The U.S. Role in the Price Determination of Major Agricultural Commodities

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Abstract

The United States has historically played a dominant role in the global trade, and therefore price formation, of major food, feed and fiber commodities. As the share of agricultural commodities exports produced by the US has recently declined, international supply and demand fundamentals likely play a larger role in setting even domestic commodity prices. Using wavelet coherence methods, this article examine the relationship between U.S. and international prices for corn, soybeans, and cotton. Our results reveal that integration between the markets of major exporters and importers of these commodities evolves over time: short-run (around 20 trading days) relationships between domestic and international prices are, in many cases, not stable, and even the long-run relationships between many price pairs is subject to distinct structural breaks. As the two major agricultural commodity exporters of corn and soybeans, the US and Brazil exhibit integration in the form of consistently significant long-run price relationships. In contrast, we show that Chinese agricultural commodity prices share little or no distinguishable relationship with the U.S., even though China is one of the biggest importers of U.S. products. This is likely due to Chinese trade barriers and price support policies that, while insulating domestic prices from external shocks, kept its own prices substantially higher than other countries from 2009-2016.

Keywords: agricultural commodity price, cointegration, integration, price discovery, wavelet coherence analysis

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Commodity prices in a given region are a reflection of local (current and expected) supply and demand fundamentals. Markets that are not insulated from international trade contribute to the evolution of common fundamentals that govern the path of export prices. Prices in those regions, help shape—but in turn are shaped by—prices of other exports and importers. Anecdotally, shifting production and trading patterns for several major commodities have affected the degree to which U.S. prices inform global prices, and also the influence international production and demand shocks have over prices paid to farmers, domestically.

Historically, the United States has played a dominant role in global agricultural commodity trading, and therefore price formation, for major food, feed and fiber commodities. Because the marginal commodity unit traded on the world market is no longer likely to originate in the US, international supply and demand fundamentals play a larger role in setting its price. Just as well, the role of international shocks in setting U.S. prices may have increased, and potentially shifted the seasonality of trading cycles and domestic marketing practices. Although efficient price transmission reduces price variability, price determination that is affected by overseas events carries welfare effects for both producers and consumers, who are more vulnerable to external shocks (Arnade and Hoffman 2015).

We assess the role that the United States plays in price determination for agricultural commodities, by studying the integration between the U.S. and major international markets for several commodities, identifying any structural changes in the relationship over time, and searching for evidence of changes in the direction of fundamental shock transmission. We examine corn, soybeans and cotton, three important agricultural commodities in the US. Each of

these commodities has different export dynamics, and, potentially, transmission patterns: corn, where the US is the world's largest exporter; soybeans, where it has a single major competitor (Brazil); and cotton, where the U.S. role is clearly shrinking in favor of other competitors such as Brazil and India.

Traditionally, market integration is studied by focusing on cross-border price transmission. To allow for temporary departures from the equilibrium and the study of adjustments to that long-run relationship, economists routinely apply error-correction models. But these models assume that under integration, prices follow a single, long-run linear relationship. In addition to using these traditional time series methods, we apply the continuous wavelet framework--a model-free approach to time series analysis--to analyze the price discovery process. Compared to more traditional time series models, wavelets are more flexible to the presence of structural change—of particular concern when studying the interaction of daily global prices. We also include the traditional models, which are mostly based on Error correction models (ECM), that can be used as a robustness check for the wavelet analysis.

We estimate the bivariate wavelet coherence between the U.S. and international corn, soybean, and cotton price series; our analysis reveals that the relationship between U.S. and international prices is in many cases not stable. Daily shocks to U.S. and international prices bear no significant relationship: short-run dynamics are not highly correlated, while temporary medium-run relationships appear and disappear regularly. Long-run relationships emerge in U.S. - Brazil and U.S. - Japan for corn; U.S. – Brazil, U.S. - India, and U.S.-South Africa for soybeans, and U.S. - India for cotton prices. In addition, U.S. and Brazilian soybean cash prices do share a positive

relationship at higher frequencies from mid-2011 through the end of 2013 and then from mid-2015 through the mid-2016. One explanation for this is that the 2012/13 U.S. drought, short crop, and tight supplies may have made international soybean prices more responsive to common fundamentals. Afterwards, the bumper 2013/14 crops in both countries may have had the reverse effect, allowing prices to drift further apart (in the medium-term). Vacha et al. (2013) share a similar result in the biofuel complex: market uncertainty appears to have driven a greater co-movement in prices during the financial crisis; after the crisis lessens, commodity prices drift apart more easily at higher frequencies. None of the commodities we studied exhibit a significant, consistent price relationship between the U.S. and China. This is unsurprising, given the efforts Chinese policymakers have taken to insulate their markets from international price shocks (Gale, Arnade, and Cooke, 2016).

