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A futures market for distillers' dried grains (DDGs) was introduced on the Chicago Mercantile Exchange in early 2010, but became inactive only four months after its inception. While many new futures contracts do not develop into high-volume traders, significant interest from DDG cash market participants seemed to indicate that this contract could be successful. This study determines whether factors found in the literature to affect the success of futures contracts may have predicted the ineffectiveness of the DDG contract. We also test the impacts of market participants and the activeness of supporting futures markets, and use the empirical to determine whether the lack of activity in the ethanol futures market may have contributed to the ineffectiveness of the DDG contract. Estimation results indicate that while the existing literature would have predicted a high likelihood of success for a DDG futures contract, accounting for the inactiveness of the ethanol futures market led to the opposite conclusion.

Keywords*:* active cash markets, distillers' dried grains, expectations, futures contract, supporting futures markets

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. The latest RFS program is a federal mandate requiring 36 billion gallons of renewable fuels to be blended into gasoline by 2022, with a maximum of 15 billion gallons from corn-based ethanol by 2015 (Renewable Fuels Association, 2012). Currently, excessive production costs and technological constraints limit the quantity of non-corn based biofuels, implying that a greater burden is placed on the use of corn to fulfill the mandated ethanol production requirement and has precipitated substantial reallocation of corn from its traditional uses in feed. For example, 53.4% of U.S. corn was used in livestock and poultry feed and 12.5% in ethanol production during the 2004–2005 marketing year; in the 2011–2012 marketing year, however, 38% of the corn was used for feed while 40% was an input to biofuel production. A partial saving grace of this market transformation were the technological advances that allowed a corn-ethanol byproduct—distillers' dried grains (DDGs)—to be used as a supplement to livestock feed. The result was an emergence of a relatively large domestic market (and more recently an international market) for DDGs.

The rapid growth of the DDG market increased market participants' demand for tools that can effectively hedge associated price risks. 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). However, the CME Group introduced a more direct price risk management tool on April 26, 2010—the distillers' dried grains futures contract—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). The new contract was designed to be a comprehensive substitute to alternative price hedging instruments, reducing cross-hedging basis risk and improving DDG producers' and consumers' effectiveness in managing price variability.

Despite the perceivably growing market for DDGs (Hoffman and Baker 2011) and industry interest to hedge price risk (Stroade, Martin, and Schroeder 2010), trading activity of the contract was initially low and the contract became almost entirely inactive in August 2010—only four months after its introduction. The seemingly peculiar and rapid demise of the DDG contract suggests that there may have been broader, more fundamental factors underlying the contract's underachievement. While previous studies have offered important theoretical and empirical evidence of factors critical to the success and viability of futures contracts (for example, see Silber, 1981; Tashjian, 1995; Pennings and Leuthold, 2000; Brorsen and Fofana, 2001; Rausser and Bryant, 2004; Bergfjord, 2007; Siqueira, da Silva, and Aguiar, 2008), the introduction of the DDG contract by the CME Group suggests that market conditions for this contract were deemed to be sufficient.

This study revisits the questions of what market factors are important to the success of potential futures contracts and their role in affecting the demand for existing futures contracts. We develop a relatively comprehensive, market data-driven method for predicting whether market conditions are favorable to the introduction of a new futures contract and the activeness of this contract after its introduction. Using variation in futures and cash market data, we empirically identify and quantify factors that impact the likelihood and trade volume of a successful futures contract. We first describe elements found by previous studies to be relevant to the success of futures contracts, 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. Then, we model the likelihood of a futures market as a function of these elements using market information for 21 commodities with and without existing futures contracts during 2007–2012. In doing so, we address the challenge of empirically measuring the activeness of an underlying cash market, which has been characterized by numerous studies as a critical (perhaps, necessary) condition for a futures contract. While much of the literature has relied on making assumptions about cash market activeness or has been unable to measure its importance empirically, we demonstrate a data-driven measure that is consistent with past assumptions and provides an opportunity to directly its role in futures contract success. Furthermore, unlike previous studies, we incorporate information about futures contract traders to gauge their contributions to futures market activity.

Results from the empirical analysis indicate that the activeness of the cash market, underlying cash market risk, product homogeneity, industry vertical integration and market power concentration, and the activeness of the futures market with which cross-hedging opportunities exist are important factors in predicting futures market success. Moreover, we show that the cash market size and availability of alternative price hedging tools, rather than the cash market activeness, are the most important determinants. The estimated model is then used to test whether factors identified in the existing literature could have predicted the ill-fated outcome of the DDG futures contract, but find that the out-of-sample predictions largely support the contract's introduction.

We posit that there may be additional, previously unaccounted, effects of futures market participants and their objectives for participating (i.e., hedging or speculating). Using Heckman's sample selection model, we find that variables describing trader types significantly contribute to explaining changes in futures contract trade volume and that a balance of different participants is most conducive to increased trade volume. The importance of participants in a futures market suggests that trader characteristics in related futures markets could also be essential. In the case of products that are complementary in production or are co-products within the same marketing channel, such as ethanol and distillers' dried grains, the types of participants and trade activity of futures contracts for one of the products can affect participation in the related market. Estimation results largely support this hypothesis.

This study's outcomes offer several contributions to the evaluation of futures contract success. First, we develop an easily implementable data-driven methodology for assessing the likelihood of a futures contract, including a method for estimating the activeness of a cash market. The empirical approach can be a useful tool for determining conditions that are most favorable for introducing new price risk hedging products, improving an exchange's cost-effectiveness in researching and introducing new price risk instruments. In addition, we show that the outcome of new futures markets is dependent on the availability and activeness of complementary futures markets, rather than only on cross-hedging opportunities. Accounting for such complementarities can be critical for correctly assessing the success of new futures contracts.

2. Determinants Identified by the Literature

The number of available futures contracts has increased more than twofold during the past 30 years and proposals for new products are constantly debated (Rausser and Bryant, 2004). The eagerness to introduce new contracts is perplexing, however, because many new futures contracts are unsuccessful and fail to maintain trading volumes necessary to sustain profitability.[1] Silber (1981) estimates that less than one third of all new contracts had profitable trading volumes within three years of introduction and Tashjian (1995) shows that in 1984–1993, only 27% of contracts offered by the Chicago Board of Trade recorded any trades. Rausser and Bryant (2004) and Pennings and Leuthold (2000) argue that social welfare from hedging and market price discovery tools and the facilitation of firm relationships within a marketing channel may also be important reasons for futures markets, but to a futures exchange, trade volume and a contract's profitability are typically among the most important indicators of a contract's continued use or eventual decline and termination.

