Price Determination and Margin Volatility in Thinly Traded Commodity Markets: An Application to Major U.S. Field Crops

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Introduction

As agricultural commodity markets across the world have become more concentrated horizontally and coordinated vertically through direct integration or use of production or marketing contracts, spot or cash markets have in many cases diminished in their reliability or disappeared entirely. In addition, as agricultural products become ever more differentiated and new market niches are created, discovery of prices in these specialized market segments represents a major challenge for participants and government officials.[1] Markets that have few traders on either the buying or selling side and lack active cash or spot markets are often termed "thin markets." Conditions in these markets are a concern to both market participants and policy makers because prices tend to be volatile (Hayenga 1979), subject to possible manipulation (Mueller 1996; Xia and Sexton 2004; Zhang and Brorsen 2010), and, without the discipline of strong market forces, may not allocate resources efficiently. A particular concern is that farmers selling in such market conditions may be at a disadvantage relative to buyers and receive prices that are systematically below the competitive equilibrium price. Low farm gate prices and restricted production characteristics of buyer power can also threaten the global competitiveness of U.S. agriculture.

Adjemian, Saitone, and Sexton (2016) explored the link between thin markets and the modern agricultural markets (MAM) paradigm developed by Crespi, Saitone, and Sexton (2012) and Sexton (2013). Their work applied the elements that describe a MAM to settings characteristic of thin markets, making the fundamental point that, in markets satisfying these elements, the aforementioned concerns regarding thin markets are obviated because conditions favor the emergence of a symbiotic relationship between buyers and sellers, and efficient price and production levels. In this article, we expand on that approach

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[1] For example, the USDA Agricultural Marketing Service provides—free of direct charge—prices and sales data to assist market participants with the marketing and distribution of their products. As commodities differentiate, that goal becomes more difficult due to privacy restrictions when the number of respondents in each category narrows. Likewise, the lack of reliable market data has led the USDA Risk Management Agency (RMA) to make available a contract price addendum for organic and transitioning producers since late 2016. Growers can now choose to use their contracted price as a base price in their crop insurance policy instead of the RMA organic price election.

to develop a technique that can be used to test for thin-market pricing efficiency in cases where data are available. We contend that establishment of a clear link between prices of conventional and specialty or niche versions of a product can likewise address the aforementioned thin-market issues: even if markets for the specialized product are thin, they are unlikely to suffer from thin market concerns due to the discipline provided by the conventional market. We propose that the key hypothesis to test is whether in the short or long run a stable pricing relationship (i.e., a stable price premium) exists between the enhanced and conventional version of the product.

In this article, we apply this method to a convenient empirical example: conventional and differentiated versions of major domestic field crops. Organic and non-genetically engineered (non-GE) varieties of these commodities offer a useful thin-market experiment from our perspective because while they are nutritionally identical to their conventional counterparts, their production processes can involve the use of different seeds, row-planting, and rotation practices—often including an idle year, cultivating for weeds, and the strict avoidance of chemical pest control (McBride and Greene 2008).[2] As a result, organic and non-GE farms face different costs of production, and farmers who choose to plant the thinly traded commodities are willingly accepting attendant thin-market price dynamics. In contrast, with large numbers of buyers and sellers, the benchmark conventional market for each commodity is clearly competitive. If organic and/or non-GE crops are a MAM, then the relatively few buyers who *are* in the market would offer a price that compensates for organic and/or non-GE producers' additional costs and commensurate with the higher production risks.

Organic, non-GE, and conventional crops are grown in largely the same regions, and therefore confront similar production shocks. Though demand-side innovations for organics and non-GE may be specific (Würriehausen, Ihle, and Lakner 2015), markets for conventional crops place a lower bound on

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[2] Throughout the article, we refer to non-organic, non-GE crops as simply "non-GE", reserving the term "organic" for the non-GE crops grown using organic farming methods.

prices, since the differentiated version of the commodity can always be sold conventionally. This reality poses an empirical opportunity to judge how well prices conventional and niche, thin-market versions of the same crop move together, and whether premia paid for differentiation are sufficient to cover incremental production costs and stable over time. Moreover, differing market structures among organic and non-GE field crops offer an additional opportunity to observe how they affect thin market performance. While the process for transitioning to organic agriculture is organized, well-known, and intensive—calling for a substantial time and financial commitment on the part of growers—growing a non-GE version of a crop can be (nearly) as easy as buying a different type of seed from one year to the next. And, without a government-approved label, third-party non-GE certification may not carry credibility among consumers. Both of these circumstances —lack of a substantial producer commitment and poorly recognized differentiation on the demand side—can adversely affect the ability of a thin market to organize and function well.

We use a rich series of bi-weekly price data available for organic feed commodities (corn, soybeans, wheat, and oats), and a new weekly series for non-GE corn and soybeans, to explore the price relationships between niche versions of field crops and their conventional counterparts. Using threshold asymmetric cointegration models, we show that as the price premium for organics surpasses a certain positive threshold, market forces (likely competition from foreign growers) applies downward pressure in the organic price series toward the conventional price, a relationship that a linear cointegration framework would miss. Given that corn, soybeans, and wheat prices do not adjust similarly after a negative shock to the premium, continued producer entry into the differentiated field crop markets suggests that the organic premium is high enough to cover economic costs. Our findings are consistent with the idea that niche prices are best modeled using a nonlinear approach, given that linear cointegration models fail to find a symmetric relationship between organic and conventional crops, even when accounting for structural breaks. These results imply that organic field crops have the necessary conditions to be characterized as a MAM. On the other hand, observed non-GE premia could not be characterized as either stable or sufficient when observed over the same timeframe.[3]

It is likely that the differences in market structure between the organic and non-GE markets drive these disparate results. Adjemian, Saitone, and Sexton (2016) argue that a well-functioning MAM needs reliable commitments from both buyers and producers to form stable, mutually beneficial partnerships. Organic agriculture requires a much larger sunk investment in the form of a transitional period of three years, intensive certification process, and knowledge-acquisition regarding organic farming practices. Moreover, the USDA-certified label serves to assure organic producers that their efforts are recognized, and offers credence to retail buyers that a given product is truly organic. In comparison, the certification process is far less robust for non-GE growers, which may enhance consumer demand for third-party non-GE certification. At the same time, non-GE producers have lower compliance costs and face a non-existent transitional period, allowing them to switch from non-GE to GE planting on a yearly basis.

Background

Organic Market for Feed Crops

The U.S. Department of Agriculture's National Organic Program (NOP) was established as part of the Organic Foods Production Act, under the 1990 Farm Bill, to define standards of organic farming practices. Prior to the mandate, organic agricultural goods were marketed in farmers' markets or natural food stores without consistent labeling or certification (Greene 2009). The rapid rise in organic food demand since then is partly in response to the development and success of the organic regulatory program and label (Batte et al. 2007; Kiesel and Villas-Boas 2007; Molyneaux 2007). From the producer perspective, certification is an insurance that their organic product will be properly differentiated from non-organic

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[3] It should be noted that the time period for which we have non-GE data is relatively short -- just under two years.

products, and that only agricultural goods possessing the right qualifications will be endowed with the label; on the consumer side, the label serves as a credibility signal that the product is indeed organic.

Growers' decisions to enter the market take into account expectations of prices and costs. Typically, studies have found that farming organic produces positive returns when compared to conventional (Delate et al. 2003; Pimentel et al. 2005; Chavas, Posner, and Hedtcke 2009; Clark 2009; Delate et al. 2013; McBride et al. 2015;). Converting a field from conventional to organic production is a three-year process, regulated by USDA. Over that period, no prohibited substances may be applied.[4] After review of the land's history, production plans, and inspection by USDA officials, farms found to be in compliance are certified for organic production. Displaying the certification ensures that organic feeds can be marketed as organic officially, although they can always be sold into the conventional market; not having the certification prevents conventional grains from being marketed under an organic label.

Organic growers' do not absorb the totality of the cost, as a portion of organic certification is offset by cost-sharing programs offered by the National Organic Certification Cost Share Program (NOCCSP) and the Agricultural Management Assistance (AMA) Organic Certification Cost Share Program. Through these programs USDA distributes funds to eligible State agencies, which in turn, reimburse certified organic operators a portion of the cost paid to maintain organic certification. The USDA-accredited certifying agent sets the total cost, which includes application fee, annual renewal fee, assessment on annual production, and inspection fees. Because the agents set their own fees, the cost can range from "a few hundred to several thousand dollars" (USDA-AMS 2017). In 2017, the program provides reimbursement for up to 75% of certification costs, or $750 per year per farm, increased from $500 as part of the 2008 Farm Bill.

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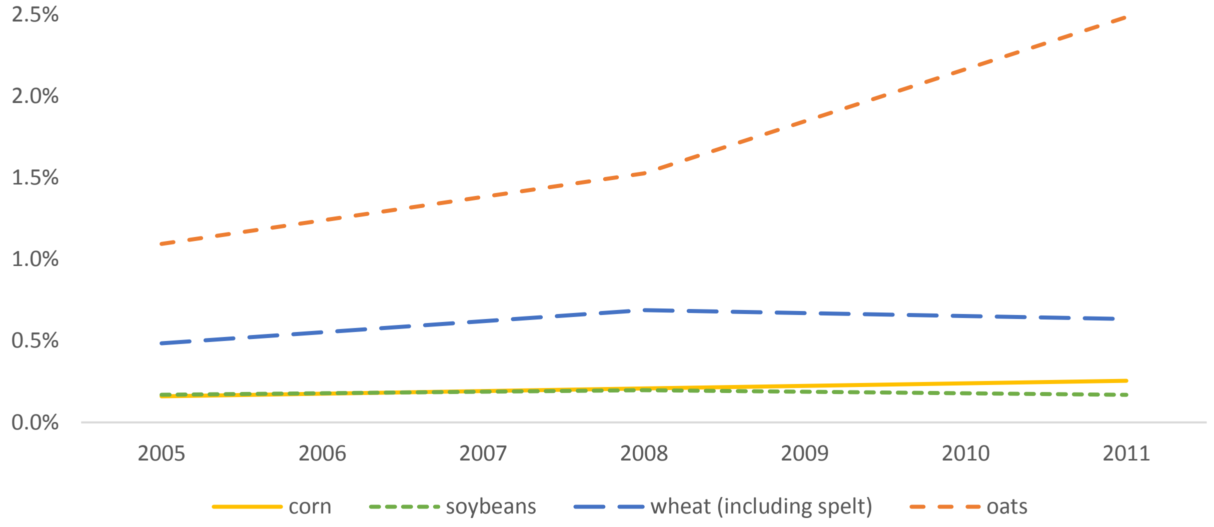
[4] The National List of Allowed and Prohibited Substances establishes the substances that may and may not be used in organic agriculture. As a general rule, synthetic substances are prohibited, whilst natural substances are permitted.