Changing international trading patterns

The United States plays an important role in the global trade of major food, feed and fiber commodities, exporting a large proportion of its agricultural production. As shown in figure 1, in the 1980s U.S. exports accounted for over 75 percent of corn and soybeans traded in the world, half of the wheat, and a quarter of the rice that crossed borders. Since then, on average, the United States has lost more than 2 percent of the export market share annually, for each of these commodities; currently, it accounts for only about 40 percent of corn and soybean exports, 15 percent of wheat exports, and less than 10 percent of traded rice. In between 1980 and 2010, U.S. cotton experienced a relative expansion in international trade, and reached around 45

percent market share. Since then, however, it has lost around 3 percent market share each year, on average, and currently accounts for around 30 percent of the world cotton export market.

During the past few decades, the global trade for agricultural commodities has experienced several important structural and technological developments. For example, many countries are either entering the export markets for the first time, or playing a larger role. As shown in figure 2, today Brazil accounts for more than 20 and 40 percent market share for corn and soybeans, respectively, growing from less than five percent for each commodity prior to the 1980s. Former Soviet Union (FSU) nations, mainly Russia and Ukraine, now make up more than 25 percent of the global wheat trade; these countries were barely involved in the international grain market as exporters before mid-1980s. Over the same timeframe, Asian countries--mainly India and Thailand--grew from 5 percent to 20 percent of the world rice trade. In recent years, exports from India have represented more than 15 percent of global cotton market share. As a result of trade liberalization and the expansion of agriculture into new producing regions, Brazil has also emerged as one of the world's leading cotton producers and an important competitor of the United States (Kiawu, Valdes and MacDonald 2011).

In terms of technological changes, rising shares of the U.S. corn crop devoted to ethanol production have weakened its participation in the export market. Currently, U.S. ethanol uses around one-third of domestic corn production, as shown in figure 3, compared to less than two percent in early-1980s. At the same time, the share of U.S. corn exported fell from around 22 percent to about 10 percent. Expansion of U.S. exports for Distiller's Dried Grains with Solubles (DDGS), a by-product of grain ethanol, has partially compensated for a small amount of lost corn

and soybean exports market share, and domestic feed use.[1] Despite these changes, U.S. exports are still expected to remain an important factor in grain price discovery, and exports from a number of countries are supposed to affect U.S. prices (Etienne, Irwin, and Garcia 2014). Hence, investigating price of discovery process based commodity prices in major exporting countries is both theoretically and empirically sound practices.

Background

Liquid commodity futures markets, where they exist, are commonly accepted as strong facilitators of the price discovery process (Figuerola-Ferretti and Gonzalo 2010; Carter and Mohapatra 2008). For storable commodities, futures and spot markets are intimately connected via arbitrage (Etienne, Irwin, and Garcia 2014). But futures markets may have a comparative advantage at incorporating new fundamental information (Yan and Zivot 2010).[2] This follows from the fact that well-functioning derivatives markets have higher liquidity, more transparency and lower transaction costs than most spot markets, so can react more quickly to new information (Working 1962; Black 1976; Adämmer, Bohl, and Gross 2015). Several researchers have studied the price discovery process for internationally traded agricultural commodities. Boyd and Brorsen (1986) focused on the U.S. and European Community prices of corn gluten feed and Soybean meal markets. Goodwin and Schroeder (1991) studied the U.S., Canadian, Australian

[1] Using 130 million metric tons of corn, U.S. produced around 15 billion gallons of ethanol and 37 million metric tons of DDGS in 2015. Around 37 percent of DDGS produced was exported to more than 50 countries (USDA/ERS, 2016b).

[2] Some authors, for instance Kavussanos, Visvikis, and Alexakis (2008) argue that new information is simultaneously reflected in both spot and future prices in perfectly competitive markets (Chang and Lee, 2015). In addition, the advent of Internet marketing has led to quick information sharing and to rapid price discovery (Just and Just 2006).

and Argentine roles in the wheat export market, and the Japanese and Rotterdam wheat import markets. Likewise, Bessler, Yang and Wongcharupan (2003) concentrated on the role of five major exporters in affecting international wheat price dynamics.

