futures market, we empirically revisit the question of what factors contribute to a futures contract's success and extend the literature by investigating the roles of market participants and the significance of supporting futures markets. Estimation results indicate that the market participant type—hedger or speculator—affects futures contract trade volume. More importantly, we find that the viability of new futures contracts for commodities that are jointly produced with other commodities is impacted by hedgers' trade volume of the related futures contract. These results provide important additions into the portfolio of indicators used by commodity exchanges to more cost-effectively evaluate new futures contract products.

1. Introduction

The Renewable Fuel Standard (RFS) program introduced in the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007 prompted significant changes in agricultural markets. Prior to changes in 2015, the RFS program mandated that 36 billion gallons of renewable fuels be blended into gasoline by 2022, with a maximum of 15 billion gallons from corn-based ethanol by 2015 (Renewable Fuels Association 2012). Excessive production costs have continued to limit the quantity of noncorn-based biofuels, placing a greater burden on corn to fulfill the mandated ethanol production requirement and leading to a reallocation of corn away from its traditional uses in domestic livestock and poultry feed. For example, 53.4% of U.S. corn produced was used in livestock and poultry feed and 12.5% was used in ethanol production during the 2004–2005 marketing year; in the 2011–2012 marketing year, however, only 38% of the corn was used for feed, while 40% was an input to biofuel production (WASDE-USDA Report, December 9, 2011). Technological advances that allowed a corn-ethanol byproduct—distillers' dried grains (DDGs)—to be used as a supplement to livestock feed was a partial saving grace during this market transformation. The result was a quickly emerging domestic market (and more recently, an international market) for DDGs.

The rapid growth of the DDG market increased market participants' demand for tools to effectively hedge price risks of selling and buying DDGs. A limited literature has shown that a portion of these risks can be managed using a composite cross-hedging strategy with corn and soybean meal futures contracts (Brinker et al. 2009; Schroeder 2009, Tejeda 2012) in a similar way to cross-hedging the coproduced ethanol product (Franken and Parcell, 2003). However, the CME Group introduced a direct price-risk management tool on April 26, 2010: the distillers' dried grains futures contract, which intended to bring "price discovery tools and price transparency to

the market and complete the [Chicago mercantile] exchange's product suite for the corn crush for ethanol" (CME Group, Inc. 2012).

Despite the DDG market growth (Hoffman and Baker 2011) and industry interest in price risk management instruments (Stroade, Martin, and Schroeder 2010), trading volume of the new contract was low. Dahlgran (2010) shows that for ethanol, a closely related commodity, thin markets may not necessarily be an indicator of a futures contract's ineffectiveness in hedging price risk. However, this was clearly not the case for the DDG contract, which became entirely inactive after only four months of its introduction. This rapid demise raises concerns about commodity exchanges' ability to introduce successful new contracts, especially in light of the substantial research, development, and implementation costs associated with new futures contracts. Therefore, we pose two questions. First, could the theoretical and empirical inferences from previous studies about the factors affecting futures contracts' success (for example, Silber 1981; Tashjian 1995; Pennings and Leuthold 2000; Brorsen and Fofana 2001; Simmons 2002; Rausser and Bryant 2004; Bergfjord 2007; Pannell et al. 2008; Siqueira, da Silva, and Aguiar 2008) have helped explain the fate of the DDG futures contract? And if not, what other factors may have led to the outcome?

This study empirically revisits the broader question of factors affecting the demand for futures contracts. We first describe relevant elements found by previous studies, including factors that characterize a commodity's underlying cash market, the structure of the industry, and the opportunities to hedge price risk using existing tools. We then use cross-sectional variation in futures and cash market characteristics of twenty-three agricultural products during 2007–2012 to test the impacts of these factors by jointly modeling the conditional likelihood that a commodity would have a futures contract and the trading volume of contracts that are offered by an exchange. Our empirical analyses lead to three important contributions. First, we develop an empirical approach for measuring the activeness of an underlying cash market, which characterizes the

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degree to which information about changes in market conditions is publicly available. Second, we test the relevance of two new variables in determining futures contract trade volume: information about the quantity and types of futures contract traders, and the role of complementary futures markets for jointly produced commodities. Third, we provide empirically-informed rankings of each factors' importance to explaining variation in trade volume across futures contracts.

Consistent with existing literature, our estimation results indicate that cash market activeness, underlying cash market risk, product homogeneity, industry vertical integration, market power concentration, and the trade volume of a cross-hedge futures contract are relevant for predicting commodities for which futures contracts are likely to exist. Of these elements, we find the most important are the size of the cash market and availability of alternative price-hedging tools, rather than the cash market activeness as reported in prior studies. We then use an exponential type II Tobit model to estimate the impact of the type and relative balance of futures market participants and find that both factors help explain variation in futures contract trade volume. Furthermore, for multiple commodities that are co-produced within the same marketing channel—such as ethanol and distillers' dried grains—the types of participants and trade activity in one market affect participation and trade volume in the related market.

2. Determinants of Futures Contract Success as Identified by the Literature

The number of available futures contracts has more than doubled during the past thirty years and proposals for new products are constantly evaluated (Rausser and Bryant 2004). However, many new futures contracts are unsuccessful because they fail to maintain sufficient trading volumes to make these contracts profitable to the exchange.[1] Silber (1981) estimates that less than one-third of

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[1] It is reasonable to argue that the increasing use of electronic exchanges has reduced the costs of introducing new contracts and their potential failure. However, empirically investigating the effects of electronic exchanges is beyond the scope of this study.

all new contracts had profitable trading volumes within three years of introduction, and Tashjian (1995) shows that for three selected years between 1984 and 1993 only 27% of contracts offered (11 of 41) by the Chicago Board of Trade recorded trades in all three years. As a result of the apparent disconnect between the high number of contracts offered by an exchange and the low number that are traded with sufficient volume, numerous studies have sought to determine conditions for the success of futures contracts and markets.

Black (1986) suggests that factors such as the size and riskiness of a cash market, the futures contract's specifications, and existence of close substitute contracts are critical. In agricultural markets, Brorsen and Fofana (2001), Simmons (2002), and Pannell et al. (2008) argue that the activeness of a commodity's cash market (and the price information revealed through active cash markets) is a necessary condition for a successful futures market. Research into the failures of the stocker cattle futures contract (Perversi, Feuz, and Umberger 2002) and the white shrimp contract (Sanders and Manfredo 2002) shows that low basis volatility and market participants' general knowledge of futures markets are also important. Evaluations of potential salmon (Bergfjord 2007) and Brazilian milk (Siqueira, da Silva, and Aguiar 2008) futures contracts concluded that product homogeneity, high price risk, and the absence of competing risk-management tools were among the factors contributing to the viability of futures markets.