As a result of the apparent disconnect between the high number of newly introduced contracts and their low success rate, a number of studies sought to determine conditions for the success of futures contracts and markets. Black's (1986) research 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) argue that the activeness of a commodity's cash market is the primary necessary condition for a 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. Similarly, 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 that would contribute to the viability of futures markets for those products.

In general, there are nine major considerations that we have identified from the existing research to be important in predicting the potential success of an agricultural futures market. These can be classified into two sets: one that pertains to the components of the underlying cash

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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 out of the scope of this study.

market and the second to related futures markets. Cash market conditions help characterize the potential need for a futures market by commercial traders (i.e., hedgers). If such fundamental conditions suggest that a futures market may be viable, then the attributes of existing futures markets can offer insights about the opportunities to successfully manage price risk using existing tools.

Cash Market Components

1. <u>Cash price variability</u>
   The variability of the spot market is an indicator of price uncertainty. A market with low uncertainty is unlikely to create demand from commercial hedgers to hedge price risk nor from non-commercial speculators seeking to gain returns on risky investments. A highly volatile cash market with few alternatives to hedge away and/or speculate about price risk is more likely to develop a futures market.

2. <u>Size of the cash market</u>
   Cash market size helps indicate the potential size of price risk associated with the production or acquisition of the commodity. Adverse price risk in larger markets can lead to higher revenue losses, and, therefore, expected to increase the demand for futures hedging, from both the producers and consumers or the commodity. Brorsen and Fofana (2001) measure the cash market size as the annual production of a commodity.

3. <u>Activeness of the cash market (ACM)</u>
   Commodities with larger and more active spot markets are more likely to exhibit higher price risk, increasing the hedging and speculation incentives. The resulting high activity and participation by independent investors with different interests would contribute to greater volumes of risk exchange and a potential higher demand for an organized futures market. Furthermore, a larger, more active cash market is more likely to have available and credible price information Fortenberry and Zapata (2002).

4. <u>Product homogeneity or an extensive knowledge of the product grading system</u>
   Successful 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 variation among commodities can lead to significant market segmentation, effectively reducing the size and activity of each sub-market and lowering the likelihood of a successful futures market.

5. <u>Product storability</u>
   Bergfjord (2007) argues that ineffective storage, which can lead to quality degradation and faster perishibility, can constrain the product homogeneity requirement. Furthermore, a well-established storage and transportation infrastructure can provide commodity exchange opportunities throughout the marketing year, increasing arbitrage opportunities between cash and futures markets.

6. Degree of vertical integration in the market
   A market with a high degree of vertical integration is expected to have fewer number of points in a product's marketing channel at which exchanges among buyers and sellers occur (Brorsen and Fofana 2001). For example, if the procurement, handling, transportation, and export of wheat is managed by a single operator, competitive price determination at each of the four marketing stages is unlikely and most price hedging will occur within the firm structure. Consequently, in a market where vertically integrated firms control a large share of contracting, the activeness of the cash market and price variability are likely to be lower.

7. Degree of market power concentration and number of market participants
   The concentration of market power can reduce the activeness of a cash market and constrain the adjustment of prices to fundamental market conditions. In cash markets with a high degree of concentration or only a few participants, futures markets are not expected to be successful.

Futures Market Components

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

9. Liquidity of cross-hedge futures contract
   While risk reduction through cross-hedging is an important factor in determining the success of a commodity's own-hedge future contract, the trade volume of the cross-hedge contract is also critical. Black (1986) explained that the opportunity costs of an own-hedge futures contract are higher when a a cross-hedge product is more liquid. Moreover, Brorsen and Fofana (2001) provide empirical evidence of the inverse relationship between the likelihood of an own-hedge contract and the liquidity of a cross-hedge.

3. Additional Considerations: Supporting Markets

Previous studies have extensively characterized the requirements for an underlying cash market and opportunity costs from competing futures contracts (i.e., substitutability of alternative futures market products); however, no considerations have been made about futures market complementarities that could enhance a new contract's success. One form of market complementarities is supporting futures contracts, which offer price risk hedging tools for goods that are co-products within the same marketing channel. For example, in the dairy market, the cheese and dry whey futures markets are supporting markets, because dry whey is a by-product of cheese production. Similarly, the butter market is a support to the nonfat dry milk contract. For the DDG futures contract, it is reasonable to consider the fuel ethanol futures market as a support. When a new futures contract is introduced, the existence, trade activity, and trader characteristics in a support market could be critical to increasing (or generating) the demand and use of the new contract.

Most new contracts are initially traded primarily by commercial participants (i.e., hedgers) rather than non-commercial participants (i.e., financial speculators), requiring that there is appropriate demand for a futures contract as a risk hedging tool (CME Group, Inc. manager, personal communication, March 4, 2013). Supporting markets can naturally help increase such demand due to the multi-sector market channel relationships among an established and new contract. For example, Figure 1 shows a representation of the multi-sector market, which we assume to be comprised of two outputs, i and j.[2] The demand curves for each output are labeled D_i and D_j, respectively, and the curve D_k represents the vertical sum of the D_i and D_j curves and is the aggregate output, k.[3] Only one quantity level, Q, is specified, because the production of outputs i and j is proportional to the production of the aggregate output. The prices for each output at a particular quantity are represented by the term P_m, where $m \in (i, j, k)$.

Figure 1 also helps illustrate the dependencies among multiple sectors. Suppose that in period t_0, a producer wishes to hedge her downside price risk of output j and does so by taking a short position on a futures contract for good j. In the next period, t_1, there is an increase in the demand for j, leading to an upward shift of its demand curve from D_j^0 to D_j^1. Because output j is part of a multi-product output portfolio, increased demand for j will result in an associated increase in the demand for the aggregate output k and an associated quantity supply response by the producer, characterized by a quantity increase from Q^0 to Q^1. The increased demand for output j and higher production quantities will increase the producer's revenues from sales of output j (as shown), but the proportional increase in the quantities supplied of output i are expected to lower its market prices from P_i^0 to P_i^1.

While a short futures contract position for output j would protect the producer from downside risk in that market, the price risk of the co-product in her marketing portfolio is not hedged. If the share of total revenues from sales of co-product i is substantially large, then the inability to reduce downside price risk for this output could lead to non-trivial reductions of the portfolio revenues. Consequently, commercial traders in the futures market of output j would have appropriate incentives to also participate in a futures market for output i. Moreover, trade volume in the futures market for output j may be an important indicator of the demand for (and potential activeness of) a futures contract of output i. The importance of a support market could also be conditional on the relative size (measured as the proportion of total revenues, for example) of each output within a multi-sector industry. For example, if the sales of output j contribute 80% of a portfolio's revenues, then the futures contract for output i is likely to be more heavily dependent on the activeness of output j's futures market. As the proportion of revenue contributions becomes more equal, the dependence is expected to weaken.