Organic farming is inherently riskier, both in terms of production and marketing, than farming conventionally. Yield-adjusted average economic costs of production for organic corn, soybeans, and wheat are higher than for conventional production—a recent study found them to be between \$83 to \$93 higher per acre for organic corn, \$55 to \$62 higher per acre for organic wheat, and \$106 to \$125 per acre higher for organic soybeans (McBride et al. 2015). Organic agriculture relies on ecologically-based practices, and excludes most synthetic chemicals. As a result, the chemical costs of production are far lower, but fuel and labor costs can be substantially higher due to the increased use and operation of farm machinery. Organic farms require greater attention to soil fertility, and weed and pest control on the part of producers, increasing their labor intensity (Moncada and Sheaffer 2010). In regard to marketing, most organic feed production is contracted bilaterally (Singerman, Lence, and Kimble-Evans 2014), so farmers bear the counterparty risk that a buyer will not fulfill their obligations. Whatever portion of the crop that is not contracted for forward sale is harvested when market prices are typically lowest, so it is generally recommended that organic farmers have the capacity and ability to store on-farm until local prices improve (Heiniger 2017). While organic feed markets are still becoming established, producers can incur considerable search costs to find the best price from a reliable buyer, or even to process their crop at harvest-time. USDA regulations require that the equipment and facilities used to harvest, handle, transport, store, and process differentiated versions be separated from conventional crops; most elevators are not certified or equipped to handle organics, and as a result, the marketing and distribution system for organic feeds is much less organized.

The number of producers and buyers in the organic markets is also much smaller (Mainville et al. 2009), but the demand for organic crops is growing. Although they are also used for human consumption, most organic field crops are processed and sold to livestock producers as feed. The demand for the latter is derived from the retail demand for organic eggs, dairy, and meat. Buyers of organic grains and oilseeds—including feed processors and brokers—seek out and form long-term contractual relationships with producers who offer quality and consistency (Midwest Organic and Sustainable Education Service 2012). Successful organic producers establish and cultivate long-term contractual relationships with these buyers (Born and Sullivan 2005), because, in a thin market like organic crops, producer reputation is key to future sales (Mainville et al. 2009).

Figure 1: Share of US corn, soybean, wheat, and oats cropland that is certified organic

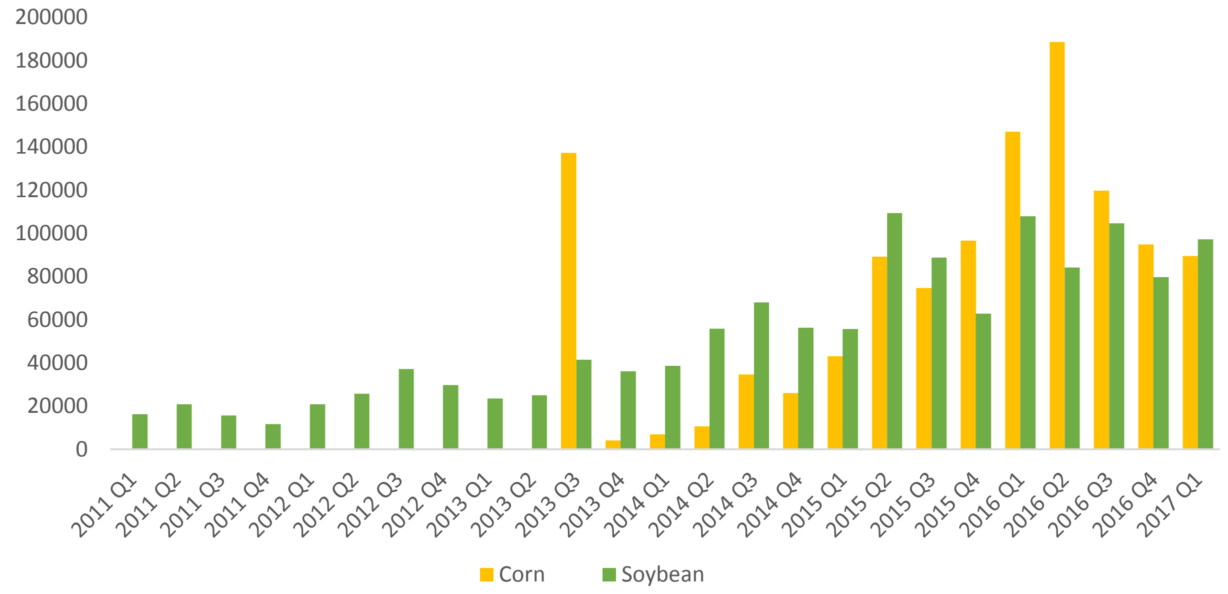


Source: USDA Economic Research Service

Growers of organic corn, wheat, and soybeans surveyed by the Agricultural Resource Management Survey (ARMS) report that their major challenges as producers include achieving high yields (12%, 40%, and 12% of surveyed respondents, respectively), controlling weeds (40% for corn and wheat producers), and certification paperwork (17% for wheat, and 33% corn growers) (McBride et al. 2015). The survey found that a limiting factor to organic transitioning, despite the potentially greater returns, is the myriad of additional challenges to farming organic, such as effective weed control and lower crop yields. Still, average organic corn and soybean prices were found to be high enough among sampled farmers to cover the higher total economic costs, including annual prorated share of transition costs and annual certification costs. Yet, only a small fraction of corn and soybeans are planted in certified organic fields, as shown in figure 1. Prices for organic wheat were high enough to cover the additional operating plus capital costs, but not high enough to cover the additional total economic costs (McBride, et al. 2015).[5]

Because of the potentially higher production costs and hardships associated with the transition to organic production, to attract enough farms into production buyers of organic products must offer a premium over the prices of their conventional counterparts. Organic feeds are consumed differently, so they are at least subject to some independent demand-side innovations (Würriehausen, Ihle, and Lakner 2014); while organic livestock operators must source organic feed to maintain their own USDA certification, consumers are more likely to substitute away from organic meat and eggs should their incomes fall. It should be noted that organic grains and oilseeds could be sold into the conventional market, implying that price shocks in the benchmark conventional market may transmit to organics.

Figure 2: Organic Imports of Corn and Soybeans (in metric tons)



Source: U.S. Department of Commerce, U.S. Census Bureau

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[5] Total economic costs include operating costs, capital costs, opportunity costs for land, and opportunity cost for unpaid labor.

Due to the challenges posed by organic agriculture, and because a large portion of organic corn and soybean production in the U.S. supports the growth in the organic dairy sector, which has increased almost fourfold from 2002 to 2011 (USDA-ERS 2017), sourcing for feed has in some cases turned to importing organic corn and soybeans, as shown in figure 2.[6]

How organic feed prices are established, whether they respond to the supply and demand shocks of conventional grains, and the degree of linkage between these markets are empirical questions that have not received adequate attention in the literature. They also provide a useful example of thin-market price dynamics, given the competitive nature of the broader commodity markets. If organics are integrated with their conventional counterparts, and the premium is high enough to cover the increased economic costs associated with organic production, then concerns about manipulated or depressed prices for the niche product are not supported. On the other hand, a finding of no significant integration is not necessarily a sign of manipulation, particularly if price premiums work in a producer's favor. The latter does, however, indicate that organic prices do not share a statistically identifiable long-run relationship with the conventional market, and therefore are apt to drift apart.

Non-GE Market for Feed Crops

U.S. farmers began using genetically engineered (GE) varieties of major field crops containing herbicides and pest resistant traits in 1996 (USDA-ERS 2016). The term "GE" encompasses genetic engineering techniques used to change or improve plants, animals, and microorganisms, affording the engineer the precision to alter a specific trait or group of traits. U.S. farms have adopted GE field crops very rapidly: today, less than 10% of U.S. production of corn and soybeans is non-GE, as shown in figure 3, compared to about 75% and 45%, respectively, less than two decades ago. According to the USDA National

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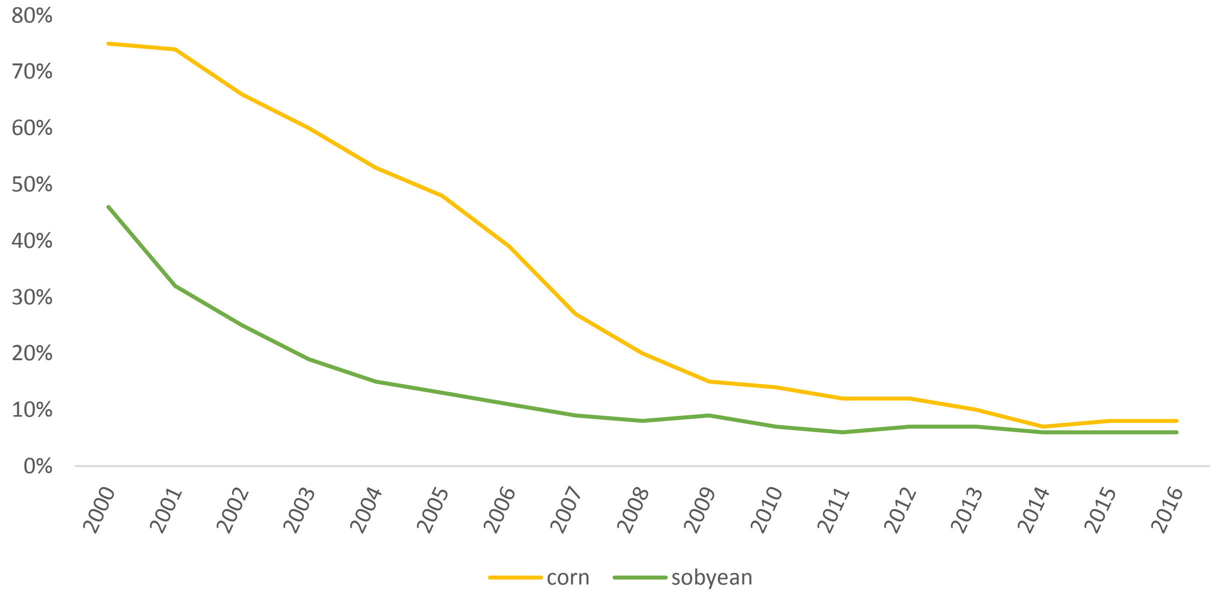
[6] Because the U.S. Commerce Department began recording organic corn imports in July of 2013, we cannot say for certain that the volume observed in Q3 corresponds to a spike. However, it is likely that the volume observed in 2013 Q3 is related to the drought that affected the 2012 and 2013 domestic crops.

Agricultural Statistics Service (NASS) Acreage Report 2016, 92% of corn and 94% of soybeans planted in the U.S. relied on a biotechnology (insect resistant, herbicide resistant, stacked gene varieties); both shares were stable from the prior year.