Among the many features of agricultural commodities that theoretically affect the price discovery process are storability of the commodity, the volume of trade involved in the commodity market, and commodity's price variability. The greater the cost associated with storing a commodity could, for instance, lead to a greater informational disparity between cash and futures prices (Covery and Bessler 1995). On the other hand, Yang, Bessler, and Leatham (2001) and Carter and Mohapatra (2008) found that asset storability may not affect the long-run relationship between cash and futures. Recently, Adämmer, Bohl, and Gross (2015) investigate the price discovery process of two thinly traded agricultural futures contracts traded at the European Exchange in Frankfurt. In their findings they confirm that the very low trading volume does not necessary restrict price discovery efficiency. In addition, for the U.S. soybeans and soybean meal, Arnade and Hoffman (2015) analyzed whether an exogenous measure of price variability influences the price discovery process and they found during 2005-13, when price variability was high, that the cash market played a more significant role in price discovery than in the 1999–2005 period.

Baillie et al. (2002) indicated that the majority of price discovery studies are undertaken using some form of common factor or cointegration models, which were separately developed by Hasbrouck (1995) and Gonzalo and Granger (1995). Yan and Zivot (2010) analytically investigated the price discovery process using a vector error correction model (VECM) by isolating information

share (IS) and component share (CS) measures from the residuals of VECM. A relatively similar approach was applied by Figuerola-Ferretti and Gonzalo (2010) for investigating the price discovery process for five metals' spot and futures prices. Lien and Shrestha (2014) also applied a modified IS approach to analyze the price discovery process in interrelated securities markets. Adding an exogenous measure of lagged price variability, Arnade and Hoffman (2015) used a-VECM for the cash and futures prices of soybeans and soybean meal.

For international wheat market price dynamics, Goodwin and Schroeder (1991) used a vector autoregression model and found that the U.S. price had a significant effect on international wheat prices. Bessler, Yang, and Wongcharupan (2003) used VECM along with directed acyclic graphs to investigate price dynamics in five international wheat markets and found that Canada and the U.S. are leaders in the pricing of wheat in international markets. This was contrary to other previous research that failed to find evidence of significant price leadership role for the U.S. and Canada using a cointegration and error correction approach (Mohanty, Meyers, and Smith 1999). Liu and An (2011) study the contribution of U.S. and Chinese futures markets to the discovery of soybean prices using an information share framework, and data from 2004-2009.

Some of the potential limitations of the cointegration models include: the analyses only work for testing the unbiasedness of the price discovery process (Yang , Bessler, and Leatham 2001), or that their findings only account for the immediate (one-period) responses of market prices to a linear long-run relationship, which may miss important price discovery dynamics (Yan and Zivot 2010). Moreover, if a structural break occurs, models with fixed parameters yield flawed results (Vacha et al. 2013).

Strict assumptions used in constructing IS and CS measures could, for instance, provide different views of the price discovery process (Baillie et al. 2002; Adämmer, Bohl, and Gross 2015). Wavelet coherence analysis avoids the limitations of cointegration models, and is a good candidate to study periodic phenomena in time series (Rösch and Schmidbauer 2014), because it offers a model-free method of time series analysis that is highly flexible to structural changes (Vacha and Barunik 2012). In addition, wavelet analysis offers the ability to assign directionality to the relationship between two series, identifying statistically significant lead and lag relationships that characterize the price discovery process. Moreover, wavelet analysis is more flexible both in modeling and data requirements. For instance, it does not necessarily require global (strict) stationarity of the time series (Joseph, Sisodia, and Tiwari 2015).

By decomposing a time series into the time - frequency domain, wavelet coherence reveals the evolving nature of the relationship between two price series, over a continuous range of frequencies (running from short, to medium, to long run). This approach offers important advantages over traditional models for studying the price discovery process (Chang and Lee 2015), and the integration of markets more generally. Indeed, avoiding the linear restrictions imposed by cointegration-based models affords wavelets more flexibility in modeling heterogeneity in financial and economic time series data, and studying price co-movement and the price discovery processes (Joseph, Sisodia, and Tiwari 2015).

Wavelet tools are relatively new to economics, and the study of financial data.[3] Some of the first few related applications of such methods include studying macroeconomic variables (Aguiar-Conraria, Azevedo and Soares 2008), measuring the business cycle (Yogo 2008), understanding co-movements in stock market returns (Rua and Nunes, 2009) and co-movements in energy prices (Vacha and Barunik 2012; Vacha et al. 2013). Recently, Chang and Lee (2015) applied wavelet coherence analysis to study price discovery in oil prices, and found that wavelet analysis is preferable in revealing the comovement and causal relationships between oil spot and futures prices than the VEC framework. Joseph, Sisodia, and Tiwari (2015) used wavelet analysis to study price discovery in the Indian markets for bullion, energy, metals and agriculture, and found that the futures market serves a powerful price discovery function in all of the selected commodities. Kristoufek, Janda, and Zilberman (2016) use wavelet coherence to study the relationships between ethanol and feedstock markets in Brazil and the U.S. Unlike earlier findings of no long-run relationship using cointegration models among prices of ethanol, corn, and gasoline, they find that the price of feedstocks (corn in the U.S. and sugarcane in Brazil) lead the prices of ethanol.