DDG market characteristics suggest that active supporting futures markets could be critical to the success of a DDG futures contract. For example, distillers' dried grains are produced in fixed proportion with ethanol, implying that distillers could seek to manage price risk across the portfolio of outputs. Furthermore, as the use of DDGs for livestock feed, its prices, and its proportion of a grain distillers' total revenues have increased during the late 2000s, the failure to hedge DDG price risk could have substantial economic impacts on distillers.

[2] The two-output case is assumed for simplicity. A model with *n*-outputs can be implemented without a loss of generality.
[3] Corresponding supply curves for each demand curve are not shown to ease the interpretation of the figure.

Despite this growth, DDG revenues continue to comprise only 15%–25% of grain distillers' total revenues (Lockman 2013; Cargill, Inc. feed markets analyst, personal communication, February 12, 2013), suggesting that it is risk hedging incentives in the ethanol market that are likely to be catalysts for the use of DDG futures contracts. That is, without an active ethanol futures support market, it is unlikely that DDG production would be sufficiently large to independently require a futures market. Although the existence of an ethanol futures market may be a necessary condition for a successful DDG futures contract, sufficiency is ensured only if the ethanol futures market is adequately active.

4. Data Description and Determination of Cash Market Activeness

The nine major factors described by the literature as important to the success of a futures contract provide an initial opportunity to empirically evaluate the *a priori* likelihood of a successful DDG futures contract. Could the economics literature have predicted the quick demise of the DDG futures market? And how does information market participants' characteristics contribute to the determination of success? We loosely follow the methodological approach in Brorsen and Fofana (2001) by exploiting variation across commodities that have and do not have futures markets to identify factors that contribute to the viability of a futures contract.

We collect market data for 21 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), oilseeds and related products (soybeans, soybean oil, soybean meal, sunflower seed, DDGs), livestock (fed cattle, hogs), and poultry (broilers, eggs). Weekly cash market price information was obtained 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, and these prices are used to determine a national average.[5] To ensure that prices represent current conditions (rather than expectations), we retain only price information quoted for immediate transactions or 10-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 quantities and prices except eggs (which are in per egg units) were converted into per ton basis. Table A1 in the Appendix 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 21 products, futures contract activity for 13 products, and support market impacts for 7 products. We used only futures contracts that are traded on a North American futures exchange, including the Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT), Minneapolis Grain Exchange (MGEX), Kansas City Board of Trade

[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%.

(KCBT), and the Intercontinental Exchange (ICE).[7] Table A1 summarizes the assumptions for assigning cross-hedge and support market futures contracts. The cross-hedge assumptions largely follow those made in the existing literature (for example, see Zacharias et al. 1987, Graff et al. 1997, Brinker et al. 2009). For all futures contracts, we also obtain weekly trade volumes and commitment of trader information, which indicate the number of commercial, non-commercial, and non-reportable types of 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 characterize hedgers, non-commercial traders are speculators, and non-reportable traders represent the remaining portion of the market.

Table 1 and Table **2** provide the descriptive statistics for each product. To specify the product homogeneity, industry vertical integration, and market power concentration, we follow Brorsen and Fofana (2001; Table 3) because these market properties are unlikely to substantially vary over time. The authors provide only the means of industry experts' valuations of the product and industry characteristics, and we assume that a product or industry exhibits a particular characteristic if the mean value is above 5 (on a scale of 1–10). For products that are not assessed by Brorsen and Fofana (i.e., barley, dry whey, oranges, and DDGs), we assume that the products and industries are similar to those of the closest substitute product (i.e., wheat, dry milk, apples, and soybean meal and corn). In Table **2**, the coefficient of variation (CV) is calculated using cash market price data across 52 weeks. The market size is the natural log of annual production (in tons) and the cross-hedge contract activity is the natural log of the annual average of weekly trade volume. Lastly, the residual risk (RR) represents the variation in a product's weekly cash price that cannot be explained by the variation in the price of an assumed cross-hedge futures contract. That is, after estimating a linear regression of a product's weekly cash price on cross-hedge futures prices and obtaining the regression $\tilde{R}^2$, the RR is calculated as $(1 - \tilde{R}^2)$.

4.1 Activeness of Cash Markets

Studies investigating the success of futures markets have consistently identified the activeness of the underlying cash market (ACM) as a necessary condition for a viable futures contract. Despite the apparent importance of this component, only few attempts had been made to measure cash market activeness using market data. For example, Brorsen and Fofana (2001) quantified survey responses about activity from 10 industry experts, but did not offer supporting evidence that the responses correctly characterize the activeness of evaluated cash markets. We develop a data-driven, replicable approach that can be used to determine this cash market characteristic for commodities for which new futures contract products are being considered.

The activeness of a cash market represents the frequency with which price bids and offers are made. It is reasonable, therefore, to consider price changes between periods as potential indicators of market activity. Observing consistent variation in market prices is likely representative of a market in which buyers and sellers are regularly participating in the price determination process. Conversely, recurring instances of trivial or no changes in prices could reflect low bidding frequency and anemic activeness. Furthermore, it should be noted that a measure of price differences across periods (i.e., changes in price levels) is not analogous to cash price variability, which is often quantified as variance, standard deviation, or coefficient of variation. These measures typically reveal the inherent risk faced by participants in a cash

[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).

market, which may not be positively correlated with a market's activeness. For example, participants in cash markets with large, infrequent price changes are subject to higher price risk, but may not enjoy the price discovery benefits of a more active market.

To calculate the ACM, we first-difference the weekly cash price data for each product and generate 26-period lags of the differenced prices. Weekly, rather than daily, cash market prices were used because, while it is not uncommon for daily price levels to exhibit trivial or no changes between days, a lack of activity between weeks is less likely to be idiosyncratic and may be more indicative of underlying market behavior. In each rolling 26-period window, we recorded the number of times that a price did not change between weeks. These values were averaged across all weeks during the 2007–2012 period, and a 95% confidence interval was calculated around each mean. Commodities for which the mean number of times that the weekly price levels were significantly different from zero (i.e., had few times when prices changed within a 26-week period) were designated as low activeness markets. High activeness markets were those where we could not statistically reject at least one instance within a 26-week period when prices did not change between weeks.[8] Table 3 shows the ACM estimation results and ACM valuations from Brorsen and Fofana (2001, Table 3). The results indicate that this data-driven valuation of cash market activeness is analogous to the industry experts' opinions about these markets. The only strong discrepancy is in the cheese market, which we predict to be a high activeness market and may be a result of an increase in cash transaction activity in the late 2000s.