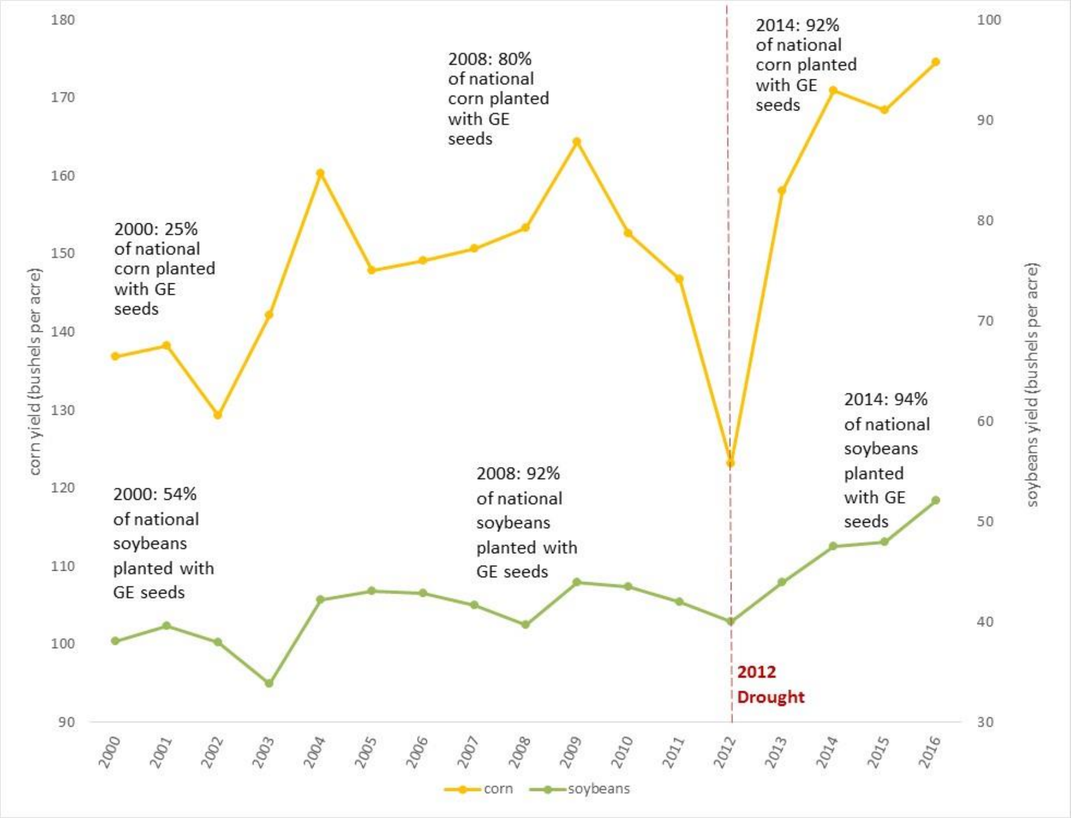
Figure 3: Non-genetically engineered corn and soybeans varieties



Source: USDA-NASS

Notably, GE techniques have been used to improve crop yields and productivity; as shown in figure 4, the increase in GE traits is correlated with an increase in yields for both corn and soybeans. USDA's Animal and Plant Health Inspection Service (APHIS) has regulatory oversight authority over new GE varieties. For example, herbicide-tolerant (HT) varieties allow plants to tolerate more effective herbicides, while Bt crops are engineered to produce the bacteria Bacillus thringiensis, a crystal protein that is toxic to many pests. Both of these types of GE are intended to improve crop yields.

Figure 4: Corn and soybeans yield (bushels per acre) and GE adoption



USDA: USDA-NASS

As with organic production, an added cost of farming non-GE crops is preventing their accidental commingling with conventional versions, which would force growers to forgo the differentiated-product price premium and have potential legal ramifications. Methods to prevent or reduce the risk of commingling include buffer strips—physically separating conventional and niche growing areas—and delayed planting (to reduce the overlap of pollination between GE and non-GE crops). However, the latter strategy may also further lower yields, as farmers may not be able to sow each crop by its optimal planting date. Otherwise, production practices for non-GE are similar to conventional: farmers of both rely on synthetic pesticides or insecticides for pest control and synthetic herbicides for weed control (Greene et al. 2016).[7] USDA Cost and Returns estimates reports prices of non-GE corn and soybeans seeds to be lower

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[7] Although organic foods are necessarily non-GE, non-GE foods themselves do not necessarily qualify for organic certification since non-GE growers may continue to use fertilizers and herbicides as approved by the Environmental Protection Agency (EPA).

than those of GE seeds (USDA-ERS 2017). However, planting non-GE varieties increase insecticide, herbicide, and seed costs per acre, and thus labor and/or mechanical costs as well.

The certification process for non-organic, non-GE crops is not as robust as it is for regular organic foods. That poses a potential credence issue for both producers and consumers. For growers, the lack of well-recognized certification system calls into question whether their efforts will be remunerated appropriately; at the retail level, the lack of a universally-accepted label might affect consumer willingness to pay a premium for the differentiated product, affecting the strength of any non-GE premium from the demand side. While the USDA leads the certification process for organics, it relies on the Non-GMO Project, a nonprofit organization that offers third-party non-GE verification and labeling for consumers, to identify non-GE foods and products in the United States. The National Bioengineering Food Disclosure Law, signed in July 2016, requires that within two years, the Secretary of Agriculture develop and implement a mandatory national bioengineering food disclosure process (USDA-FSIS 2017). This legislation also introduced a streamlined process for companies to obtain approval for labels that verify lack of GE ingredients, including the term “Non-GMO” in the claim, something that was not previously permissible. For organic farms, FSIS verifies proper label use during normal verification inspections and routine NOP certification inspections, which are scheduled on an annual basis for organic operations. However, there is no similar official government inspection process that verifies that non-organic farms follow the currently accepted non-GE practices.

Despite the rapid growth of GE crops over the last 15 years, there is an emerging market for non-GE foods at supermarket chains and big-box stores (Greene et al. 2016), although they still represent a small share of retail food markets (Fernandez-Cornejo et al. 2014). Consumers’ perception of GE foods varies, but studies generally find that some consumers are willing to pay a premium over conventional alternatives (Lusk, Roosen, and Fox 2003; Lusk et al. 2005; Hall, Moran, and Allcroft 2006; Dannenberg

2009). Use of GE in foods is viewed as a larger concern internationally; European consumers are typically found to be willing to pay a higher premium to avoid GE foods (Lusk, Roosen, and Fox 2003; Moon and Balasubramanian 2004; Dannenberg 2009).

Given the fast uptake of GE field crops, the maintained demand for identity-preserved non-GE varieties—now a niche product like organic feeds—created a need for supply-chain coordination and use of bilateral contracts. Sykuta and Parcell (2003) describe contract characteristics from a survey of two large non-GE soybean buyers for the crop years 1999 through 2002. Price premiums over the conventional price for all contracts were for bushels delivered given GE content not surpassing the maximum threshold, taking into account quality and delivery specifications. The survey revealed the use of acreage contracts, which shift some risk to the buyer: growers commit to delivering all bushels produced to the buyer, thus not suffering a penalty if yield falls below expectation and not having to find a market given a surplus.[8] However, the commitment on the producer side when it comes to non-GE production is not as clear. Growing non-GE varietals is (nearly) as simple as purchasing a different variety of seeds, with the additional concern and cost of keeping the crop free of contamination from GE pollen. Indeed, a producer can decide, from one year to the next, whether to plant a given plot to GE or non-GE, based on the expected market premium.

Therefore, non-GE versions lack both a sunk cost (i.e., producer commitment) to the production of the differentiated version of the commodity, and an official, government-sanctioned label—which may affect its credence or popularity among both producers and consumers. Both of these ingredients are important to the establishment of a well-functioning thin market (Adjemian, Saitone, and Sexton 2016).

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[8] Two delivery options were available in 1999 and 2000: harvest delivery (HD) and buyer's call (CD), with differing premiums. However, only CD was offered in 2001 and 2002. This delivery choice creates additional uncertainty for the producers in terms of storage; the delivery window can span a year, with a stipulated two-week warning period.

It is no surprise then that Greene et al. (2016) report that the price premium for identity-preserved soybeans fell between 2012 and 2016, and that in 2012, fully 41% of non-organic, non-GE producers sold their harvest in conventional markets.

Because the non-GE market is still in its developing stages, the relationship between non-GE and conventional prices has yet to receive much notice. Its newness reveals itself in the availability of data. There are currently no Schedule B numbers associated with non-GE agricultural goods in the U.S. Harmonized System so that only non-GE commodities that are also farmed organically are tracked separately from the general conventional Schedule B number. Despite the lack of available trade data, both the export and import markets comprise an important part of U.S. field crop processors' and brokers' demand (Greene et al. 2016).

Methods and Data

Methods

Three recent studies explore the relationship between prices for organic and conventional versions of major commodities. Singerman et al. (2014) study cointegration between organic and conventional corn and soybeans in six selected locations, and are unable to uncover evidence of a short- or long-run relationship between any series for the period between 2004 and 2009. Likewise, Ferreira et al. (2017) test for linear cointegration between monthly prices for organic and conventional corn, soybeans, oats, and barley during the years 2007-2016 against cash prices series, and find that the prices are not linearly cointegrated. However, in a study of German markets, Würriehausen, Ihle, and Lakner (2014) use an asymmetric Markov-switching VECM and find three differing premium regimes; the authors find that German prices for organic and conventional wheat adjust to a long-run equilibrium between 1997 and 2011 and that positive shocks to the organic premium were followed by organic price adjustment back to the equilibrium.

No previous U.S. study of organic and conventional crop prices has allowed for asymmetric responses from organic prices to conventional shocks.[9] One drawback of linear cointegration is that it assumes small short-run deviations from equilibrium dissipate just as quickly as large ones, so that cointegrated prices cannot wander too far away from one another before market forces draw them back towards equilibrium, and that different sorts of deviations are resolved at the same pace. Implicit in the definition is that a small deviation from the long-run equilibrium will lead to instantaneous corrections of the error. However, there are reasons to suspect that organic prices may not respond symmetrically to changes in the premium. For example, if the difference between the organic and conventional price series increases, the premium could attract imports into the market and rapidly decrease the premium level. On the other hand, if the gap between the two series is squeezed sufficiently, that might serve to reduce future premium expectations and cause marginally efficient organic producers to exit the market over time, and/or reduce the rate of entry among marginally profitable farms. Quick decreases in the premium could also signal to producers (and importers) that either the market has been oversaturated or demand for the niche product has decreased. However, exit could occur slowly and only be noticeable if expected future premia from organic and non-GE were below economic costs.

To allow for more flexibility in the integration between the price series under study than is possible in a standard linear model, we use an asymmetric threshold cointegration approach to study the relationship between organic and conventional grains. We estimate both the Threshold Autoregression (TAR) model, which captures potential asymmetric deep movements in the residuals, and the Momentum Threshold Autoregression (MTAR) model, which takes into account steep variations in the residuals (Enders and Granger 1998; Enders and Siklos 2001; Sun 2011). TAR is useful when it is believed that

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[9] Although Singerman et al. (2016) tested for threshold cointegration, they did not find evidence for it. One possibility for why is that organic markets had yet to converge to fit the characteristics of a MAM in these years. It could also be that the smaller sample sizes and sometimes unvarying prices at each of the six distinct geographic localities in the analysis limited the power of the tests.

troughs or peaks deviate by a different amount from the trend, while MTAR is the right approach when it is believed that adjustments to deviations exhibit more momentum in one direction than other — i.e. different speed of adjustment upward versus downward (Sichel 1993). The TAR and MTAR models extend the linear cointegration model to allow for adjustments toward equilibrium only after the deviation has exceeded a critical threshold, thus allowing for a no-arbitrage band. The no-arbitrage band is essential because it allows us to account for transaction costs and stickiness in market prices. For example, given a large increase in the premium level (TAR model) or a large change in the premium (MTAR model), importers may be enticed to enter the market. However, several months may go by from the time the market signal is observed to the time that grain and oilseed importers contract with foreign exporters and ship the product to the U.S.