From these studies, we have identified eight major considerations that are important in predicting the potential success of an agricultural futures market. These can be classified into two groups: one that pertains to the components of the underlying cash market and another related to existing futures markets. The cash market components include six: (a) cash price variability, which is an indicator of market uncertainty (volatility); (b) the size of the cash market, measured by the total production and indicative of the total potential market risk; (c) activeness of the cash market, which represents the frequency of credible price information transmission throughout the

market; (d) product homogeneity and standardized product grading systems, both of which increase the interchangeability of traded commodity units; (e) degree of market vertical integration, which determines the number of points in the supply chain at which exchanges occur and cash prices are established; and (f) the degree of market power concentration, which can also affect price information transmission. Additionally, there are two futures market components that have been identified as being important to determining futures contract success: (a) the ability to reduce risk through futures cross-hedging and (b) the liquidity of cross-hedge futures contracts. Appendix A provides a more detailed description and examples of how these eight cash market and futures market components help explain futures contract success.

3. Additional Considerations: Supporting Markets

Previous studies have extensively described cash market characteristics and futures market opportunity costs (i.e., substitutability of alternative futures market products) as factors affecting futures markets' success. However, no considerations have been made for futures market complementarities that could enhance a new contract's success. One market complementarity is a supporting futures contract, which offers price-risk hedging tools for goods that are jointly produced and/or marketed. When a new futures contract is introduced, the existence, trade activity, and trader characteristics in a support market could be critical to increasing (or initially generating) demand for the new contract. For example, in the dairy market, the cheese and dry whey futures contracts represent supporting markets because dry whey is a by-product of cheese production. The futures market for the jointly produced ethanol would be a support for DDGs.

Most new futures contracts are initially traded primarily by commercial participants (i.e., hedgers), requiring that there be appropriate demand for a futures contract as a risk hedging tool (CME Group, Inc. manager, personal communication, March 4, 2013). Speculators are less likely

to participate in newer, thinner markets because of limited opportunities to offset an open futures contract position. Therefore, supporting markets can naturally increase commercial traders' demand due to the market-channel relationship between jointly produced commodities.

Consider a representative commercial trader who jointly produces two commodities.[2] In its simplest form, the supply of each commodity can be characterized as a function of its own price and the production of the other commodity, because any changes in the production of one commodity necessarily changes the quantity supplied of the coproduct. The joint production function for two commodities is assumed to be a continuous, concave, twice-differentiable function of outputs Q_1^S and Q_2^S, which are functions of their own prices, P_1 and P_2.[3] That is,

$$Q^S = f[Q_1^S(P_1), Q_2^S(P_2)]. \tag{1}$$

This model can be used to provide insights about the relationship between market prices of the two commodities. For example, solving equation (1) for $Q_2^S(P_2) = g[Q^S\{Q_1^S(P_1), Q_2^S(P_2)\}, Q_1^S(P_1)]$ and differentiating with respect to P_1 (e.g., an exogenous demand shock that results in a price change) yields

$$\frac{dQ_2^S}{dP_1} = \frac{\partial g}{\partial Q^S}\frac{\partial Q^S}{\partial Q_1^S}\frac{\partial Q_1^S}{\partial P_1} + \frac{\partial g}{\partial Q_1{}^S}\frac{\partial Q_1^S}{\partial P_1} > 0 \ . \tag{2}$$

That is, an exogenous shock that increases (decreases) the price of good 1 will increase (decrease) the supply of good 2 through an increase in the total output of the jointly-produced commodities. Assuming an upward sloping supply curve for good 2, $\frac{dP_2}{dQ_2^S} < 0$, the result in equation (2) implies that $\frac{dP_2}{dP_1} < 0$.

The trader maximizes her expected utility by hedging price risk for both commodities using futures markets. The trader acquires futures contract positions, F_1 and F_2, for each of the two commodities and seeks to maximize the expected revenues, $E[R_1]$ and $E[R_2]$, from each position. Each return has a variance, σ_1^2 and σ_2^2, and because the commodities are jointly produced, the term σ_{12} represents the relationship (covariance) between the returns. That is,

$$\max\ E[U] = \{F_1 E[R_1] + F_2 E[R_2]\} - \frac{\lambda}{2}\{F_1^2 \sigma_1^2 + F_2^2 \sigma_2^2 + 2F_1 F_2 \sigma_{12}\} \tag{3}$$

where λ is a scaling term. An exogenous shock to the demand of commodity 1 will result in the producer changing her decisions to hold the number of futures contracts for both of the commodities because a quantity-supplied response to the demand shock will necessarily affect the supply of the coproduct. The optimal change in the number of futures contracts for commodity 2 can be determined by differentiating the expected utility function with respect to F_2, setting equal to zero, and solving for the variable; that is,

$$F_2 = \left\{\frac{E[R_2]}{\lambda \sigma_2^2} - \frac{F_1 \sigma_{12}}{\sigma_2^2}\right\} = \frac{E[R_2] - \lambda F_1 \sigma_{12}}{\lambda \sigma_2^2} \tag{4}$$

Because the result shown in equation (2) implies that the relationship between prices in two related markets is negative, $\frac{dP_2}{dP_1} < 0$, the covariance term in equation (4) is also negative, $\sigma_{12} < 0$. Therefore, when holdings of F_1 increase, the trader will also increase F_2. Intuitively, as the producer increases her quantity supplied of commodity 1 and, accordingly, the quantity of commodity 2, she will increase her holdings of futures contracts for commodity 2. Equations (3) and (4) show that commercial traders in the futures market of a particular commodity would also participate in a futures market for the other output. Moreover, trade volume of commodity 1 may be an important indicator of the demand for a futures contract of commodity 2.

4. Data Description

We first use the eight major factors described by the literature as important to the success of a futures contract, to develop an initial empirical evaluation testing the success of a new futures contract. We loosely follow the methodological approach in Brorsen and Fofana (2001) to exploit cross-sectional variation across commodities that have and do not have futures markets. We collect cash and futures market data for twenty-three agricultural products between January 2007 and September 2012. Data were chosen to represent a wide range of sectors, including dairy (cheese, nonfat dry milk, dry whey), fruits and vegetables (apples, oranges, potatoes), field crops (corn, rice, hard red spring wheat, hard red winter wheat, soft red winter wheat, sorghum, barley), oilseeds and beans (pinto, soybeans, soybean oil, sunflower seed), animal feed products (soybean meal, DDGs), livestock (fed cattle, hogs), and poultry (broilers, eggs).

Weekly cash market price information is from the Agricultural Marketing Service (USDA) market reports, and annual production data are from the National Agricultural Statistical Service (NASS).[4] Cash prices were frequently provided for multiple locations or regions throughout the United States and for varying delivery periods. We create weekly national average cash prices and then average them across 52 weeks to determine a national annual average for each year in the sample period.[5] To ensure that prices represent current conditions (rather than expectations), we use only price information quoted for immediate transactions or ten-day delivery contracts. For fruits and vegetables, data were available for multiple production origins, but we retained only U.S. locations that represent the largest market shares in production.[6] Lastly, all production

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[4] Monthly production data were also collected for broilers, cheese, nonfat dry milk, dry whey, eggs fed cattle, hogs, soybean oil, and soybean meal. All other commodities are not continuously produced throughout the calendar year.
[5] A production-weighted national average would be preferred, but because production data were not available for most locations, a simple national average was calculated for all products for consistency.
[6] In all cases, the selected origins represented a much larger production market share than any other location. For example, during 2000–2010, Washington produced approximately 60% of all apples in the United States. The next largest producer, New York, produced approximately 11%.

quantities and prices except eggs (which are in per egg units) were converted into per ton basis. Table B1 in Appendix B presents a summary of cash market information and assumed conversion units used to transform the prices and quantities.