The success of the ACM estimation strategy to empirically classify a cash market's activeness is critical, because it significantly lowers the costs of determining a product's ACM relative to existing methods. We apply the method to the distillers' dried grains market to determine whether this necessary condition for a futures contract success is met. Table 3 shows that we cannot reject the hypothesis that the cash market for DDGs is highly active. Therefore, the results suggest that the initial conditions for a successful futures market are satisfied and factors other than an inactive cash market could have contributed to the unsuccessful DDG futures market.

5. Evaluating the Likelihood of the DDG Futures Contract

We first exploit variation in products' cash market characteristics and cross-hedge opportunities to empirically determine the factors that contribute to a product having a futures market. Specifically, we model whether a product has a futures market as a function of characteristics identified by the literature to impact futures market success; that is,

$$FM_{i,t} = \beta_0 + \beta_1 CV_{i,t} + \beta_2 ACM_{i,t} + \sum_{\boldsymbol{k=1}} \boldsymbol{\beta_k W_{k,i,t}} + \beta_3 \ln\left(XVol_{i,t}\right) + \beta_4 RR_{i,t} + \alpha_t + \varepsilon_{i,t} \qquad (1)$$

The term $FM_{i,t}$ represents a binary variable indicating whether product i has a futures market in year i; $CV_{i,t}$ is the cash market price coefficient of variation; $ACM_{i,t}$ is the cash market activeness; $\boldsymbol{W_{k,i,t}}$ is a vector of variables describing the product homogeneity, whether the

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

industry is characterized by high degree of vertical integration and buyer power concentration, and the cash market size; $XVol_{i,t}$ is the annual average trade volume of the cross-hedge futures contract; $RR_{i,t}$ 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.[9] A variable describing the degree of product storability is excluded from the specification because it is highly correlated with a combination of other product and industry factors.

5.1 Probit Regression Results of Futures Contract Likelihood

Table 4 presents the probit regression results of equation (1), average marginal effects, and parameter estimates after all continuous variables were standardized to have a mean of zero and standard deviation of one. The results indicate that all factors except residual risk are statistically different from zero and exhibit the expected effect on the probability of a product having a futures market. Specifically, increases in the activeness of the cash market—indicating improved price discovery—are expected to increase the likelihood of an agricultural product having a futures market. Similarly, products that are more homogeneous and which have more points of transaction because of low vertical integration or market power concentration are also more likely to have futures markets. Higher production levels, on average, increase the likelihood of futures markets, but increases in the trade volume of a futures contract that can be used to cross-hedge price risk reduced the probability of a futures contract for a direct hedge. The latter result suggests that market participants may be willing to trade off basis risk (resulting from lower correlation between the cash market prices and the futures contract prices of a related good) for higher liquidity in a related futures market.

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. However, this result may be due to the fact that products for which futures market exist have lower price variability than if those products did not have future markets. That is, if it was possible to perform a counterfactual analysis in which products' prices could be observed before and after a futures market is introduced for those products, it is likely that the correct relationship between futures market probability and price risk would be observed.[10]

Table 4 also provides estimated parameter values after continuous variables were standardized. In a linear regression with a continuous dependent variable, the standardized parameter estimates can be interpreted as a change in the standard deviation of the dependent variable associated with a one standard deviation change in the value of the regressor. Because all variables are on the same scale, the absolute value of the estimated coefficients is typically interpreted as the relative strength of each regressor in predicting the dependent variable. In models with binary dependent variables, such straightforward transformations and interpretations are not possible. Kaufman (1996) developed a semi-standardized approach for transforming regressors, thus allowing for a similar interpretation of estimated parameters. That is, the standardized coefficient estimates describe the change in predicted probability associated with a one standard deviation change in the value of the regressor.

[9] The ACM measure actually represents one minus the cash market activeness measure calculated in section 4.2. This linear transformation allows for a more straightforward interpretation of regression results.

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

The standardized parameter estimates shown in Table 4 indicate that market size is the most important variable in explaining the likelihood of a product having a futures market. This is an expected outcome, because annual production is often a binding constraint for an exchange to introduce a new futures contract (personal communication with an individual closely familiar with an exchange's research process for new futures contracts; May 5, 2013). The number of marketing and transaction points and the liquidity of cross-hedging opportunities are the next most important predictors. Somewhat surprisingly, cash market activeness and cash price risk are less important in explaining changes in the likelihood of a futures contract, even though these factors have been consistently hypothesized as having the most influence (for example, see Bergfjord 2007, Brorsen and Fofana 2001, Siqueria et al. 2008). This is likely 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. To our knowledge, this is the first study that provides an empirically informed relative ranking of these factors.

Lastly, we examine whether factors identified in the existing literature could have been used to predict the low likelihood of success for a DDG futures contract. Using the estimated parameters from the probit regression, we performed in-sample predictions for the commodities used to estimate the model and an out-of-sample analysis of the DDG market. Table 5 presents a summary of these predictions and indicates that the cash market characteristics and cross-hedge opportunities for DDGs suggest that a DDG futures contract would have a relatively high probability of success.[11] The rapid demise of the DDG futures market, however, suggests that other factors may be critical to determining futures contract success.

5.2 Contribution of Futures Market Participants to Contract Activity

Several studies have suggested that the types of futures market participants can impact the contract's trade volume. For example, Sanders and Manfredo (2002) suggest that the failure of the white shrimp futures contract was related to the market's inability to attract speculative trade, who can offer long positions for contracting with short-position hedgers. Bollman, Garcia, and Thompson (2003) hypothesized that the downfall of the diammonium phosphate futures contract was also due to a lack of speculators. However, there is limited empirical evidence of these reasons and general insights about the role of futures market participants.