For each organic-conventional commodity pair, we follow these steps: (1) test for stationarity using the Augmented Dickey-Fuller test and the modified Dickey-Fuller test for unit roots proposed by Elliot, Rothernberg, and Stock (1996); (2) test for linear cointegration via Johansen trace; (3) test for non-linear cointegration; (4) if non-linear cointegration is found, we employ the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to identify whether TAR or MTAR generate a better data fit, and estimate an asymmetric threshold error correction model (ECM) to correct the long-run equilibrium. Because our non-GE data series is far shorter, we refrain from statistical analysis and instead compare non-GE to conventional prices graphically, and discuss the differences we observe in premium behavior across product types in light of different market structures.

Data

Organic corn, soybeans, wheat and oat prices are drawn from the bi-weekly USDA Agricultural Marketing Service's (AMS) National Organic Grain and Feedstuffs Report (now the Bi-Weekly National Organic

Comprehensive Report).[10] Prices for corn and soybeans span April 2007 to March 2017, April 2011 to March 2017 for wheat, and February 2011 to September 2015 for oats. Prices contained in each report are collected over the period of two weeks' time on a voluntarily basis from domestic grain purchasers.[11] At times, because too few observations are made, AMS does not publish a price to maintain participant anonymity. From 2007-2010, AMS reported two sets of organic prices, representing distinct U.S. regions: the Upper Midwest, and the Eastern Cornbelt. These prices series were later combined and reported as a unified national price (i.e., a weighted average). For consistency, we combined each commodity's pre-2011, regional price data into a single time series of national prices.[12]

Until August 2016, organic wheat prices were reported by class (i.e., hard red winter, hard red spring, soft red winter, soft white, hard white, durum), at which point they replaced the multiple series with a single weighted-average wheat price, which includes hard red spring, soft red winter and hard red winter wheat. We use the same approach discussed above to combine previously differentiated wheat observations into a single price series. Missing observations were interpolated linearly. The raw and interpolated data is presented in a later section.

Our non-GE corn and soybean price series are much shorter, owing to a newer collection regime at USDA; each are drawn from the weekly USDA AMS National Weekly Non-GMO/GE Grain Report spanning September 2015 to March 2017.[13]

Two different series are considered for conventional prices. The first price series was created using the Chicago Board of Trade (CBOT) futures contract prices for conventional corn, soybeans, wheat, and oats. Because futures contracts exist only for a pre-defined period of time, the authors generated a

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[10] Prices are grain grower spot feed grade prices, FOB Farm Gate.

[11] From discussions with AMS, prices are sourced from industry stakeholder contacts that trade these commodities. The data for every report is collected from the day after the report is posted through the day of the next report's post.

[12] No weights are available to create a weighted average. A simple average using equal weights was created from the two series.

[13] Prices are grower bids in dollars per bushel, thresher run delivered to the elevator/warehouse in car lot or truck lots.

continuous price series for each commodity that splices together the nearby and first-deferred contracts at the first day of the expiration month for the nearby contract, applying a roll method that uses a weighted-average price over the last four trading days.[14] To ensure the comparison between prices for conventional and organic and non-GE feeds are temporally accurate, we compute the average market closing price for each commodity's futures series observed over the two weeks' time represented by every AMS report. The second series we consider for conventional prices are the monthly NASS published cash prices for corn, soybeans, and wheat. To compare organics against this price series, we aggregated their price observations to the monthly level.

Although logarithmic transformation is generally applied to data prior to time series analysis, because it linearizes the relationship between variables, facilitates interpretations, approximates percentage changes at the first difference, we do not take logarithms of the original price series. As shown in figure 6, our price data does not appear to grow exponentially over time and a Box-Cox transformation reveals that logging variables does not normalize the data. Furthermore, while not affecting direction of significant coefficients, some hypotheses test results differ. We postulate that this could be due the transformation reducing the variability of the data and confusing the true correlation between the series' co-movements. Furthermore, we follow the asymmetric threshold cointegration technique as highlighted by Sun (2011) that analyzes cointegration between the prices levels of Chinese and Vietnamese wooden bed imports; like us, he does not apply a logarithmic transformation to his data before estimating his time series models. For completeness, we highlight in the text when the application of logarithmic transformation would have affected test results.

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[14] The roll over method smooths out the transition between the nearby and first-deferred contract. In practice, four days before the beginning of the contract expiry month, price is equal to 80% of the nearby and 20% of the deferred contract. Three days prior, the nearby is weighted 60%, while the deferred contract is weighted 40%, and so on. Typically, continuous futures price series freely available online roll over on the last-trading day (two weeks into the contract expiry month). That is problematic becuase trading activity will likely have moved to the next contract by the first day of the expiration month.

Empirical Results and Discussion

Descriptive Statistics for Organics

Naturally, because organic price series are thin, they sometimes have missing data points. We interpolated missing observations linearly. Tables 1 and 2 display descriptive statistics for raw and interpolated prices, alongside CBOT futures prices and NASS cash prices, respectively, by commodity. Pairwise correlation between futures and cash prices at the monthly level are high and highly significant for all commodities (corn: 0.9482, p=0.000; soybeans: 0.9524, p=0.000; wheat: 0.9503, p=0.000; oats: 0.7523, p=0.000).

On average, organic corn fetches a price that is 110% greater than the conventional corn futures price, and 120% greater than the NASS cash price. These differences were 87% and 92% for soybeans, 80% and 74% for wheat, and 70% and 63% for oats, respectively. The coefficient of variation (CV) in the tables reveal that volatility in each organic market is similar to that observed in the conventional market, and similar across futures and cash prices for each commodity. In the conventional market, corn is the most volatile of the commodities, followed by wheat, soybeans, and oats. In the organic market, corn is the most volatile crop, followed by wheat and soybeans, and finally oats. The gap in volatility between the conventional and organic market is widest for oats and wheat. We examine all statistics using both futures and cash prices, though report futures since it allows for more richness in the data, and we found that aggregation to a monthly organic series leads to no notable change in our results or their interpretation.

Table 1: Descriptive Statistics of bi-weekly organic prices and futures

	Corn Prices			Soybean Prices			Wheat			Oats		
	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures
Count	254	261	261	221	261	261	104	155	155	87	121	121
Mean	10.10	10.10	4.80	21.64	21.465	11.57	10.86	10.43	6.03	5.79	5.80	3.41
Median	10.30	10.32	4.12	21.14	20.76	10.93	10.69	10.26	6.13	5.77	5.77	3.47
Std. Dev.	2.84	2.83	1.40	4.20	4.20	2.26	1.92	2.09	1.30	0.71	0.72	0.48
CV	0.28	0.28	0.29	0.19	0.20	0.20	0.18	0.20	0.22	0.12	0.12	0.14

Source: USDA-AMS, CBOT, authors' calculations

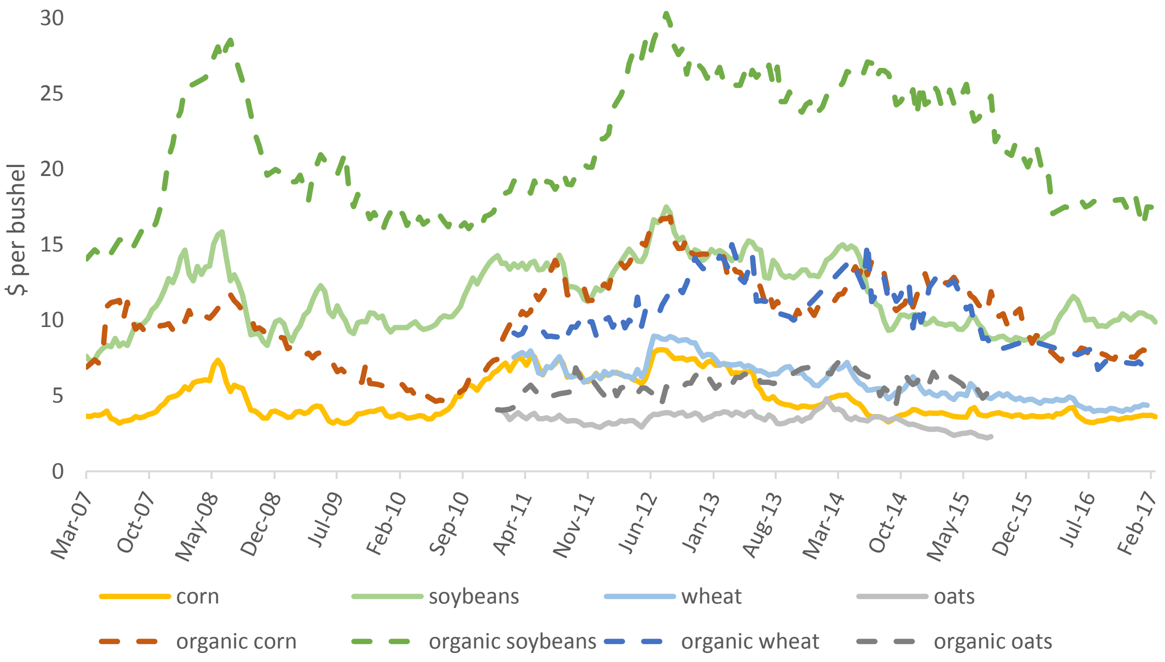
Table 2: Descriptive statistics of monthly organic prices and cash

	Corn Prices			Soybean Prices			Wheat Prices			Oat Prices		
	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures	Organic Raw	Organic Interpolated	Futures
Count	118	119	119	113	119	119	60	71	71	51	56	56
Mean	10.14	10.12	4.60	21.46	21.51	11.19	10.86	10.51	6.24	5.74	5.77	3.52
Median	10.32	10.30	4.01	20.94	20.94	10.30	10.68	10.35	6.67	5.75	5.79	3.58
Std. Dev.	2.85	2.84	1.28	4.22	4.22	2.14	1.98	2.11	1.42	0.71	0.71	0.51
CV	0.28	0.28	0.28	0.20	0.20	0.19	0.18	0.20	0.23	0.12	0.12	0.14

Source: USDA-AMS, USDA-NASS, authors' calculations

Figure 5 plots the organic and conventional price series over the period of observation. As expected, organic prices virtually always reap a price premium. The conventional price functions as a price floor for the organic commodities, since organic growers always have the option of selling into that market. Furthermore, the soybean series appears to display a fairly consistent relationship over time. Apart from a period in late-2010 and early-2011, conventional and organic soybean prices tend to move in the same direction, so likely respond to the same fundamental shocks. The corn price series follow a similar pattern, but its organic premium appears more volatile. Organic prices fell between 2009 and 2011, causing some farmers to switch to conventional crops (Center for Integrated Agricultural Systems 2012). One reason, at least in the case of corn, may be that the demand for the conventional version of the commodity was supported to a large degree by government ethanol mandates, so planting the niche product became relatively less attractive. Like corn, the relationship between the series for wheat and oats is not as obvious; the two series seem to wander apart more easily for both commodities.