Futures market data are from the Commodity Research Bureau (CRB) and are used to evaluate cross-hedging opportunities for all twenty-three products, futures contract activity for thirteen products, and support-market impacts for seven products. We used only futures contracts traded on a North American futures exchange: the Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT), Minneapolis Grain Exchange (MGEX), Kansas City Board of Trade (KCBT), and the Intercontinental Exchange (ICE).[7] Table B1 summarizes the cross-hedge and support-market futures contracts, which are assumed following those described in the existing literature (Zacharias et al. 1987, Graff et al. 1997, Brinker et al. 2009).[8] For all futures contracts, we also obtain weekly trade volumes (normalized to the same units as those used for the associated cash markets) and commitment of trader information, which indicate the number of commercial and noncommercial traders. Following regulations established by the U.S. Commodity Futures Trading Commission (CFTC Regulation 1.3z, 17 CFR 1.3z), we assume that commercial traders are hedgers and noncommercial traders are large speculators.[9]

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[7] A potato futures contract is traded on the National Commodity and Derivatives Exchange (NCDEX; India) and sunflower seeds are traded on the South African Futures Exchange (SAFEX; South Africa). Also, a barley contract was introduced by the ICE in October 2012, but this is outside of our data sample.

[8] When no clear information about cross-hedging contracts was located, we used an empirical approach by identifying futures contracts for which prices were most closely correlated with the cash price of the commodity.

[9] As Irwin and Sanders (2012) point out that even when relying on CFTC classifications, it is difficult to precisely identify traders' hedging or speculative activity. For example, it is certainly reasonable to argue that commercial traders may engage in some speculative trading. However, it is difficult to identify this type of activity using publicly available data. Although arguable a weakness, without additional data we must assume that any speculative activity by categorized commercial traders is trivial.

5. Estimating Cash Market Activeness

The activeness of an underlying cash market (ACM) has been consistently identified as an important (perhaps even necessary) condition for futures market success. However, limited attempts have been made to measure cash market activeness using market data (Brorsen and Fofana, 2001). We, therefore, develop a straightforward and replicable data-driven approach for determining this cash market characteristic.

The ACM represents the degree to which (cash) market information is available to market participants. Because prices represent market information, it is reasonable to use price reporting behavior as a proxy for information transmission activity. For example, markets in which new price information (e.g., bids and offers) is publicly reported – frequently - would be characterized as being relatively active. Conversely, a low activeness cash market might be one in which most transactions are contracted and the associated price information is not publicly available. We exploit variation in cash price changes between reporting periods to measure ACM, because sustained market price variation represents regular buyer and seller interactions within the price determination process, but fewer price changes reflects limited information transmission.[10]

We estimate the ACM as follows. First, we first-difference the weekly cash-price data for each product and generate twenty-six-period rolling lags of the differenced prices. In each rolling twenty-six-period window (i.e., 26 time windows per year), we record the number of times that a price did not change between consecutive weeks.[11] Lastly, we estimate the central tendency of

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[10] Measures of price changes across periods is not analogous to cash price variability, which is often quantified as variance, standard deviation, or coefficient of variation. Price variability measures typically reveal the inherent risk faced by participants in a cash market, which may not be positively correlated (or be uncorrelated) with a market's activeness. For example, participants in cash markets with large, infrequent price changes are subject to higher price risk and would have fewer price discovery benefits that exist in more active markets. Furthermore, we estimate a Pearson correlation between cash price variability and ACM and find only weak empirical evidence, a correlation of 0.153,

[11] To check the robustness of the results, we altered the length of the largest lag to numerous values ranging from 10 to 52 weeks. We also restricted the data set to observations that fell within 6 months of a commodity's harvest, to

price differences in a twenty-six week period across all of the years in our sample and the 95% confidence interval around each expected price difference value.[12] Low activeness markets were those for which we rejected the null hypothesis that, on average, the number of weeks when no price change occurred was zero (i.e., markets in which cash prices remained the same for more than one week). High activeness markets were those for which we could not statistically reject the null hypothesis (i.e., markets in which prices changed every week).[13]

Table B2 in Appendix B shows the ACM estimation results and, for comparison purposes, ACM valuations by industry experts reported by Brorsen and Fofana (2001, Table 3). The results indicate that the data-driven valuation of ACM is quite consistent with industry experts' opinions, with the cheese and rice markets being the only exceptions. One explanation for the two exceptions may be a change in market activity of the two markets since the late 1990s—the time window used in Brorsen and Fofana (2001). Other reasons might include changes in U.S. dairy policy during the 2000s and the continuing consolidation and structural changes in the U.S. rice sector (Baldwin et al. 2011).[14] The relative success of this ACM estimation strategy is an important finding because it lowers the costs of determining a product's ACM relative to previously used methods. Application of this methodology to the DDG market shows that we cannot reject the hypothesis that the cash market for DDGs is highly active.

6. Empirical Model for Evaluating Futures Contract Success

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ensure that the results are not affected by lower market activity resulting from low market stocks. These alterations did not qualitatively change the estimation inferences from the base case scenario.

[12] Because of the bounded nature of the data, the confidence intervals are also presented with a lower bound at zero.

[13] The magnitude of price differences between weeks is less important than an indication of a price change, because any price change is a signal of new information transmission. An active cash market is characterized by a constant flow of information, regardless of whether the information reveals a small or large price change.

[14] Two other markets—dry milk and potatoes—appear to be on the margin of being classified as high activeness cash markets and the results could be an artifact of the selected time window. To check the robustness of the results, we collected cash market data for an additional 52 weeks (through August 30, 2013) and re-estimating the ACM measure for the two commodities. The re-estimation results were qualitatively identical, with only minor quantitative differences.

Many studies empirically assess futures market success by estimating a model of contract trade volume. However, while a trade volume analysis is important after a contract has been introduced, there could be unobservable correlations between characteristics of the underlying cash market that help determine whether a commodity has a futures contract and the characteristics of trade volume for commodities with a futures contract. A correlation is likely to exist because factors considered by a commodity exchange when deciding whether to introduce a contract are likely relevant in determining trade volume. Therefore, it is useful to consider a two stage modeling approach: the first "entry" stage is an exchange's decision to launch a futures contract and the second "activity" stage that characterizes market participants' demand for the instrument. Furthermore, the second stage specification needs to appropriately characterize the trade volume distribution, which has a corner solution (i.e., negative values are never observed).