Using data describing products that have futures markets, we model the trade volume of these contracts. However, a simple regression of trade volume on the associated explanatory variables is likely to produce inconsistent parameter estimates, because trade volumes are observed only for those products that have futures markets. One approach to account for this sample selection problem is to use the two-stage Heckit estimator. In the first stage, we estimate a probit model to identify characteristics for predicting the existence of a futures market and then include the estimated inverse Mills ratio from the probit model in the specification for futures trade volume. The first stage probit model is specified in equation (1) and the trade volume specification for futures contract j:

[11] 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 alternative product and market assumptions. The high probability of success for a DDG futures contract was consistently robust to these different specifications.

$$\ln(Vol_{j,t}) = \gamma_0 + \sum_{m=1} \boldsymbol{\gamma_m V_{m,j,t}} + \gamma_1 \left(\frac{Comm_{j,t}}{All_{j,t}}\right) + \gamma_2 \left(\frac{Comm_{j,t}}{NComm_{j,t}}\right) + \gamma_3 \ln(NComm_{j,t}) + \gamma_4 \hat{\lambda}_{j,t} + \theta_t + \nu_{j,t} \quad (2)$$

The term $\ln(Vol_{j,t})$ represents the natural log of annual trade volume in year t for contract j, $\boldsymbol{V_{m,j,t}}$ represents a vector of all regressors in equation (1) except the degree of vertical integration and market power concentration, $\left(\frac{Comm_{j,t}}{All_{j,t}}\right)$ is the ratio of commercial traders to all futures market traders, $\left(\frac{Comm_{j,t}}{NComm_{j,t}}\right)$ is the ratio of commercial traders to large non-commercial participants, $\ln(NComm_{j,t})$ is the natural log of non-commercial traders, $\hat{\lambda}_{j,t}$ is the estimated inverse Mills ratio, θ_t is a time fixed effect, and $\nu_{j,t}$ is an idiosyncratic error term.[12] The vertical integration and market power concentration information is not included to satisfy the exclusion restriction for identifying the relationships in equation (2). These variables correspond to the underlying cash market and the likelihood of a futures market. For products that already have futures markets, there is little variation in these industry characteristics across those products.[13]

Table 6 presents the estimated parameters and White's heteroskedasticity-robust standard errors for the second stage selection model of futures contract trade volumes. The table indicates that cash market activeness and product homogeneity are the only cash market characteristics that are statistically significant in affecting futures trade volume. However, changes in all futures market participant information have statistically significant and economically relevant impacts. First, we empirically show that speculators are important to a futures market's activity. A 1% increase in the number of large non-commercial traders, on average, increases trade volume by 0.99%. Moreover, the standardized parameter estimate indicates that speculator participation has the most relative importance in explaining trade volume variation.

The estimated parameters also suggest that the concentration of any single type of traders relative to all participants can be detrimental to futures market activity.[14] However, increases in the ratio of commercial hedgers to non-commercial speculators are expected to improve trade volume. These results suggest that there are important trade-offs among the quantity and types of futures market participants. For example, while increases in the number of speculators can raise market liquidity, when they lead to the concentration of interest within that group of traders, trade volume is likely to decline. These results suggest that active and successful futures markets are characterized by a balance among hedgers (short positions) and speculators (long positions).

6. Assessing the Role of Support Markets

The importance of the quantity and types of futures market participants suggests that similar factors in supporting futures markets could affect trade volume. We test this hypothesis by

[12] 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.

[13] Wooldridge (2013) also suggests that all of the explanatory variables used to model the second stage equation are 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 and including these variables could affect inconsistent estimation of the first stage regression.

[14] While we estimate the model using the ratio of commercial traders to all traders, altering the specification to include ratios of non-commercial or small-scale speculator traders to all traders lead to qualitatively similar insights.

investigating variation in the trade volumes of products that have both a futures market and a support futures market. These include cheese, nonfat dry milk, dry whey, fed cattle, soybean oil, and soybean meal, and the assumed support products are presented in Table A1. Information about these futures markets are used to estimate the model:

$$\ln\left(Vol_{j,t}\right) = \delta_0 + \delta_1 CV_{j,t} + \delta_2 ACM_{j,t} + \delta_3 RR_{j,t} + \delta_4 \ln\left(WSVol_{j,t}\right) + \delta_5\left(\frac{SComm_{j,t}}{SAll_{j,t}}\right) + \delta_6\left(\frac{SComm_{j,t}}{SNComm_{j,t}}\right) + \mu_t + \phi_{j,t} \tag{3}$$

where the terms $\ln\left(Vol_{j,t}\right)$, $CV_{j,t}$, $ACM_{j,t}$, $RR_{j,t}$ are defined in equation (2), $\ln\left(WSVol_{j,t}\right)$ represents the trade volume in the support market weighted by the ratio of commercial traders to non-commercial participants, $\left(\frac{SComm_{j,t}}{SAll_{j,t}}\right)$ is the ratio of commercial traders to all traders in the support market, $\left(\frac{SComm_{j,t}}{SNComm_{j,t}}\right)$ is the ratio of commercial traders to non-commercial traders in the support market, μ_t is a time fixed effect, and $\phi_{j,t}$ is an idiosyncratic error term. The commercial participant-weighted support market trade volume, $\ln\left(WSVol_{j,t}\right)$, is of primary interest and helps reveal the impacts of support market trade volume conditional on the relative participation of hedger-to-speculator traders.

Using a relatively small subset of products presents several challenges. First, continuing to use annual-level data would substantially limit the sample size. To overcome this issue, we estimate equation (3) using monthly data to increase the available degrees of freedom. Second, the variables characterizing the cash market and cross-hedge opportunities in equation (3) are highly correlated with product homogeneity, market size, and cross-hedge contract volume. Using condition index and variance inflation factor analyses, we retain those regressors that uniquely explain variation in the cash markets and cross-hedge opportunities.[15] Third, because many commodities are not produced monthly, we are unable to estimate equation (3) using the Heckit method. However, results associated with the annual data estimation, shown in Table 6, indicate that the inverse Mills parameter is not significantly different from zero, implying that the sample selection problem is absent. This result suggests that equation (3) can be consistently estimated by ordinary least squares. Lastly, we do not include information about futures markets that are directly associated with the product, because we wish to use this model for out-of-sample prediction purposes. That is, the results would be used to predict the trade volume of a potential new futures contract, which already has a support futures market.

Table 7 presents the parameter estimates and White's heteroskedasticity-robust standard errors 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 effect of the ratio of commercial to non-commercial participants in the support market is not statistically different from zero and as expected, the increased participation of any single type of trader in the support market decreases the futures contract trade volume of product j.