Figure 5: Conventional and Organic Grain Prices in $/bu, 2007-2017

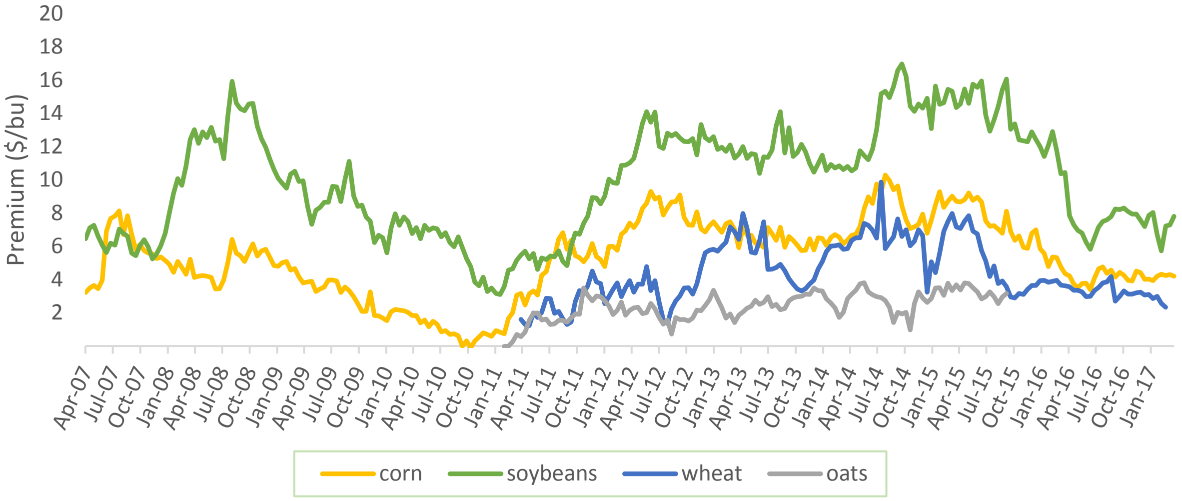


Source: USDA-AMS, CBOT, authors' calculations

Differences in organic premium stability across commodities could stem from differences in the structure of each market (Adjemian, Saitone, and Sexton 2016). Feed users will create animal feed rations composed of several crop varieties to fulfill particular needs for energy (derived from carbohydrates and fats) and protein. Corn is the standard feed used for supplying energy. Wheat and oats are traditionally used as an energy source as well. Protein is derived from meals that are produced from oilseeds; soybeans being the standard. Lysine is the first limiting essential amino acid in rations made of corn and soybeans; that means that given a necessity to replace a grain, it is vital the new grain will make up the lysine deficit. Oats and wheat are higher in lysine and crude protein than corn, so when their price is relatively lower, they could be a good substitute (Monogastric Nutrition Laboratory 2017). These substitutes have a larger lysine content so they also reduce some of the need for soybeans. However, soybeans meal is typically the most economical vegetable protein supplement for rations (Dairy Extension 2017).

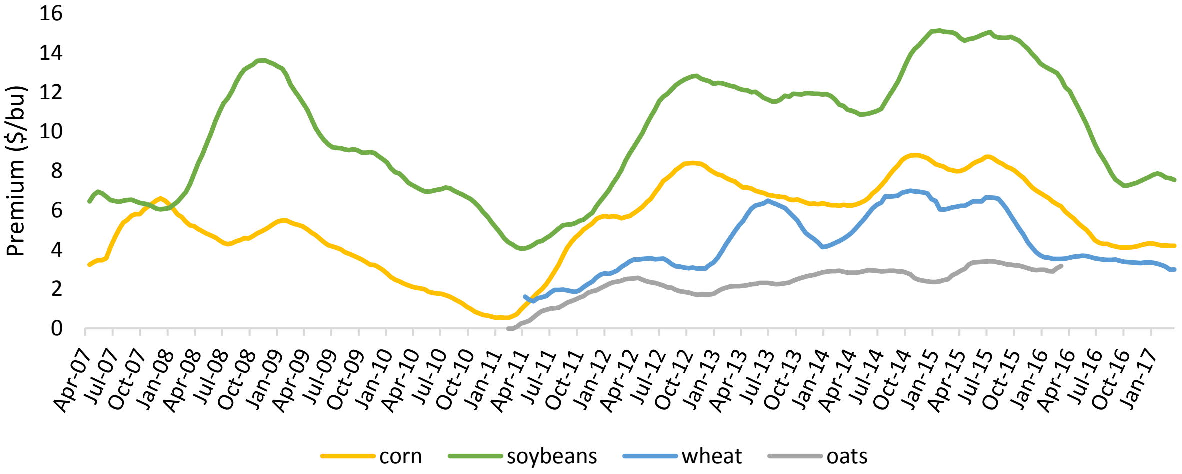
Organic premiums are shown in figure 6, and as a 13-period (half a year) moving average in figure 7. The range of the organic corn premium stretched from over $10 per bushel in mid-2014 to near equality in October 2010. Soybeans also experienced peaks and troughs in its organic premium – reaching a maximum of $17 per bushel, but never dropping below $3 per bushel. The wheat and oats premiums the least volatile, but their data are drawn from a period that generally saw lower price volatility across all commodities. The relative stability of the soybeans organic premium over the conventional market could be viewed as on characteristic of a MAM; organics cost more to produce. Thus buyers would need to commit to paying producers a sufficient premium to cover those higher costs (Adjemian, Saitone, and Sexton 2016).

Figure 7: Organic Grain Premiums, 2007-2017



Source: USDA-AMS, CBOT, authors' calculations.

Figure 8: 13-Period (6 months) Moving Average of Organic Grain Premiums, 2007-2017



Source: USDA-AMS, CBOT, authors' calculations.

Testing for and Characterizing Temporal Relationships between Organic and Conventional Grain Prices

Before we model each set of commodity price series using a VECM, we first examine their stationarity properties. Using a VECM to characterize a conventional and organic price series pair is appropriate only if the two are non-stationary random processes. We test for non-stationarity using the augmented Dickey-Fuller test (ADF) and the modified Dickey-Fuller approach proposed by Elliott, Rothenberg, and Stock (1996), in which the time series undergoes a Generalized Least Square (GLS) transformation prior to the Dickey-Fuller regression (DF-GLS). Lag lengths for the unit root tests were identified by using Akaike's information criterion (AIC), Hannan and Quinn's information criterion (HQIC) and Schwarz's Bayesian information criterion (SBIC).[1] Using these information criteria, corn, soybeans and wheat are modeled with a lag length of 2, while the oats price series is modeled with a lag length of 1. The joint significance F-test for a unit root and a constant or drift term (null: $\gamma = 0 = \alpha_0$) fails to reject the joint hypothesis that $\gamma = 0$ and $\alpha_0 = 0$ for all commodities, so a constant term is not included in any of the following models.

Table 3 presents results for stationarity tests we performed for organic and conventional corn, soybeans, wheat, and oats prices. All series accept the null hypothesis of a unit root. As shown in the table, all series are first difference stationary, so we conclude that they are all I(1).

Table 3: Results from unit root tests of organic prices

	Organic Corn	Corn	Organic Soybeans	Soybeans	Organic Wheat	Wheat	Organic Oats	Oats
Unit Root Tests								
ADF	-0.378	-0.502	-0.123	-0.237	-0.558	-1.223	0.003	-1.074
DF-GLS	-1.110	-1.405	-0.830	-1.196	-1.054	-0.600	-1.276	-0.844
Unit Root Tests for 1st Difference								
ADF	-8.128***	-8.863***	-7.573***	-8.077***	-9.199***	-6.616***	-9.133***	-10.010***
DF-GLS	-6.655***	-8.736***	-6.453***	-5.740***	-8.556***	-5.058***	-9.138***	-10.104***

Note: Null hypothesis of a unit root present in the series. *** denotes significance at the 1% level.

Before proceeding to nonlinear cointegration analysis, we explore possible linear cointegration, as in previous studies. Results from the Johansen trace, a procedure used to test the number of cointegrating relationships are shown in table 4; the method works recursively – first test the null hypothesis that the number of cointegrated vectors, r, equals zero, if rejected, test $r = 1$, and so on until null is accepted. The model is specified to restrict the constant and trend to equal zero, in line with our prior test results. In the table, cointegration cannot be established for corn, wheat and oats. However, the

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[1] The information criteria are based on information theory, and indicate the relative information that is lost when the data are fit using a different specification (preferring the lag length that produces the minimum value).

test rejects $r = 0$, and cannot reject $r = 1$ for soybeans, indicating that that commodity may be linearly cointegrated.[17,18]

Table 4: Johansen trace tests for organic prices

	Corn	Soybeans	Wheat	Oats
$r = 0$	4.43	7.23***	1.95	3.09
$r \leq 1$	16.53	29.07	13.84	17.43

Note: "r" represents the number of cointegrating vectors under the test null. A significant test hypothesis rejects the null. *** denotes significance at the 1% level; ** at the 5% level.

Given the results from the Johansen trace test, table 5 provides results from the linear VECM for organic and conventional soybeans. The estimated cointegrating vector ($\beta = -0.530$) is statistically significant at the 5% level, indicating that in equilibrium the price of conventional soybeans is about half of that of organic. The speed of adjustment to equilibrium (α) shows that the conventional soybeans market does not adjust to shocks. This result is intuitive, since the conventional market is far larger than the market for organics. However, the organic soybean error correction is positive, suggesting that a shock to equilibrium would cause the price of organic soybeans to rise, further increasing the gap between the two series. This could suggest that the linear cointegration is not a robust approach to model the series.

Table 5: Linear Vector Error Correction Model Results for Soybeans

	α	β	Granger Causality
conventional soybeans	-0.0058	1	0.8094
organic soybeans	0.100***	-0.530***	6.24**

Note: Model AIC: 3.58; The α parameters represent the short-run adjustment, or loading, coefficients. The cointegrating vector coefficients are reported by the β terms; Johansen's method normalizes the first coefficient to unity. *** denotes significance at the 1% level; ** at the 5% level.

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[17] Results from the Johansen test using monthly organic and cash prices (not shown here) soundly fail to reject the null that there are no cointegrating relationships for all four commodities. These results are in line with those found by Ferreira (2017), indicating that our findings of certain cases of linear cointegration could be chalked up to using a richer data set.

[18] Structural breaks tests (cumulative sum test and a supremum Wald test) found breaks in the series. The Johansen test could not reject the null of no cointegration for partitions of the price series. Therefore, we believe that non-linear cointegration is better suited to model the relationship between series.