Mixture models are convenient for representing the two-stage futures contract assessment as well as providing flexibility to suitably characterize a corner-solution distribution. Cragg's (1971) truncated normal hurdle model is a classic example, but it assumes the independence of errors across the two stages. Therefore, we use an exponential type II Tobit model, which allows the errors from each stage to be correlated.[15] Following Wooldridge (2010), the log-likelihood of the exponential type II Tobit model is

$$ll_i(\boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma, \rho) = 1[y_i = 0] \log[1 - \Phi(\boldsymbol{w_i \gamma})]$$

$$+ 1[y_i > 0] \left\{ \log\left[\Phi\left(\frac{\boldsymbol{w_i \gamma} + \frac{\rho}{\sigma}(\log y_i - \boldsymbol{x_i \beta})}{\sqrt{(1 - \rho^2)}}\right)\right] + \log\left[\phi\left(\frac{\log y_i - \boldsymbol{x_i \beta}}{\sigma}\right)\right] - \log \sigma - \log y_i \right\} \quad (5)$$

where for observation i, $1[y_i > 0]$ represents an indicator variable that equals one when the futures contract's volume, y_i, is positive and equals zero otherwise; $1[y_i = 0]$ is an analogous

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indicator variable for commodities that do not have futures contracts; $\boldsymbol{w_i}$ is a vector of variables that explain an exchange's decision to introduce a futures contract for the commodity; $\boldsymbol{x_i}$ is a vector of variables that help explain the variation in a traded contract's volume; ρ is the correlation between the errors in the first and second stage equations; σ is the standard deviation of the second-stage error term; $\Phi(\cdot)$ and $\phi(\cdot)$ represent the normal cumulative and probability density functions; and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the associated parameter vectors.

An important requirement of this model is the appropriate identification of the unknown correlation parameter, ρ, and the parameters of the second, "activity" stage, $\boldsymbol{\beta}$. Poor identification can occur when the set of variables identifying the first stage is the same as the variable set for the second stage; that is, $\{\boldsymbol{w}\} = \{\boldsymbol{x}\}$ (Wooldridge 2010). Therefore, this mixture model approach requires that the "entry" stage have exclusionary restrictions that uniquely characterize the likelihood of a futures contract, but do not impact a contract's trade volume.

We exploit cross-sectional variation in agricultural commodity markets that have and do not have futures contracts to estimate the following two-stage mixture model,

$$FM_{i,t} = \gamma_0 + \gamma_1 CV_{i,t} + \gamma_2 ACM_{i,t} + \sum_{k=1} \gamma_k U_{k,i,t} + \gamma_3 \ln(XVol_{j,t}) + \gamma_4 RR_{i,t} + \alpha_t + \varepsilon_{i,t} \qquad (6a)$$

$$\ln(Vol_{i,t}) = \beta_0 + \sum_{m=1} \beta_m V_{m,i,t} + \beta_1 \left(\frac{Comm_{i,t}}{NComm_{i,t}}\right) + \beta_2 \ln(NComm_{i,t}) + \theta_t + v_{i,t} \qquad (6b)$$

In the "entry" stage—equation (6a)—we exploit variation across products' cash market characteristics and cross-hedge opportunities that can impact a product's likelihood of having a futures market. The term $FM_{i,t}$ represents a binary variable indicating whether product i has a futures market in year t; $CV_{i,t}$ is the cash market price coefficient of variation; $ACM_{i,t}$ is cash market activeness; $U_{k,i,t}$ is a vector of variables describing the product homogeneity, whether the industry is characterized by high degree of vertical integration and buyer power concentration, and

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cash market size; $XVol_{j,t}$ is the annual average trade volume of the cross-hedge futures contract

for product $j \neq i$; $RR_{i,t}$ is the residual risk after a cross-hedge is used; α_t is a time fixed effect;

and $\varepsilon_{i,t}$ is the idiosyncratic error term.[16]

Equation (6b) characterizes the second-stage futures market "activity" model. The term

$\ln(Vol_{i,t})$ represents the natural log of annual trade volume in year t for product i, conditional on

product i having a traded futures contract.[17] Furthermore, $\boldsymbol{V_{m,j,t}}$ represents a vector of all

regressors in equation (6a), except the degree of vertical integration and market power

concentration, which are omitted as exclusionary restrictions. For commodities with futures

contracts, industry characteristics vary minimally and offer a natural first-stage identification.

Studies have also suggested that the types of futures market participants can impact a

contract's trade volume. For example, Sanders and Manfredo (2002) and Bollman, Garcia, and

Thompson (2003) hypothesize that the failures of the white shrimp and diammonium phosphate

futures contracts, respectively, were related to the markets' inability to attract speculative trade.

Guilleminot, Ohana, and Ohana (2014) also show that trade activity depends on the interaction of

speculators and commercial traders. However, there is limited empirical evidence to support these

hypotheses and an absence of broader insights about the role of futures market participants. To

gain a better understanding of this role, we include two additional variables into the "activity"

stage equation. The term $\left(\frac{Comm_{i,t}}{NComm_{i,t}}\right)$ in equation (6b) represents the ratio of volume held in

commercial traders' positions to that of large noncommercial participants and $\ln(NComm_{i,t})$ is

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[16] Note that in the regression model, ACM represents one minus the estimated continuous cash market activeness measure presented in Table B2 in Appendix B, which provides an easier interpretation of the regression results (i.e., higher ACM values represent more active cash markets).

[17] It is possible to estimate a similar model using open interest as the dependent variable. However, the high correlation between trade volume and open interest leads to qualitatively similar results.

the natural log of noncommercial traders' overall contract volume.[18] The term $\ln(NComm_{i,t})$ characterizes the overall volume of speculative trade activity in the market while $\left(\frac{Comm_{i,t}}{NComm_{i,t}}\right)$ can help identify the relative balance of commercial and speculative participants. Lastly, θ_t characterizes a yearly fixed effect, and $\nu_{i,t}$ is an idiosyncratic error term.

All variables are measured annually to correspond to the fact that crops are produced on annual basis. For year t, the term $CV_{i,t}$ is calculated using cash market price data across fifty-two weeks within that year and $ACM_{i,t}$ is the annual average of weekly estimated ACM measures. Product homogeneity, industry vertical integration, and market-power concentration measures are based on Brorsen and Fofana (2001; Table 3). Industry-level characteristics are unlikely to substantially vary over this study's time period and we, therefore, assume that an industry exhibits either a high or low behavior for a particular characteristic, corresponding to the mean value being above or below 5 (on a scale of 1–10). For products that are not assessed by Brorsen and Fofana (i.e., barley, DDGs, dry whey, oranges, pinto beans, and sorghum), we assume that the products and industries are similar to those of the closest substitute product (i.e., wheat, soybean meal and corn, dry milk, apples, rice, and corn).[19]

The cash market size is calculated by taking the natural log of annual production (in tons) and the cross-hedge contract activity, $\ln(XVol_{j,t})$, as the natural log of the annual average of weekly trade volume for the cross-hedge commodity j. Lastly, the residual risk ($RR_{i,t}$) represents the variation in a product's weekly cash price that cannot be explained by the variation in the price

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[18] Wooldridge (2010) also suggests that all of the explanatory variables used to model the second-stage equation be included in the first-stage probit model unless there are theoretical reasons to exclude those variables. In our case, products without futures markets would not have information about futures market participants; including these variables could affect consistency of the first-stage estimation.