The positive and statistically significant coefficient associated with the commercial participant-weighted support market trade volume indicates the importance of hedgers'

[15] 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.

participation in related futures markets. The result demonstrates that increases in the support market trade volume and the ratio of hedgers to speculators—that is, improvements in trade volumes are likely due to entry of commercial traders—are associated with increases in the futures contract trade volumes of product j. This increased demand may be a result of market participants' attempts to successfully manage a portfolio of risks related to the production of co-products. Specifically, a 1% increase in the hedger-driven support market activity leads to 0.93% increase in the trade volume of product j. The standardized parameter estimates also show that this variable has largest relative impact on explaining changes in a co-product's futures market trade volume.

Using the estimation results presented in Table 7, we assess the out-of-sample predicted trade volumes for the DDG futures contract. That is, even though standard cash market and cross-hedge opportunity characteristics indicate a high probability of a DDG futures contract, we evaluate whether such contract would be sufficiently traded. Assuming that the ethanol futures market represents the support market, we find that the predicted average monthly DDG futures trade volume is approximately 28. This represents a trade volume that is 0.15% of the average 18,130 monthly trades occurring in futures markets of other products in the sample. The result suggests that despite a positive outlook about a DDG futures contract success predicted by traditional measures, the relatively low hedger-driven trade in the ethanol support futures market was an important signal against the introduction of a DDG futures market.

7. Conclusions and Implications

Understanding and successfully evaluating the viability of new futures contracts can provide important efficiencies in the development and introduction of the new price risk tools. This study offers a new perspective on assessing the feasibility and activeness of futures contracts 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. First, we introduce an empirical method for estimating the activeness of cash markets—a factor that has been considered by the literature to be critical in determining market demand for a futures contract. Second, we develop a conceptual framework that demonstrates the potential importance of support markets for commodities that are produced in fixed proportion with other goods. We then provide empirical evidence that active support markets are the most important factor in predicting futures contract trade volume of co-products.

The role of support market participants partly helps explain the anemic performance of the DDG futures contract. While the introduction of this contract was met with mixed feelings by the industry, the typical standards for evaluating whether the product could be successful strongly indicated that this may be the case. Therefore, it was somewhat surprising to observe such a rapid demise of the contract's trade volume. We show that this outcome may have, in large part, been a result of thin ethanol markets, especially with respect to commercial traders. These findings indicate that trade activity in complementary markets, in addition to markets that can be used for cross-hedging, should be considered to gain greater insights about new futures contract possibilities.

Bibliography

Bergfjord, O. (2007). Is There a Future for Salmon Futures? An Analysis of the Prospects of a Potential Futures Market for Salmon. *Aquaculture Economics and Management, 11*, 113-132.

Black, D. (1986). *Success and Failure of Futures Contracts: Theory and Empirical Evidence.* New York: Salomon Brothers Center for the Study of Financial Institutions.

Bollman, K., Garcia, P., & Thompson, S. (2003). What Killed the Diammonium Phosphate Futures Contract? *Applied Economic Perspectives and Policy, 25*, 483-505.

Brinker, J., Parcell, J., Dhuyvetter, K., & Franken, J. (2009). Cross-Hedging Distillers Dried Grains Using Corn and Soybeans Futures Markets. *Journal of Agribusiness, 27*, 1-15.

Brorsen, B., & Fofana, N. (2001). Success and Failure of Agricultural Futures Contracts. *Journal of Agribusiness, 19*, 129-145.

CME Group, Inc. (2012). *Distillers' Dried Grains Futures*. Retrieved October 6, 2012, from CME Group: http://www.cmegroup.com/trading/ agricultural/distillers-dried-grain-futures.html

Fortenberry, T., & Zapata, O. (2002). An evaluation of price linkages between futures and cash markets for cheddar cheese. *Journal of Futures Markets, 17*, 279-301.

Graff, J., Schroeder, T., Jones, R., & Dhuyvetter, K. (1997). *Cross Heding Agricultural Commodities.* Kansas State University. Manhattan: Agricultural Experiment Station and Cooperative Extension Service.

Hoffman, L., & Baker, A. (2011). *Estimating the Substition of Distillers' Grains for Corn and Soybean Meal in the U.S. Feed Complex.* Washington, D.C.: USDA Economic Research Service.

Kaufman, R. (1996). Comparing Effects in Dichotomous Logistic Regression: A Variety of Standardized Coefficients. *Social Science Quarterly, 77*, 90-109.

Lockman, C. (2013). *Illinois Ranks Among Top States for Ethanol Production*. Retrieved March 28, 2013, from Farm Flavor: http://farmflavor.com/us-ag/illinois/top-agriculture-products-illinois/illinois-ethanol-production/

Pennings, J., & Leuthold, R. (2000). The Motivation for Hedging Revisited. *Journal of Futures Markets, 20*, 865-885.

Rausser, G., & Bryant, H. (2004). Contract Market Viability. *Presented paper at the NCR-134 meetings.* St. Louis, MO.

Renewable Fuels Association. (2012). *Ethanol RFA*. Retrieved October 6, 2012, from Statistics: www.ethanolrfa.org/page/statistics

Sanders, D., & Manfredo, M. (2002). The White Shrimp Futures Market: Lessons in Contract Design and Marketing. *Agribusiness, 18*, 505-522.

Schroeder, T. (2009). *Distillers Grain Prices: Spatial Relationships, Arbitrage Opportunities and Risk Management.* Kansas State University Agricultural Experiment Station and Cooperative Extension Service. Manhattan, TX: North America Institute for Beef Economic Research.

Silber, W. (1981). Innovation, Competition, and New Contract Design in Futures Markets. *Journal of Futures Markets, 1*, 123-155.

Siqueira, K., Silva, C., & Aguiar, D. (2008). Viability of Introducing Milk Futures Contracts. *Agribusiness*, *24*, 491-509.

Stroade, J., Martin, A., & Schroeder, T. (2010). *Distillers Grain Industry Price Discovery and Risk Management.* Manhattan, KS: Kansas State University Agricultural Experiment Station and Cooperative Extension Service.

Tashjian, E. (1995). Optimal Futures Contract Design. *Quarterly Review of Economics and Finance*, *35*, 153-162.

Tejeda, H. (2012). Time-Varying Price Interactions and Risk Management in Livestock Feed Markets—Determining the Ethanol Surge Effect. Seattle, WA: AAEA Annual Meetings.

Wooldridge, J. (2013). *Introductory Econometrics: A Modern Approach* (Vol. 5). Mason: South-Western, Cengage Learning.

Zacharias, T., Lange, M., Gleason, W., & Traylor, H. (1987). A Producer-Level Cross-Hedge for Rough Rice Using Wheat Futures. *Southern Journal of Agricultural Economics, 19*, 75-82.