Despite our findings of no linear cointegration for corn, wheat, and oats in table 4, it is possible that market characteristics could lead the series to be nonlinearly cointegrated. For example, we could observe a no-arbitrage band (that is to say, a range in which the series do not adjust to each other) if there are transaction costs which make imports less attractive such that importers would not be capable of affording transport, or we could observe asymmetry in shock responses if entry is more likely than exit into the market.

We estimate both the TAR and MTAR model for each commodity, and rely on standard information criteria to identify the best model fit. The two models relax the traditional constraint that cointegrated time series adjust to different sorts of shocks equally. The TAR model states the threshold as a function of the level of the organic premium; if TAR model is a better fit, then the series adjust when the gap between the two prices is too large or too small. Meanwhile, the MTAR model identifies how variables adjust to large swings in the residuals. If the MTAR model is a better fit for the data, then the series adjust when the change in the indicator variable, i.e., the premium, is larger or smaller than the threshold. For both models, the threshold value can either be specified at zero, or a "consistent" threshold can be estimated using the method developed by Chan (1993). In order to obtain the consistent estimate of the threshold value, the threshold variable for the model is sorted in ascending order, then possible threshold values are determined. In order for the threshold value to be meaningful, the price series must cross the threshold value (Enders 2004). The highest and lowest 15% of values are excluded from search. Then the model is estimated with all potential values, and the sum of squared errors are calculated. The threshold value that minimizes the error sum of squares (SSE) is considered to be the consistent estimate of the threshold.

Tables 6 - 9 present our nonlinear cointegration results. The first four columns of each table represent TAR and MTAR models (with both zero and consistently estimated thresholds) that use our data of choice, the non-transformed organic price series, and futures price. The final two columns in each table represent two alternative models as a robustness check: “cash” uses monthly cash prices instead of futures, while “logs” imposes the natural logarithmic transformation on the price series. These alternative results are drawn from the model (TAR versus MTAR) and threshold choice (zero versus consistent) that minimized the information criterion for each alternative scenario. The number of sufficient lags was selected via AIC, BIC and Ljung-Box Q statistics. Portmanteau tests report that model residuals are not autocorrelated.

Table 6: Results of the threshold cointegration tests for organic and conventional corn

					Alternative models	
	Cointegration Results				Cash	Logs
lags	1	1	1	1	1	1
model	TAR	C.TAR	MTAR	C.MTAR	C.MTAR	C.TAR
threshold	0	-1.85	0.00	0.18	-0.24	0.04
ρ+	0.042*	0.05**	-0.038*	-0.071***	-0.02	-0.061**
ρ-	-0.023	-0.01	-0.03	-0.01	-0.146***	-0.02
total obs	261	261	261	261	119.00	261.00
coint obs	259	259	259	259	117.00	259.00
model AIC	475.209	474.14	475.44	471.85	225.31	-721.61
model BIC	489.436	488.36	489.66	486.08	236.35	-707.38
$\boldsymbol{Q_{LB}(4)}$	0.876	0.86	0.87	0.88	0.97	0.59
$\boldsymbol{Q_{LB}(8)}$	0.687	0.67	0.69	0.70	0.65	0.58
$\boldsymbol{Q_{LB}(12)}$	0.81	0.80	0.81	0.78	0.63	0.76
H1: no cointegration	2.069	2.609*	1.96	3.768**	4.477***	2.457*
H2: no asymmetric price transmission	0.366	1.43	0.14	3.715*	4.565**	1.75

Note: Results from the MTAR model using consistent threshold, non-transformed data and futures prices. The preferred information criteria are highlighted in green. Alternative models present the best fit using (a) cash instead of futures; and (b) log-transformed prices. Lags included given AIC and BIC tests, ρ+ and ρ- are the positive and negative price adjustments to shocks. $Q_{LB}(p)$ denotes significance level of the Ljung-Box Q statistic which tests the serial correlation based on p autocorrelation coefficients (p = 4, 8, 12). *** denotes significance at the 1% level; ** at the 5% level; * denotes significance at the 10% level.

For corn, the MTAR model with a consistent threshold minimizes the AIC and BIC so is preferred as the best model. Rejection of Enders-Siklos hypothesis test H1 indicates the series are cointegrated nonlinearly, while rejection of H2 suggests the presence of asymmetric adjustment effects. The consistent threshold of $0.18/bushel is interpreted as the minimum size change in the organic corn premium that induces adjustment toward long-run equilibrium. The point estimate in table 6 of the positive price adjustment is negative and significant at -.071, while the negative shock is not. Together, these results imply that changes in the organic corn premium that exceed \$0.18/bushel—whether caused by an increase in the price of organics or a decrease in the conventional price—are eliminated by reductions in the price of organics at a rate of 7.1% per period. The alternative models show that the rejection of no cointegration (against the alternative of nonlinear cointegration) is robust to whether futures or cash prices are used and to whether the data are transformed. Rejection of symmetry is robust to using cash prices, but the null cannot be rejected after the logarithmic transformation ($p = 0.19$).

The MTAR model with a consistent threshold is selected as the best model for soybeans, too, based on information criteria in table 7. Once again, this model implies that market forces respond if the organic soybeans premium changes by an amount larger than the threshold of \$0.30/bushel in a single period, inducing adjustment toward equilibrium. The H1 and H2 tests reject the null hypotheses of no cointegration and symmetric adjustment (this at the 10% level). Therefore, the model results are interpreted to mean that positive deviations from the long-term equilibrium resulting from increases in the premium larger than the threshold (from either soybeans organic price rises or a falling conventional soybean price) are eliminated at 6.8% every biweekly; like corn, there is no corresponding adjustment for negative shocks to the premium. From the last two columns in table 7, rejection of no cointegration is robust to both alternative models, though the symmetry hypothesis cannot be rejected in either ($p = 0.338$ and $p = 0.316$ respectively).

Table 7: Results of the threshold cointegration tests for organic and conventional soybeans

					alternative models	
	cointegration results				cash	logs
lags	1	1	1	1	1	1
model	TAR	C.TAR	MTAR	C.MTAR	C.MTAR	C.TAR
threshold	0.00	2.89	0.00	0.30	-0.642	0.163
ρ+	-0.45**	-0.058**	-0.056**	-0.068***	-0.051	-0.055**
ρ-	-0.02	-0.01	-0.01	-0.01	-0.135*	-0.017
total obs	261	261	261	261	119.00	261
coint obs	259	259	259	259	117.00	259
model AIC	659.58	658.35	657.83	656.89	360.044	-937.609
model BIC	673.81	672.58	672.059	671.12	371.093	-923.382
$Q_{LB}(4)$	0.96	0.93	0.94	0.93	0.368	0.937
$Q_{LB}(8)$	0.93	0.92	0.93	0.88	0.336	0.939
$Q_{LB}(12)$	0.96	0.96	0.97	0.95	0.28	0.872
H1: no cointegration	2.347*	2.969**	3.231**	3.709**	2.413*	2.714*
H2: no asymmetric price transmission	0.61	1.84	2.35	3.295*	0.924	1.402

Note: Results from the MTAR model using consistent threshold, non-transformed data and futures prices. The preferred information criteria are highlighted in green. Alternative models present the best fit using (a) cash instead of futures; and (b) log-transformed prices. Lags included given AIC and BIC tests, ρ+ and ρ- are the positive and negative price adjustments to shocks. $Q_{LB}(p)$ denotes significance level of the Ljung-Box Q statistic which tests the serial correlation based on p autocorrelation coefficients (p = 4, 8, 12). *** denotes significance at the 1% level; ** at the 5% level; * denotes significance at the 10% level.

For wheat, the TAR model with a consistent threshold minimizes the information criteria. Once again, the model that best fits the data rejects both H1 and H2, accepting the hypotheses of both nonlinear cointegration and asymmetric adjustment. We interpret the results in table 8 to mean that when the organic premium for wheat exceeds $2.162/bu, positive premium shocks are eliminated at a rate of 22.9% per period. The rejection of no cointegration and symmetric adjustment are robust to both alternative models.

It is curious that while both the corn and soybean markets are best characterized by an MTAR model, the wheat market is better explained by the TAR model, which introduces nonlinearity in the cointegrating relationship on the basis of at levels in the premium instead of sharp changes from one period to the next.[19] Corn and soybeans are the two largest domestic feed markets, for both conventional

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[19] Although it should be noted that, while it wasn't preferred on the basis of data fit, the consistent MTAR model results for wheat are in line with what we found for corn and soybeans in tables 6 and 7.

and organic varieties because they provide the most popular forms of energy and protein components of livestock feed. It is possible that a sufficiently large change in the biweekly corn and soybean price premium is sufficient to draw the attention of importers. Being much smaller and less active, our best model of the organic wheat market indicates that the premium itself must widen significantly before market forces intervene to return prices to equilibrium. Unfortunately no organic wheat trade data is available, so we cannot observe how trade in organic wheat has changed over time.

Table 8: Results of the threshold cointegration tests for organic and conventional wheat

					Alternative models	
	Cointegration Results				Cash	Logs
lags	1	1	1	1	1	1
model	TAR	C.TAR	MTAR	C.MTAR	C.MTAR	C.TAR
threshold	0	2.162	0	0.41	0.297	0.196
ρ+	-0.099**	-0.229***	-0.107**	-0.212***	0.00	-0.198***
ρ-	-0.062	0.029	-0.055	-0.03	-0.194***	0.008
total obs	155	155	155	155	71	155
coint obs	153	153	153	153	69	153
model AIC	355.694	342.15	355.443	350.345	155.97	-392.482
model BIC	367.816	354.272	367.565	362.467	164.907	-380.361
$\boldsymbol{Q_{LB}(4)}$	0.292	0.595	0.302	0.458	0.952	0.72
$\boldsymbol{Q_{LB}(8)}$	0.646	0.775	0.668	0.765	0.477	0.65
$\boldsymbol{Q_{LB}(12)}$	0.58	0.628	0.597	0.598	0.705	0.70
H1: no cointegration	2.852*	10.058***	2.98*	5.622***	3.965**	7.428***
H2: no asymmetric price transmission	0.27	14.178***	0.517	5.616**	2.844*	9.426***

Note: Results from the MTAR model using consistent threshold, non-transformed data and futures prices. The preferred information criteria are highlighted in green. Alternative models present the best fit using (a) cash instead of futures; and (b) log-transformed prices. Lags included given AIC and BIC tests, ρ+ and ρ- are the positive and negative price adjustments to shocks. $Q_{LB}(p)$ denotes significance level of the Ljung-Box Q statistic which tests the serial correlation based on p autocorrelation coefficients (p = 4, 8, 12). *** denotes significance at the 1% level; ** at the 5% level; * denotes significance at the 10% level.