[19] While Brorsen and Fofana (2001) provide mean valuations for some commodities, we convert those to binary indicators because we extrapolate industry and market information for other commodities that are not included in that study. Assuming a specific magnitude for extrapolated values may create larger measurement bias than using binary indicators.

of a cross-hedge futures contract. We first estimate a linear cash price model of commodity i as a function of a cross-hedge futures contract price in week ; that is, $P_{i,s} = \beta_0 + \beta_1 F_{j,s} + \varepsilon_{i,t}$. The regression $\tilde{R}^2$ for each year is then used to obtain $RR_{i,t} = (1 - \tilde{R}^2)$. When two cross-hedge commodities are used, the explanatory variables are $F_{j,s}$ and $F_{k,s}$ and denote the two different futures contracts. Table C1 in Appendix C provides a detailed variable construction overview and Table 1 shows the descriptive statistics.

7. Estimation Results of the Futures Contracts Model

Table 2 presents the exponential type II Tobit regression results of the futures contracts model. The table also shows the standardized parameter estimates, which are calculated following Kaufman (1996). The standardized coefficient estimates describe the change in predicted probability associated with a one-standard-deviation change in the value of the regressor. This implies that the absolute value of the estimated coefficients can be interpreted as the relative strength of each regressor in predicting the dependent variable.

The top portion of Table 2 shows the parameter estimates for factors affecting the likelihood that a commodity would have a futures contract. All factors except residual risk and production homogeneity are statistically different from zero and all variables except CV have the expected effect on the probability. Specifically, ACM increases (indicating improved price discovery) are expected to make it more likely that an agricultural product has a futures contract, as is the case for products that have a lower degree of vertical integration or market power concentration. Higher production levels, on average, increase the likelihood of futures markets. However, increases in the cross-hedge contracts' trade volume reduce the probability of a futures contract for a direct hedge, suggesting that market participants may be willing to trade off basis

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risk for higher liquidity in a related futures market. These results are qualitatively robust to alternative assumptions about cross-hedge futures contracts in calculating residual risk measures.

The negative, statistically significant parameter associated with the coefficient-of-variation variable is surprising because higher cash price risk is expected to increase the demand for a price-risk tool. An analysis of pre- and post-regression collinearity statistics (condition index matrices and variance inflation factors) did not indicate a misspecification issue. A plausible economic reason for the result may be the fact that products for which futures markets exist have lower price variability than if those products did not have futures markets. That is, if it were possible to perform a counterfactual analysis in which products' prices could be observed before and after a futures market were introduced for those products, we would likely observe the correct relationship between futures market probability and price risk.[20]

The standardized parameter estimates indicate that market size is the most important variable for explaining the likelihood of observing a futures market. This is expected because annual production is frequently used by exchanges as the first qualification for considering a new futures contract. The number of marketing and transaction points and the liquidity of cross-hedging opportunities are the next most important predictors. Surprisingly, cash market activeness and cash-price risk are among the least important factors in explaining changes in the likelihood of a futures contract, which is counter to the hypotheses that these factors have the most influence (Bergfjord 2007, Brorsen and Fofana 2001, Siqueria et al. 2008). This difference may be because previous works have examined case studies of specific products, did not directly measure the relative explanatory power of factors, or could not include both measures in a regression.[21] To our

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[20] Many futures contracts were introduced prior to the collection and availability of reliable market price data, so we are unable to test this hypothesis empirically.

[21] The apparent lack of importance may also be related to the fact that low ACMs may occur in highly concentrated and vertically integrated markets. However, as discussed above, there is little evidence of multicollinearity among these variables.

knowledge, this is the first study that provides an empirically-informed relative ranking of these factors.

Lastly, the parameters estimated in the "entry" stage equation are used to provide in-sample predictions for validation purposes and an out-of-sample prediction for the likelihood of a DDG futures contract. Table B3 in Appendix B shows that the model correctly predicts the existence or non-existence of futures markets for nearly all commodities (rice being the only exception) and the out-of-sample prediction indicates that the DDG has a 90.2% likelihood of a futures contract.[22] This result partially justifies the Chicago Mercantile Exchange's decision to introduce the contract based on factors shown by past research to affect futures market success.

Table 2 also presents the estimated parameters from the second "market activity" stage of the exponential type II Tobit model. The positive and statistically significant correlation statistic, $\hat{\rho} = 0.77$, indicates that there is a relatively strong relationship between unobservable factors affecting an exchange's decision to introduce a futures contract for a commodity and the contract's trade volume. This result provides support for the overall validity of the two-stage modeling approach and offers empirical evidence that introducing contracts without considering the contracts' potential for having sufficient trade volume is not recommended. The estimated marginal effects indicate that cash market activeness and product homogeneity are the only statistically significant cash market characteristics that affect futures trade volume. However, changes in futures market participants' information also have statistical and economic impacts.

The results indicate that speculators are important to futures market activity. A 1% increase in the trade volume of large noncommercial traders, on average, increases overall trade volume by 1.07%. The standardized estimate indicates that speculator activity has the most relative

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[22] Because the product homogeneity, degree of vertical integration, and market power concentration for the DDG market were assumed, we calculated success probabilities under all other combinations of alternative product and market assumptions. The high probability of success for a DDG futures contract was consistently robust to these different specifications.

importance in explaining trade-volume variation. Furthermore, an increase in the ratio of commercial hedger positions to those of noncommercial speculators is also expected to improve trade volume. These results suggest that there are important trade-offs among the types of futures market participants and the trade volume that these participants generate. For example, while increases in the volume of speculator trade can raise market liquidity, lower trade volume is observed when the proportion of those positions becomes too large relative to the number of positions held by other trader types. This offers empirical support to the generally common intuition that successful futures markets with sufficient trade volume depend on having a balance of hedger and speculator positions rather than a concentration of any single type of trader.[23]

The recently introduced ethanol futures contract provides an example of our model's application. We use ethanol cash and futures market data between 2009 and 2012 and assume the same product and industry characteristics as for the DDG market (Table 1). We also follow Dalhgran (2009) to assume that the gasoline futures contract (NYMEX) is a reasonable cross-hedge instrument, and convert production and price information to tons (1 barrel = 0.15038 tons per BP lpc, 2015). Then, applying the estimated parameters in Table 2, we make out-of-sample predictions for the probability that the ethanol futures contract would exist and for its average weekly trade volume. The results indicate that in 2009, 2011, and 2012, there is a higher than 50% likelihood that an ethanol futures contract is predicted to exist. Furthermore, average two-year out-of-sample prediction of weekly trade volume for 2011 and 2012 (the only years for which we could obtain actual trade volumes) was 166.39, being only a marginal overestimate of the actual two-year weekly average of 151.87 trade contracts.

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[23] For robustness and assurance that the results are not influenced by idiosyncrasies associated with less active futures contracts, we re-estimated the model using only commodities for which trade volumes were, on average, 10,000 contracts or greater. The estimated parameters were qualitatively identical and quantitatively marginally different from those that use the entire data sample.