Table 1: Assumptions about Cash Market Products and Industry Characteristics

Commodity	**Futures Market?**	**Product Homogeneity**	**Industry Vertical Integration**	**Buyer Concentration**	**Product Storability**
Apples	No	Low	High	High	Low
Barley	No	High	Low	Low	High
Broilers	No	High	High	High	Low
Cheese	Yes	High	Low	High	High
Corn	Yes	High	Low	Low	High
Dry Milk	Yes	High	Low	High	High
Dry Whey	Yes	High	Low	High	High
Eggs	No	High	High	High	Low
Fed Cattle	Yes	Low	High	High	Low
Hogs	Yes	High	High	High	Low
Oranges	No	Low	High	High	Low
Potatoes	No	Low	Low	High	Low
Rice	Yes	High	Low	High	High
Soybeans	Yes	High	Low	Low	High
Soybean Oil	Yes	High	Low	Low	Low
Soybean Meal	Yes	High	Low	Low	Low
Sunflower Seed	No	High	Low	High	High
HRS Wheat	Yes	High	Low	Low	High
HRW Wheat	Yes	High	Low	Low	High
SRW Wheat	Yes	High	Low	Low	High
DDG	–	Low	High	High	Low

Notes: Product homogeneity, industry vertical integration, and buyer concentration are assumed for 17 of the 21 products to be the same as those in Brorsen and Fofana (2001). For barley, dry whey, oranges, and DDGs, these measures are obtained from the literature and from personal communications with individuals who are active in the industry. Product storability assumptions follow findings and assumptions from the existing literature.

Table 2: Descriptive Statistics about Cash Markets and Cross-hedge Futures Hedging Opportunities

Commodity	Futures Market?	CV	ACM	Market Size	Volume of Cross-hedge Contract	Residual Risk
Apples	No	7.68	17.91	14.82	7.41	0.98
Barley	No	12.95	11.38	7.66	11.72	0.37
Broilers	No	5.81	9.06	16.94	10.20	0.94
Cheese	Yes	7.27	4.43	14.93	-1.33	0.41
Corn	Yes	11.81	0.35	11.60	10.77	0.22
Dry Milk	Yes	11.23	5.68	13.54	-1.33	0.17
Dry Whey	Yes	16.43	8.28	13.16	-1.33	0.73
Eggs	No	19.89	8.77	18.32	10.20	0.96
Fed Cattle	Yes	4.42	0.14	16.45	11.72	0.41
Hogs	Yes	11.12	0.03	16.51	10.21	0.50
Oranges	No	14.49	8.01	16.03	7.42	0.96
Potatoes	No	17.14	8.01	16.89	10.77	0.87
Rice	Yes	8.55	18.02	16.15	10.77	0.94
Soybeans	Yes	15.16	0.18	10.15	10.20	0.22
Soybean Oil	Yes	11.47	0.02	16.04	8.99	0.12
Soybean Meal	Yes	12.68	0.16	17.47	11.23	0.30
Sunflower Seed	No	11.45	12.53	14.15	10.49	0.20
HRS Wheat	Yes	18.66	0.18	8.40	9.22	0.25
HRW Wheat	Yes	18.53	0.23	8.97	10.76	0.10
SRW Wheat	Yes	19.99	0.16	8.11	9.22	0.20
DDG	Yes	12.07	2.74	16.53	10.20	0.13

Notes: The annual coefficient of variation (CV) is calculated using cash market price data across 52 weeks. ACM represents the estimated cash market activity and is the average number of weeks in a 26-week period when there was no price changes between weeks. Market size refers to the natural log of annual production and the volume of a cross-hedge futures contract is calculated the natural log of the average weekly trade volume. Residual risk represents the variation in a product's weekly cash price that cannot be explained by the variation in the price of an assumed cross-hedge futures contract.

Table 3: Estimation of Cash Market Activeness and Comparison to Existing Estimates

	Bekkerman and Tejeda				*Brorsen and Fofana (2001)*	
Commodity	**Mean # Zeros in 26-week period**	**Std Deviation**	**95% Confidence Interval**	**Predicted ACM**	**Commodity**	**ACM**
Apples	17.91	3.14	[11.76, 24.06]	Low	Apples	4.17 (Low)
Barley	10.88	4.49	[2.08, 19.68]	Low	–	–
Broilers	16.00	2.39	[11.31, 20.69]	Low	Broilers	1.33 (Low)
Cheese	1.54	1.22	[-0.84, 3.93]	High	Cheese	3.17 (Low)
Corn	0.35	0.52	[-0.67, 1.37]	High	Corn	8.67 (High)
Dry Milk	6.01	2.80	[0.53, 11.50]	Low	Dry Milk	3.00 (Low)
Dry Whey	8.76	4.70	[-0.46, 17.98]	High	–	–
Eggs	8.80	2.57	[3.76, 13.85]	Low	Eggs	2.00 (Low)
Feeder Cattle	0.14	0.29	[-0.43, 0.71]	High	Feeder Cattle	6.17 (High)
Live Cattle	0.11	0.22	[-0.33, 0.54]	High	Live Cattle	6.33 (High)
Live Hogs	0.03	0.11	[-0.19, 0.25]	High	Live Hogs	6.67 (High)
Oranges	7.63	3.07	[1.62, 13.65]	Low	–	–
Potatoes	7.51	3.53	[0.59, 14.43]	Low	Potatoes	3.50 (Low)
Rice	17.44	3.56	[10.45, 24.42]	Low	Rice	6.00 (Low/High)
Soybeans	0.24	0.42	[-0.59, 1.06]	High	Soybeans	8.83 (High)
Soybean Oil	0.02	0.07	[-0.12, 0.17]	High	Soybean Oil	6.50 (High)
Soybean Meal	0.15	0.21	[-0.26, 0.57]	High	Soybean Meal	7.33 (High)
Sunflower Seed	12.92	4.94	[3.23, 22.60]	Low	Sunflower Seed	3.17 (Low)
HRS Wheat	0.16	0.34	[-0.50, 0.82]	High	Minneapolis Wheat	8.67 (High)
HRW Wheat	0.21	0.40	[-0.59, 1.00]	High	Kansas City Wheat	8.67 (High)
SRW Wheat	0.16	0.32	[-0.46, 0.78]	High	Chicago Wheat	8.67 (High)
DDG	2.30	1.40	[-0.45, 5.05]	High	–	–

Notes: "ACM" represents activeness of a commodity's cash market. The 95% confidence interval is around the mean number of zeros within a 26-week period. ACM values from Brorsen and Fofana (2001) are mean survey responses of 10 industry experts who were asked to rate the activeness of each cash market on a 1–10 scale. Opinions about the activeness of the DDG cash market were not elicited by Brorsen and Fofana (2001).