For oats, the MTAR model with a consistent threshold is preferred according to AIC and BIC. Hypothesis tests accept both nonlinear cointegration and asymmetric adjustment. We interpret the results in the table to mean that changes to the premium above -31.8 cents/bu (resulting from increases in the oats organic price or decreases in the conventional oats price) are eliminated at 14.2% biweekly, and that decreases in the premium below -31.8 cents/bu are eliminated at a rate of 64.6% per ever two weeks. Therefore, for oats, positive deviations take roughly 3.5 months (or 1/.142 = 7 biweekly periods) to be fully digested, while negative deviations take less than 1 month. The rejection of no cointegration and symmetric adjustment are robust to both alternative models. Oats is the only commodity that we found reacted to a negative shock to the long-term market equilibrium, possibly owing to it having the lowest organic premium over conventional from all commodities explored in this study.

Table 9: Results of the threshold cointegration tests for organic and conventional oats

					alternative models	
	cointegration results				cash	logs
lags	6	4	6	5	1	5
model	TAR	C.TAR	MTAR	C.MTAR	C.TAR	C.MTAR
threshold	0	-0.71	0	-0.318	0.357	-0.067
ρ+	-0.099	-0.129**	-0.076	-0.142**	-0.155*	-0.157**
ρ-	-0.293***	-0.423***	-0.266***	-0.646***	0.083	-0.795***
total obs	121	121	121	121	56	121
coint obs	114	116	114	115	54	115
model AIC	102.978	101.224	102.848	96.11	-10.809	-305.144
model BIC	127.604	120.499	127.474	118.069	-2.853	-283.184
$\boldsymbol{Q_{LB}(4)}$	0.98	0.95	0.97	0.85	0.961	0.893
$\boldsymbol{Q_{LB}(8)}$	0.98	0.70	0.94	0.92	0.98	0.952
$\boldsymbol{Q_{LB}(12)}$	0.99	0.647	0.956	0.973	0.384	0.983
H1: no cointegration	5.003***	10.152***	5.069***	13.21***	1.814	15.105***
H2: no asymmetric price transmission	2.897*	6.445**	3.021*	13.374***	3.608*	16.291***

Note: Results from the MTAR model using consistent threshold, non-transformed data and futures prices. The preferred information criteria are highlighted in green. Alternative models present the best fit using (a) cash instead of futures; and (b) log-transformed prices. Lags included given AIC and BIC tests, ρ+ and ρ- are the positive and negative price adjustments to shocks. $Q_{LB}(p)$ denotes significance level of the Ljung-Box Q statistic which tests the serial correlation based on p autocorrelation coefficients (p = 4, 8, 12). *** denotes significance at the 1% level; ** at the 5% level; * denotes significance at the 10% level.

In summary, we find that organic and conventional prices for corn, soybeans, wheat, and oats are all nonlinearly cointegrated with threshold and asymmetric adjustment toward equilibrium. Analysis of the AIC, BIC and Ljung-Box Q statistics are used to select the model lags. Based on the preferred model results from the cointegration tests described above, we construct and estimate threshold ECMs with asymmetric adjustment for each commodity. Select parameter estimates from the ECMs are shown in table 10. None of the Ljung-Box Q-statistics recommended a rejection of the null hypothesis that model residuals are not autocorrelated.

Table 10: Results of the asymmetric threshold error correction model for organics

	Corn	Soybeans	Wheat	Oats
lags	2	2	1	6
conventional δ +	-0.02	-0.01	0.000145	-0.01
conventional δ -	0.00	-0.02	0.014584	-0.07
organic δ+	-0.0736**	-0.07076**	-0.2682***	-0.12098*
organic δ-	-0.01	-0.03	0.08074*	-0.68639***
conventional AIC	41.57	376.81	66.956	-59.57
conventional BIC	84.20	419.45	91.199	17.04
conventional $Q_{LB}(4)$	0.52	0.58	0.269	0.96
conventional $Q_{LB}(8)$	0.83	0.50	0.108	0.92
conventional $Q_{LB}(12)$	0.57	0.48	0.314	0.84
organic AIC	413.87	571.89	315.308	110.83
organic BIC	456.51	614.53	339.552	187.443
organic $Q_{LB}(4)$	0.90	0.18	0.2	0.979
organic $Q_{LB}(8)$	0.62	0.04	0.598	0.986
organic $Q_{LB}(12)$	0.45	0.07	0.591	0.97
conventional δ+ = δ-	0.64	0.12	0.199	0.49
organic δ+ = δ-	4.541**	2.203*	22.948***	11.04***
conventional does not Granger cause organic	2.364*	3.324**	1.364	0.51
organic does not Granger cause conventional	0.72	0.41	0.16	0.99
conventional does not Granger cause conventional	7.332***	6.709***	2.763*	1.744*
organic does not Granger cause organic	0.53	1.16	6.202***	1.34

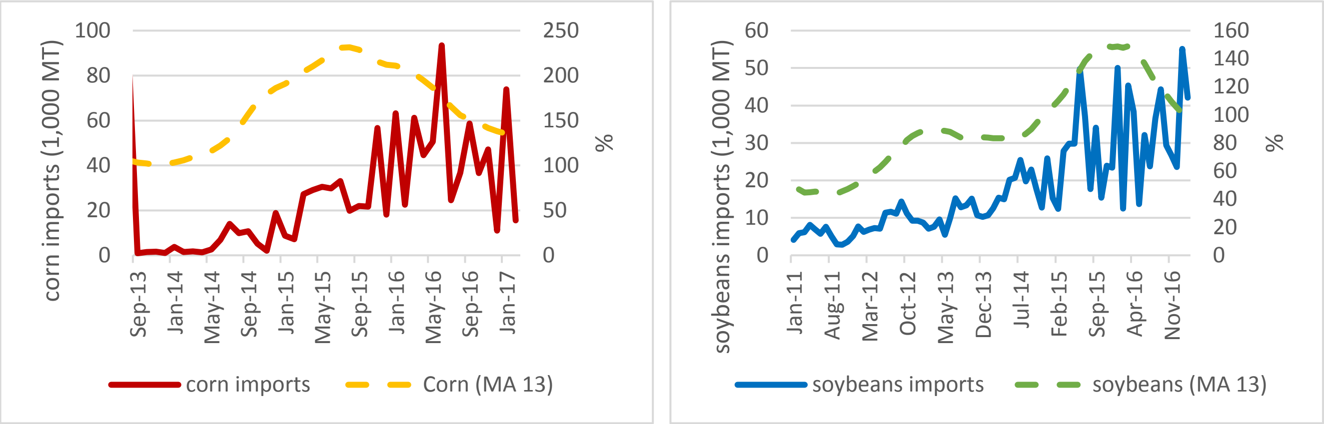
Note: Results from the asymmetric threshold error correction model. Lags included given AIC and BIC tests. $Q_{LB}(p)$ denotes significance level of the Ljung-Box Q statistic which tests the serial correlation based on p autocorrelation coefficients (p = 4, 8, 12). *** denotes significance at the 1% level; ** at the 5% level; * denotes significance at the 10% level. δ terms represent the coefficients for the error correction terms, both negative and positive.

According to model results, organic corn prices bear the burden of adjustment to the long-run equilibrium: none of the error correction coefficients are significant in the conventional equation. This result is intuitive since the conventional market for each commodity is far larger than its organic counterpart. Meanwhile, for all commodities, organic prices respond to positive short-term shocks to the premium by falling, though only the oats market responds to negative shocks (at lower than the 10% level). We also report results from a Granger causality test for each commodity pair, which indicates whether lagged values of conventional prices improves forecasts of organic prices (and vice versa). As expected, none of the organic price series add useful information in forecasting the conventional price, as the conventional markets are dominant. For both corn and soybeans, we find that conventional prices Granger cause organic prices. The F-statistic also indicates that conventional crop prices significantly impact their own price. Only the price of organic wheat has a significant impact on its own price. This is evidence that the price of conventional crops have been evolving more independently, while the price of organics has been dependent on the price of conventional in previous periods.

The hypothesis that the positive and negative error correction term are equal to one another ($\delta^- = \delta^+$) cannot be rejected for all conventional crops, but it is rejected for all organic crops. The positive error correction term for organic corn is -0.0736 indicating that in the short-term, the price of organic corn responds to positive deviations in the premium by falling 7.4%, though does not adjust to negative deviations in the short-term. Organic soybeans adjust to positive deviations in the short-term by 7.076%. Wheat adjusts to positive deviations by 26.82% in the short-term, but have the incorrect sign for negative deviations (because it suggests that deviations from the equilibrium do not trigger a return to equilibrium, but further diversion). Organic oats adjust to positive deviations in the short-term by falling 12.98%, and to negative deviations by 68.64%, such that oats has a much slower reaction to positive deviations than to negative deviations.

The results are in line with findings by Würriehausen, Ihle, and Lakner (2014); organic prices tend to fall when the organic premium gets too high (or, as we find when using the MTAR model, that organic prices fall when the change in the premium is too high). The short-term and long-term responses could be in part explained by imports of organic grains. Due to the challenges posed by organic agriculture, and because a large portion of organic corn and soybean production in the U.S. supports the growth in the organic dairy sector, which has increased almost fourfold from 2002 to 2011 (USDA-ERS 2017), sourcing for feed has in some cases turned to importing organic corn and soybeans, as shown in figure 4. Figure 9 overlays corn and soybeans imports with the 6-month moving average of the organic corn and soybean premiums. The figure clearly characterizes the positive relationship between the organic premium and changes in import quantities: organic imports or both corn and soybeans are positively correlated with the size of the organic premium in each market.

Figure 9: 6-month moving average of organic premiums (as percentage) against organic imports



Source: U.S. Department of Commerce, U.S. Census Bureau, USDA-NASS.