8. Assessing the Role of Support Markets

The importance of the types of futures market participants and the quantity of positions they hold suggests that similar factors in supporting futures markets could affect trade volume. We test this hypothesis by investigating variation in the trade volumes of products that have both a futures market and a supporting futures market. These include cheese, nonfat dry milk, dry whey, fed cattle, soybean oil, and soybean meal. Data for these products are used to estimate the model:

$$\ln(Vol_{i,t}) = \delta_0 + \delta_1 CV_{i,t} + \delta_2 ACM_{i,t} + \delta_3 RR_{i,t} + \delta_4 \left(\frac{SComm_{i,t}}{SNComm_{i,t}}\right) \quad (7)$$

$$+ \delta_5 \ln(WSVol_{i,t}) + \mu_t + \pi_{i,t}$$

where the terms $\ln(Vol_{i,t})$, $CV_{i,t}$, $ACM_{i,t}$, $RR_{i,t}$ are defined in equation (6b), $\left(\frac{SComm_{i,t}}{SNComm_{i,t}}\right)$ is the ratio of commercial traders' volume to that of noncommercial traders in the support market, $\ln(WSVol_{i,t})$ represents the trade volume in the support market ($SVol_{i,s}$) weighted by the ratio of commercial traders to noncommercial participants in the support market, μ_t is a monthly fixed effect, and $\pi_{i,t}$ is an idiosyncratic error term. The commercial participant-weighted support-market trade volume, $\ln(WSVol_{i,t})$, is of primary interest and reveals the impacts of the support-market trade volume conditional on the relative participation of hedger-to-speculator traders.

We overcome several challenges associated with using a smaller subset of products as follows. First, we estimate equation (7) using monthly data in order to increase the available degrees of freedom. Second, because the variables characterizing the cash market and cross-hedge opportunities in equation (7) are highly correlated with product homogeneity, market size, and cross-hedge contract volume, we use condition index and variance inflation factor analyses to identify only those regressors that uniquely explain variation in the cash markets and cross-hedge

opportunities.[24] Lastly, the explanatory variables exclude futures market information directly associated with the product (e.g., the number of participants in market i) because we intend this model to be used to make out-of-sample predictions. That is, the results would be used to predict the trade volume of a potential new futures contract, which has a support futures market but not its own futures market.

Table 3 presents the linear regression parameter estimates for the trade-volume model with support-market information. Parameter estimates associated with the cash market and cross-hedge opportunities are statistically significant and consistent with the results discussed above. The coefficient associated with the participant type-weighted support-market trade volume is positive and statistically significant, providing evidence of the importance of hedgers' participation in related futures support markets. An increase in the support-market trade volume (i.e., improvements in trade volumes due to relatively more positions held by commercial traders) is associated with increases in the futures contract trade volumes of product i. This increased demand may be the result of market participants' attempts to successfully manage a portfolio of risks related to the production of coproducts.

The regression results indicate that a 1% increase in hedger-driven support-market activity leads to a 0.82% increase in the trade volume of product i. The standardized parameter estimates indicate that the support-market trade volume has the largest relative impact in explaining coproducts' futures contract trade volume. In addition, the results indicate that the effect of the ratio of commercial to noncommercial participants in the support market is statistically different from zero and positively related to trade volume of product i. While the economic significance of this estimated relationship is arguably small, the result does add credence to the fact that the trade

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[24] Altering the specification to include different combinations of cash market and cross-hedge opportunity variables leads to qualitatively similar outcomes and has trivial impacts on the overall model fit and insights about support-market effects.

volume of new contracts for jointly produced commodities relies on the trade activity of hedgers in a coproduct's futures market.

The DDG market is useful in evaluating the model's predictive capabilities for new contracts of commodities that have existing futures support markets. Using the estimation results presented in Table 3 and assuming ethanol as the DDG coproduct, we find that the predicted average monthly DDG futures trade volume is approximately 28 contracts per month. This represents 0.15% of the average 18,130 monthly trades of futures contracts for other products in the sample. Therefore, while the DDG cash market characteristics suggest a high probability of observing a futures contract for this commodity, low trade volume predictions are likely explained by the relatively thinly traded support market (ethanol) futures contract. Dahlgran and Liu (2011) show that ethanol producers may be hesitant to use futures contract for price risk management because doing so increases their exposure to liquidity risks. By incorporating information about the relatively low hedger-driven trade in the ethanol support futures market, results from our model may have helped prevent the introduction of an ultimately unsuccessful.

9. Conclusions

Successfully evaluating the viability of new futures contracts can make the development and introduction of the new price-risk tools more efficient. This study offers a new perspective on assessing the feasibility and success of futures contracts by using information about futures market participants and their role in support markets. Furthermore, we develop evaluation models that rely almost entirely on market data and can therefore improve the objective, replicable research associated with new contract introduction. These data-driven assessment techniques represent useful methodological contributions for both academic and industry researchers interested in understanding market opportunities. This study's estimation results also provide insights into the

role that market complementarities have in explaining futures market success. This is advances the traditional approach that considered only competing market forces, such as cross-hedging opportunities.

Accompanying this study's methodological contributions, our findings can also help existing and emerging futures contract exchanges make more efficient and more effective decisions about introducing futures contract. For example, exchanges developing new contracts can make more targeted research efforts based on this work's estimated relative rankings of factors that contribute to a futures contract's success. Given the relative predictive accuracy of the presented models, exchanges could use this study's results to make quantitative predictions about potential new contracts in a consistent, replicable manner. This can be especially important to futures market formation in developing countries, which have been shown to be reluctant to attempt such projects due to the uncertainty of their success (Sabuhoro and Larue, 1997).

Lastly, when no support markets exist for a commodity being considered for a new futures contract, the out-of-sample trade volume predictions would require making informed scenario analyses. For example, suppose that an exchange considers a new futures contract and will gauge that contract a "success" if it, on average, meets or exceeds at least 1,000 trades per week. By combining observed data about the commodity's cash market characteristics with the estimated parameters in Table 2, the exchange can assess how different hypotheses about the total number and relative proportion of commercial and non-commercial market participants would affect the contract's 1,000 trade volume goal. While future research is necessary to develop a more quantitative approach, the results of our empirical analysis and an exchange's qualitative knowledge about potential participant characteristics within a new futures market can significantly improve that exchange's decision-making process for introducing new contracts.

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Table 1: Descriptive Statistics about Cash Markets and Cross-Hedge Futures-Hedging Opportunities

Commodity	Futures Market	Product Homogeneity	Vertical Integration	Buyer Concentration	CV	ACM	Market Size	Vol. Cross-hedge Contract	Residual Risk
Apples	No	Low	High	High	7.68	17.91	14.82	7.41	0.98
Barley	No	High	Low	Low	12.95	11.38	7.66	11.72	0.37
Broilers	No	High	High	High	5.81	9.06	16.94	10.20	0.94
Cheese	Yes	High	Low	High	7.27	4.43	14.93	-1.33	0.41
Corn	Yes	High	Low	Low	11.81	0.35	11.60	10.77	0.22
Dry Milk	Yes	High	Low	High	11.23	5.68	13.54	-1.33	0.17
Dry Whey	Yes	High	Low	High	16.43	8.28	13.16	-1.33	0.73
Eggs	No	High	High	High	19.89	8.77	18.32	10.20	0.96
Fed Cattle	Yes	Low	High	High	4.42	0.14	16.45	11.72	0.41
Hogs	Yes	High	High	High	11.12	0.03	16.51	10.21	0.50
Oranges	No	Low	High	High	14.49	8.01	16.03	7.42	0.96
Pinto Beans	No	High	Low	High	10.92	17.29	13.18	9.23	0.99
Potatoes	No	Low	Low	High	17.14	8.01	16.89	10.77	0.87
Rice	Yes	High	Low	High	8.55	18.02	16.15	10.77	0.94
Sorghum	No	High	Low	Low	14.98	0.21	8.03	11.72	0.04
Soybeans	Yes	High	Low	Low	15.16	0.18	10.15	10.20	0.22
Soybean Oil	Yes	High	Low	Low	11.47	0.02	16.04	8.99	0.12
Soybean Meal	Yes	High	Low	Low	12.68	0.16	17.47	11.23	0.30
Sunflower	No	High	Low	High	11.45	12.53	14.15	10.49	0.20
HRS Wheat	Yes	High	Low	Low	18.66	0.18	8.40	9.22	0.25
HRW Wheat	Yes	High	Low	Low	18.53	0.23	8.97	10.76	0.10
SRW Wheat	Yes	High	Low	Low	19.99	0.16	8.11	9.22	0.20
DDG	–	Low	High	High	12.07	2.30	16.53	10.20	0.13