Table 4: Estimation Results of Probit Model for Futures Markets

Variable	**Parameter Estimate**	**Standard Error**	**Average Marginal Effect**	**Standardized Parameter Estimate**
Intercept	-0.87	(2.50)	–	–
CV	-0.11***	(0.04)	-0.02	-0.83
ACM	0.16**	(0.06)	0.02	1.00
Homogeneity	1.18**	(0.60)	0.17	-0.47
Vertical Integration	-2.56***	(0.85)	-0.38	1.18
Concentration	-6.73*	(3.48)	-0.99	3.29
ln(Production)	1.02**	(0.48)	0.15	-3.43
ln(Vol. Cross-hedge Contract)	-0.41**	(0.17)	-0.06	1.54
Residual Risk	-2.63	(1.63)	-0.39	0.86
McFadden's R-squared			0.62	

Notes: The probit regression is estimated using data describing all products except DDG. The model includes yearly fixed effects but these estimated parameters are omitted for brevity. Standardized parameter estimates are obtained following Kaufman (1996). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Predicted Probability of Futures Market Existence

Commodity	**Predicted Futures Market?**	**Predicted Probability of Having a Futures Market**	**Futures Market?**
Apples	No	0.1%	No
Barley	No	19.1%	No
Broilers	No	33.3%	No
Cheese	Yes	100.0%	Yes
Corn	Yes	100.0%	Yes
Dry Milk	Yes	100.0%	Yes
Dry Whey	Yes	97.8%	Yes
Eggs	No	24.8%	No
Fed Cattle	Yes	55.1%	Yes
Hogs	Yes	82.9%	Yes
Oranges	No	2.4%	No
Potatoes	No	39.5%	No
Rice	No	23.4%	Yes
Soybeans	Yes	99.9%	Yes
Soybean Oil	Yes	100.0%	Yes
Soybean Meal	Yes	100.0%	Yes
Sunflower	No	44.7%	No
HRS Wheat	Yes	92.1%	Yes
HRW Wheat	Yes	98.6%	Yes
SRW Wheat	Yes	91.6%	Yes
DDG	Yes	90.2%	–

Table 6: Second Stage Estimation Results of the Selection Model for Futures Trade Volume

Variable	**Parameter Estimate**	**Standard Error**	**Standardized Parameter Estimate**
Intercept	-3.16	(2.95)	–
CV	-1E-03	(0.01)	-0.01
ACM	0.07*	(0.03)	0.21
Homogeneity	0.84**	(0.39)	0.15
log(Production)	-0.01	(0.04)	-0.03
log(Vol. Cross-hedge Contract)	0.31	(0.31)	0.20
Residual Risk	-0.48	(0.57)	-0.07
Ratio of Commercial to All Traders	-9.83***	(1.50)	-0.56
Ratio of Commercial to Non-Commercial	2.66***	(0.41)	0.65
log(Non-commercial participants)	0.99***	(0.09)	0.75
Inverse Mills ratio	0.06	(0.04)	0.15
McFadden's R-squared		0.82	

Notes: The second stage of Heckman's selection model is estimated using data describing only products that have a futures market, because futures contract volume information is not observed for products that do not have futures markets. The inverse Mills ratio is estimated from the probit regression results, shown in Table 4. The model includes yearly fixed effects but these estimated parameters are omitted for brevity. Coefficient estimates for standardized represent changes in the standard deviation of trade volume from one standard deviation from the mean of the corresponding variable. Absolute values of the standardized parameter estimate characterize the relative importance of each variable to changes in trade volume. White's heteroskedasticity-robust standard errors are presented. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Estimation Results of the Trade Volume Model for Commodities with Support Markets

Variable	**Parameter Estimate**	**Standard Error**	**Standardized Parameter Estimate**
Intercept	2.82***	(0.68)	–
CV	-5.68**	(2.61)	-0.03
ACM	0.39***	(0.10)	0.24
Residual Risk	7.96***	(0.88)	0.23
Commercial participant-weighted support market trade volume	0.93***	(0.08)	0.77
Ratio of commercial to all participants, support market	-7.23***	(1.00)	-0.29
Ratio of commercial to non-commercial participants, support market	-0.02	(0.05)	-0.01
R-squared		0.92	

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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

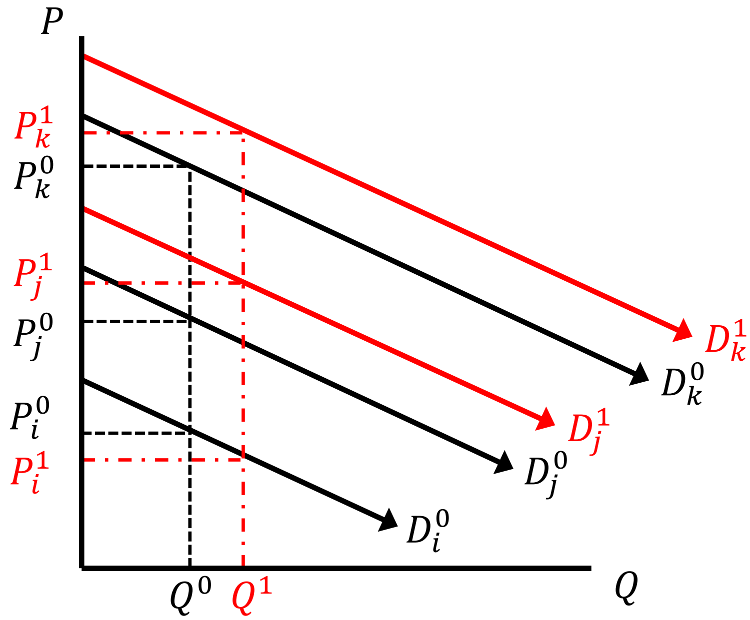

Figure 1: Multi-sector Model of Fixed Production Outputs

Table A1: Cash and Futures Markets Descriptions and Assumptions

	Cash Market			*Futures Market*	
Commodity	**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	–	–
Potatoes	Idaho origin; 50 lb. units; Russet; 70S	–	SRW	–	–
Rice	Long, 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	–	Soybeans	Soybean Meal	Soybean Oil
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: Unit conversions are assumed to convert all products except eggs into per ton basis. The cross hedge futures market represents the contract whose prices are most correlated with a particular cash market and were chosen following findings and assumptions from the existing literature.