<u>*Descriptive Statistics for non-GE corn and soybeans*</u>

As with the organic price series, we interpolated several missing observations, linearly; raw, interpolated prices, along with descriptive statistics for the CBOT commodity prices, covering the same time period are shown in table 11.[20]

Table 11: Descriptive statistics of weekly non-GMO prices

	Corn Prices			Soybean Prices		
	non-GMO raw	non-GMO Interpolated	Futures	non-GMO raw	non-GMO Interpolated	Futures
Count	76	84	84	68	84	84
Mean	3.69	3.69	3.64	10.49	10.57	9.69
Median	3.68	3.68	3.63	10.06	10.14	9.75
Std. Dev.	0.24	0.24	0.21	0.95	0.94	0.82
cv	0.07	0.06	0.06	0.09	0.09	0.08

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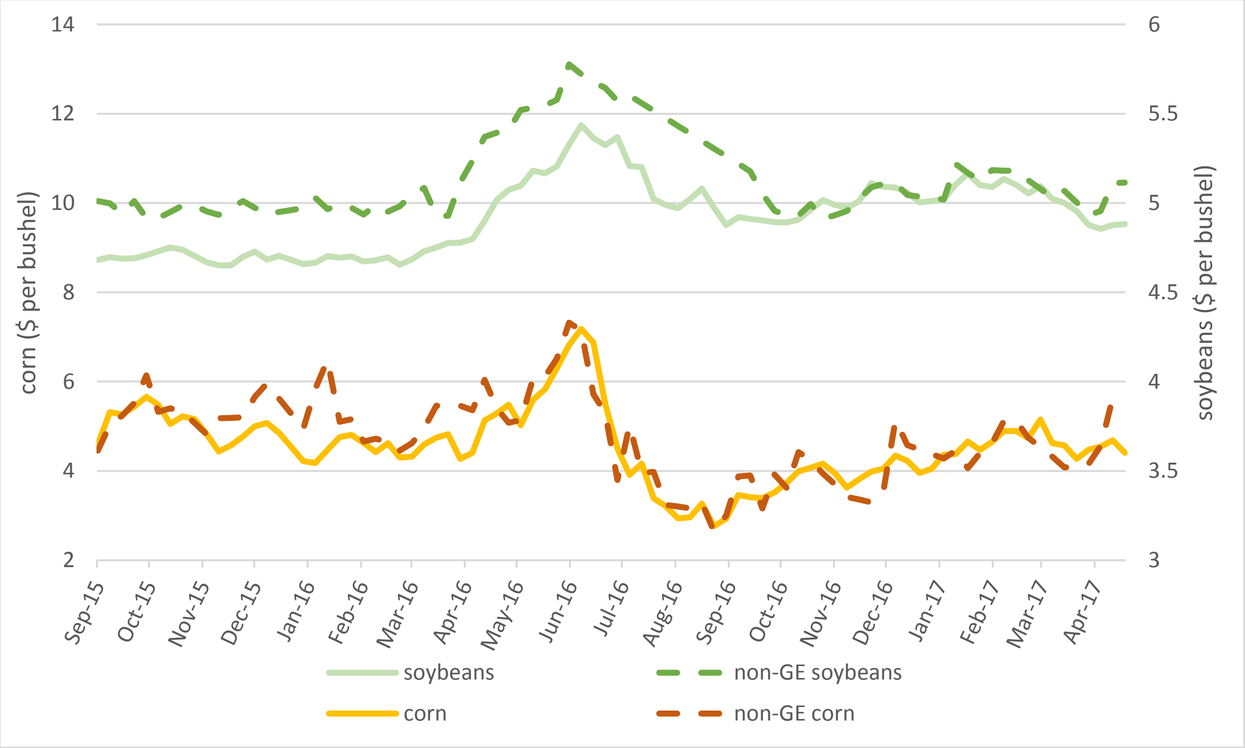
[20] Please note that, owing to data collection limitations, the time period we have for non-GE prices is shorter than we have for organics: about 1.5 years.

According to the data, non-GE corn sellers received an average premium of $0.05 over conventional prices during roughly the last two years, while non-GE soybeans earned a premium of $0.87 --far smaller than the premia observed for the organic version of either commodity. The non-GE and conventional markets have a similar coefficient of variation during the period, indicating that volatility in both price series was about equal.

However, figure 10 also shows that while non-GE soybean producers were paid about 10-15% more than growers of conventional soybeans for the year leading up to September 2016, that premium subsequently collapsed. For non-GE corn, no stable premium is observed over the sample period. Neither non-GE varietal displays the sort of stable premium that would be characteristic of a MAM.

Figure 10: Conventional and non-GE field crop prices in $/bu, 2015-2017



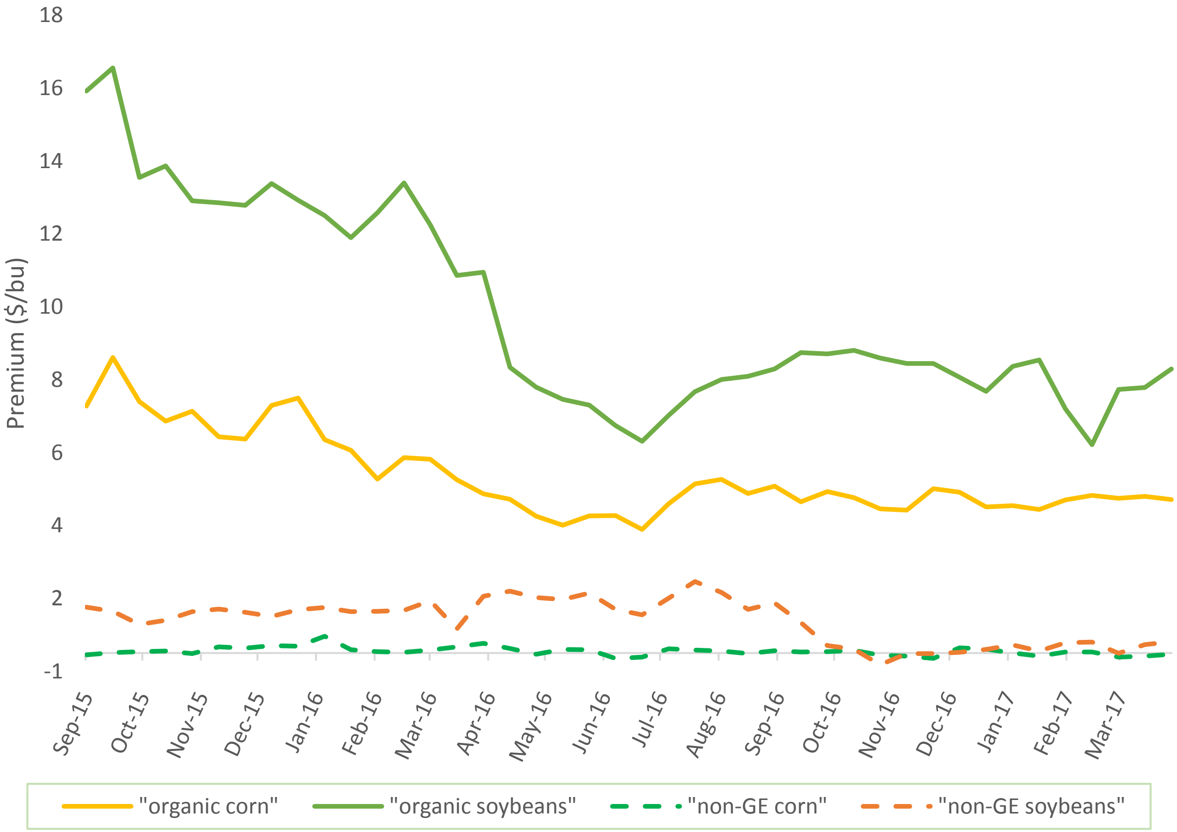
Source: USDA-AMS, CBOT, authors' calculations

Comparing the Performance of Niche Thin Markets: Organics vs. non-GE Field Crops

Our data on organic and non-GE premium levels runs from September 2015 through March 2017. Although drawing conclusions from a limited time series is difficult, comparing the premium behavior for niche feed commodities over this timeframe may be indicative. That is, if these patterns are representative of true market performance, they are enlightening about the role that market structures can play in the organization of a new, niche thin market.

Figure 11 plots the premium for organic and non-GE versions of both corn and soybeans over the period, calculated as the AMS price of the niche product measured against the price of the relevant, nearby CBOT futures contract. Clearly, the market pays producers a higher price for growing organically than it does for growing a non-GE varietal.

Figure 11: Organic and non-GE field crop premia, 2015-2017



Source: USDA-AMS, CBOT, authors' calculations.

Given the steady entry of new farmers into organic production, these premia appear sufficient to at least compensate farmers for the additional economic costs incurred in the organic production process. For example, the number of USDA-certified feed corn operations increased from 2,219 to 2,973 from 2010 to 2011, an increase of 34%. The number of certified feed corn operations have increased every year from 2010 to 2016 (with the exception of 2014). Meanwhile, the number of surrendered certificates for feed corn operations (i.e. resignation of organic certification from the producer side), decreased from 216 in 2014 to 170 in 2015, then increasing to 189 in 2016. The number of certificates suspended (i.e., resignation of organic certification from the certifier side) has trended downward, equaling 91 and 120 in 2013 and 2014, and a mere 13 and 17 in 2015 and 2016. Similar patterns are seen for soybeans, wheat, and oats.[21] The low number of surrendered certifications relative to operations entering the system is a sign that the organic premia are large enough to prevent producer exit. This may at least in part explain our econometric result of no price adjustment from negative premium shocks for most commodities: in equilibrium, they are high enough to *more than* cover the additional economic costs incurred in organic farming. In contrast, neither the level nor the stability of non-GE premia could be described as reliable over our short time period; the premia for both non-GE corn and soybeans collapsed about halfway through the sample, while—at the same time—the organic premium remained steady.

We suspect that different market structures may play a role in these contrasting outcomes. Like organic agriculture, non-GE crops are largely sold under contract (USDA-AMS various). But, relative to what the USDA mandates for organics, the certification regime for non-GE crops is not as robust. Likewise, the transition to non-GE production does not require an organics-style sunk cost (in the form of official application, plan, inspection, and three-year wait period) on the part of producers; crop producers can

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[21] These numbers were calculated using NOP integrity data. To calculate feed corn figures, we excluded mentions of popcorn, sweet corn, blue corn, kernel corn, white corn, corn flour, flaked corn, cornstarch, corn chips, ground corn, cooked corn, and corn meal. We limited the search to U.S. operations that listed crops as either their primary or secondary scope.

enter and exit non-GE production each year. Both of these conditions can preclude the development of a well-functioning MAM (Adjemian, Saitone, and Sexton 2016).

Conclusions

In this article, we explore the application of a novel method to judge the performance of a thin market in an effort to identify whether it suffers from commonly understood "thin market problems." We exploit the nutritional similarity of conventional and niche versions of feed commodities to judge the price relationship of thin market varietals to thick-market conventional benchmarks. If the market for a specific organic feed shares a long-run relationship with the conventional price, with a premium sufficient to cover the additional costs of production, or the premium is high enough that no relationship with the underlying market need be observed, then even though the niche commodity is thinly traded, there is no thin-market pricing problem as that term is commonly understood. Our analysis found that the relationship between organic and conventional corn, soybeans, wheat and oats can be best modeled using a nonlinear approach, namely an asymmetric threshold cointegration model. In contrast to previous attempts to fit these models into a linear framework, we used the nonlinear approach since it is best able to capture the relationship between organic and conventional crops. Nonlinear models can best capture asymmetric effects of large swings from one period to the next, including the characteristic impacts of imports that we observe in the organic market.

We show that the organic feed premium continues to remain relatively high such that organic and conventional prices for feed commodities are nonlinearly cointegrated, and that entry into organic production remains robust. Taken together, these results indicate that organic premia are large enough to cover additional economic costs of organic farming. We therefore conclude that organic feed markets are likely on the way to becoming MAMs. In contrast--over the same time period that organic premia steadied--premia for non-GE feed collapsed. Those markets do not appear to pay a stable or sufficient premium that would indicate MAM status. The difference in findings for the two types of niche production highlights the role that differing market structures can play in the operation of a thin market. Non-GE crops do not have the same well-recognized certification procedures, government-sanctioned label, or producer commitments that are features of organic production. Its poor performance, in terms of a premium that would be sufficient to cover the additional economic costs of non-GE production, is likely a result of those deficiencies.

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