Notes: Product homogeneity, industry vertical integration, and buyer concentration are assumed to be the same as those in Brorsen and Fofana (2001) for seventeen of the twenty-three products. For barley, dry whey, oranges, pinto beans, sorghum, and DDGs, these measures are obtained from the literature, personal communication with individuals active in the industries, or were assumed to be similar to products that are close substitutes. While DDGs technically have a futures market, we do not classify it as such because the DDG market is used as a counterfactual to motivate and test the empirical model. Table C1 in the appendix provides a full description of variable construction.

Table 2: Exponential Type II Tobit Estimation Results of the Futures Contracts Model

Variable	Parameter Estimate	Standard Error	Standardized Parameter Estimate
First-stage "Entry" Equation, Futures Market = 0/1			
Intercept	-5.79*	(3.35)	–
CV	-0.07***	(0.03)	-0.11
ACM	0.11*	(0.06)	0.15
Homogeneity	0.86	(0.53)	0.07
Vertical Integration	-2.27***	(0.73)	-0.21
Concentration	-5.98**	(2.35)	-0.56
log(Production)	1.07***	(0.34)	0.66
log(Vol. Cross-hedge Contract)	-0.43**	(0.18)	-0.31
Residual Risk	-2.82	(2.29)	-0.20
Second-stage "Activity" Equation, log(Volume)			
Intercept	-7.25***	(1.56)	–
CV	-0.02	(0.02)	-0.04
ACM	0.12**	(0.04)	0.16
Homogeneity	1.54***	(0.46)	0.12
log(Production)	0.03	(0.04)	0.02
log(Vol. Cross-hedge Contract)	0.19	(0.22)	0.24
Residual Risk	-0.98	(0.68)	-0.09
Ratio of Commercial to Noncommercial	2.82***	(0.41)	0.26
log(Noncommercial participants)	1.07***	(0.12)	0.36
Observations		115	
Equation Correlation Statistic, $\hat{\rho}$		0.77***	
McFadden's Pseudo R-squared		0.66	

Notes: The regression is estimated using data describing all products except DDG. The model includes yearly fixed effects, but these estimated parameters are omitted for brevity. Coefficient estimates for standardized parameter estimates represent changes in the standard deviation of the dependent variable from a one standard deviation from the mean of the corresponding explanatory variable. Standardized parameter estimates for the first stage binary response regression are obtained following Kaufman (1996) and represent changes in the predicted probability associated with a one-standard deviation change in the regressor. Absolute values of the standardized parameter estimate characterize the relative importance of each variable to changes in the dependent variable. Estimated second-stage results represent the marginal effects that are calculated following Wooldridge (2010) to account for the truncated nature of the dependent variable distribution. Triple, double, and single asterisks (***, **, and *) indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3: Estimation Results of the Trade-Volume Model for Commodities with Support Markets

Variable	Parameter Estimate	Standard Error	Standardized Parameter Estimate
Intercept	2.29***	(0.68)	–
CV	-5.14**	(2.60)	-0.04
ACM	0.44***	(0.10)	0.24
Residual Risk	9.06***	(0.88)	0.26
Commercial participant-weighted support-market trade volume	0.82***	(0.08)	0.71
Ratio of commercial to noncommercial participants, support market	0.04*	(0.02)	0.01
Observations		242	
McFadden's Pseudo R-squared		0.55	

Notes: Monthly data for cheese, dry whey, dry milk, fed cattle, soybean oil, and soybean meal are used to estimate the trade-volume model. Monthly coefficient of variation (CV) values are calculated using weekly cash market data for four or five weeks in each month. The model includes monthly fixed effects to control for potential seasonality, but these estimated parameters are omitted for brevity. White's heteroskedasticity-robust standard errors are presented. Triple, double, and single asterisks (***, **, and *) indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Appendix A: Factors Identified to Affect and Predict Futures Contract Success

Cash Market Components

a. Cash price variability

    A cash market's price variability is an indicator of uncertainty. Markets with low price
    uncertainty are unlikely to have demand from either participants seeking to hedge price
    risk or from those seeking to gain returns on risky investments. A highly volatile cash
    market is more likely to develop a futures market.

b. Size of the cash market

    Cash market size, measured by total production volume, helps indicate the potential size
    of price risk across all market participants. Markets with greater aggregate production are
    likely to have higher total risk and, thus, more participants seeking to hedge the risk.

c. Activeness of the cash market (ACM)

    An active cash market is one in which there is more frequent transmission of credible price
    information that is available to all market participants (Fortenberry and Zapata 1997),
    which strengthens the link between cash and futures prices. Commodities with more active
    spot markets (i.e., greater price discovery) lower the risks and increase hedging/speculating
    opportunities for futures market participants.

d. Product homogeneity and common knowledge of a product's grading system

    Futures contracts specify that traded commodity units are interchangeable, which requires
    products to have a homogeneous quality level or at least a quality grading system that is
    well established and is common knowledge to all participants. Substantial quality
    heterogeneity among products can lead to significant market segmentation, effectively

reducing the size and activeness of each submarket and lowering the likelihood of a successful single futures market.

e. Degree of vertical integration in the market

A market with a high degree of vertical integration is expected to have fewer points in a product's marketing channel at which exchanges between buyers and sellers occur. For example, if the procurement, handling, transportation, and export of a crop is managed by a single operator, then competitive price determination at each of the four marketing stages is unlikely; most price hedging will occur within the firm structure.

f. Degree of market power concentration

The concentration of market power can reduce price information transmission and constrain price adjustments to fundamental market conditions. Futures markets are not expected to be successful highly concentrated cash markets.

Futures Market Components

g. Risk reduction through futures cross-hedging

When successful price-risk hedging tools already exist, demand for alternatives is unlikely (Black 1986). In commodity markets, a futures contract that provides a direct hedge (i.e., a contract specific to a commodity) may not be adopted if cross-hedging opportunities enable buyers and sellers to reduce a large portion of price risk. Consequently, higher levels of residual risk (i.e., price risk remaining after a cross-hedge) are expected to increase market participants' demand for an own-hedge product.

h. Liquidity of cross-hedge futures contracts

Higher trade volume of a cross-hedge contract increases the opportunity costs of using an own-hedge contract (Black 1986). Moreover, Brorsen and Fofana (2001) provide empirical evidence of this inverse relationship for a number of agricultural commodities.

Appendix B: Data Description, Summary Statistics, and Predicted First-stage Probabilities

Table B1: Cash and Futures Markets Descriptions and Assumptions

| Commodity | Cash Market | | | Futures Market | | |
	Product Description	Unit Conversion	Cross Hedge	Direct Hedge	Support Market
Apples	Washington origin; Carton tray pack; 80S; Washington extra fancy grade	–	Orange Juice	–	–
Barley	Feed, US Number 2	48 lbs. per bushel	Corn	–	–
Broilers	US Grade A	5.7 lbs. per head	Soybean meal + Corn	–	–
Cheese	Cheddar; 40 lb. block	–	Class IV Milk	Cheese	Milk III
Corn	Yellow, US Number 2	56 lbs. per bushel	Soybeans	Corn	
Dry Milk	Nonfat; High heat	–	Class IV Milk	Nonfat Dry Milk	Butter
Dry Whey	Extra Grade and Grade A; Nonhygroscopic	–	Class IV Milk	Dry Whey	Cheese
Eggs	Large; Dozen	–	Soybean meal + Corn	–	–
Fed Cattle	Steers; Select and Choice 2 and 3 grade; Medium and Large frames; 900-1600 lbs.	1,250 lbs. per head	Corn	Live Cattle	Feeder Cattle
Hogs	Barrows and Gilts	275 lbs. per head	Soybean meal + Corn	Lean Hog	–
Oranges	Florida and California origins; Navel; 56S; US No 1 or Shippers 1st grade; 7/10 or 4/5 bushel cartons	–	Orange Juice	–	–
Pinto Beans	US Number 1	–	HRW	–	–
Potatoes	Idaho origin; 50 lb. units; Russet; 70S	–	SRW	–	–
Rice	Long, US Number 2	–	Corn	Rough Rice	–
Sorghum	US Number 2	–	Corn	–	–
Soybeans	US Number 2	60 lbs. per bushel	Soybean meal	Soybeans	–
Soybean Oil	–	–	Canola	Soybean Oil	Soybeans
Soybean Meal	46.5–48% protein	–	Corn	Soybean Meal	Soybeans
Sunflower	US Number 1	–	Soybean oil	–	–
HRS Wheat	Dark northern spring; 13% protein	60 lbs. per bushel	HRW	MGEX Wheat	–
HRW Wheat	Hard red winter; 11.5% protein	60 lbs. per bushel	SRW	KCBT Wheat	–
SRW Wheat	Soft red winter	60 lbs. per bushel	Corn + Oats	CBOT Wheat	–
DDG	10%	–	Soybean meal + Corn	–	Ethanol

Notes: We assume that unit conversions convert all products (except eggs) into per ton basis. The cross-hedge futures market represents the contract of a commodity whose prices are most correlated with a particular cash market and were chosen following findings and assumptions from the existing literature. The support market column represents commodities that are market channel coproducts. While DDGs technically have a futures market, we do not classify it as such because the DDG market is used as a counterfactual to motivate and test the empirical model.

Appendix C: Variable Construction Details

Table C1: Variable Construction Details

Variable name	Math symbol	Construction details
Futures contract trade volume	$\ln(Vol_{i,t})$	$\ln(Vol_{i,t}) = \ln\left(\frac{1}{52}\sum_{s=1}^{52} Vol_{i,t,s}\right)$
Coefficient of variation	$CV_{i,t}$	$CV_{i,t} = \frac{STD(P_{i,t,s=1}, P_{i,t,s=2},\dots P_{i,t,s=52})}{E(P_{i,t,s=1}, P_{i,t,s=2},\dots P_{i,t,s=52})}$
Activeness of cash market	$ACM_{i,t}$	1. Calculate first-differenced weekly prices, $\Delta P_{i,s} = P_{i,s} - P_{i,s-1}$ 2. For each week s, determine the number of times in the preceding 26 weeks that $\Delta P_{i,s} = 0$; that is, $NC_{i,t,s}$. 3. For each year t, estimate the expected value of the number of weeks within each 26 week rolling lag; that is, $ACM_{i,t} = E(NC_{i,t,s=1}, \dots NC_{i,t,s=52})$
Homogeneity	Hom_i	1. Locate homogeneity measure in BF; that is, $Hom_{i,BF}$ 2. $Hom_i = 0$, if $Hom_{i,BF} < 5$; $Hom_i = 1$, otherwise
Vertical integration	VI_i	1. Locate integration measure in BF; that is, $VI_{i,BF}$ 2. $VI_i = 0$, if $VI_{i,BF} < 5$; $VI_i = 1$, otherwise
Buyer concentration	Con_i	1. Locate concentration measure in BF; that is, $Con_{i,BF}$ 2. $Con = 0$, if $Con_{i,BF} < 5$; $Con = 1$, otherwise
Market size	$\ln(Y_{i,t})$	Natural log of annual production, in tons
Liquidity of cross-hedge contract	$\ln(XVol_{j,t})$	$\ln(XVol_{j,t}) = \ln\left(\frac{1}{52}\sum_{s=1}^{52} Vol_{j,t,s}\right)$
Residual risk	$RR_{i,t}$	1. Estimate $P_{i,s} = \beta_0 + \beta_1 F_{j,t} + \varepsilon_{i,t}$ 2. Retrieve coefficient of determination, $\tilde{R}^2$ 3. $RR_{i,t} = (1 - \tilde{R}^2)$
Commercial traders' activity	$Comm_{i,t}$	1. For each week s, determine number of positions held by commercial traders 2. $Comm_{i,t} = \frac{1}{52}\sum_{s=1}^{52} Comm_{i,t,s}$
Non-commercial traders' activity	$NComm_{i,t}$	1. For each week s, determine number of positions held by non-commercial traders 2. $NComm_{i,t} = \frac{1}{52}\sum_{s=1}^{52} NComm_{i,t,s}$
Support market commercial traders' activity	$SComm_{i,t}$	1. For each week s, determine number of positions held by commercial traders in product i's support market 2. $SComm_{i,t} = \frac{1}{52}\sum_{s=1}^{52} SComm_{i,t,s}$
Support market non-commercial traders' activity	$SNComm_{i,t}$	1. For each week s, determine number of positions held by non-commercial traders in product i's support market 2. $SNComm_{i,t} = \frac{1}{52}\sum_{s=1}^{52} SNComm_{i,t,s}$
Weighted support market trader ratio	$\ln(WSVol_{i,t})$	1. For each week s, determine futures contract trade volume in product i's support market, $SVol_{i,s}$ 2. $\ln(WSVol_{i,t,s}) = \ln(SVol_{i,t,s}) \cdot \left(\frac{SComm_{i,t,s}}{SNComm_{i,t,s}}\right)$ 3. $\ln(WSVol_{i,t}) = \frac{1}{52}\sum_{s=1}^{52} \ln(WSVol_{i,s})$

Notation: Week number is represented by the subscript s. Year number is represented by the subscript t. The cash price in a market is represented by the term P and the futures contract price is F.