Data

We obtain daily domestic and international futures prices for major grains and cotton from the premier derivatives market in each country under study for that particular commodity. In some cases, trading hours for these markets only partially overlap. We use end-of-day prices to

[3] Wavelet analysis has been used in geography, engineering, astronomy, medicine and other natural science disciplines, but it is recently used for economic and financial investigation (Ramsey 2002; Rösch and Schmidbauer 2014).

calculate returns.[4] The data cover the period 2009-present for corn, and 2011-present for soybeans and cotton. Futures markets included in the analysis are the U.S. Chicago Mercantile Exchange (CME) for corn and soybeans and Intercontinental Exchange (ICE) for cotton; the Dalian Commodity Exchange for Chinese corn and soybeans, and the Zhengzhou Commodity Exchange for Chinese cotton; the Tokyo Commodity Exchange for Japanese corn and soybeans; the National Commodity & Derivatives Exchange for India's soybeans, and the Multi Commodity Exchange for India's cotton; and the South African Commodity Exchange. For commodity prices, we instead chose to use the daily cash price index collected by the Center for Advanced Studies on Applied Economics rather than futures prices from the BM&F due to low trading volume in that market,. To control for the influence of macroeconomic factors that affect exchange rates, we convert all prices into U.S. dollars using the daily exchange rate archived by the St. Louis Federal Reserve before analyzing market integration characteristics. The U.S. and international prices in dollar per metric tons are shown in figure 4.

Because futures prices across markets represent different delivery dates, we use the nearest-to-deliver contract in every case, and generate daily returns by calculating the log changes for all series.[5] Contracts are rolled over at termination. One feature common to the commodity prices presented in figure 4 is a decline in commodity price by about 20-40 percent since the end of the 2011/12 food price crisis to 2015. (Trostle et al. 2011; Plumer 2012). A notable exception is the Chinese corn price, however, which remained relatively flat for much of the observed period.

[4] A negligible number of missing values (e.g., for holidays in one country but not another) are interpolated using the last traded value.

[5] Even though delivery dates do not often match up identically between domestic and international futures contracts, because storage ties together intertemporal prices, returns data should capture shock transmission accurately.

Since the beginning of 2016, however, commodity prices, especially Brazilian corn and cotton, have trended upwards.

Methods

Traditional Time Series Methods

To verify stationarity conditions, we apply Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller 1979) to price series and their first difference to test against the null hypothesis of the presence of a unit root. As shown in Table 1, ADF tests fail to reject the null hypothesis for all the series in the levels. Nevertheless, ADF tests applied to the first differences reject all the null hypotheses.

Our ADF test results indicate that all series are consistently integrated of order one, or I(1). Next, we test whether a linear combination of each set of paired prices is stationary using Johansen's Cointegration test (Johansen 1995) and present the results in Table 2. If the series are cointegrated, their markets are often interpreted as being integrated since their prices are shown to exhibit a long-run relationship. Using these tests, we find that the U.S. corn price is not cointegrated with price in Brazil, a major corn producer and exporter, and the price in China, a major corn importer. As one of the major corn and soybean suppliers to Japanese market, U.S. corn and soybean prices are cointegrated with those of Japan. Although the U.S. supplied more than 50 percent of Chinese soybean imports, prices in the two markets are not cointegrated. Johansen tests reveal that U.S. soybean prices are not cointegrated with those realized in Brazil, the other major exporter of global soybean products. On the other hand, U.S. cotton prices are cointegrated with those observed in the other major cotton import and export markets: China and India, respectively, as well as Brazil

These tests indicate the existence of a single cointegrating vector, $r = 1$, between U.S. prices, P^{usa}, and of the price series observed for several international countries, P^{j}, meaning that a linear combination of the series has a stable mean and variance. Engle and Granger (1987) proved that under that condition, the relationship between the two price series can be specified by an Error Correction Model (ECM)

$$(1)\quad \Delta P_t^{usa} = \alpha^{usa}\left(P_{t-1}^{usa} - \beta P_{t-1}^{j} + c\right) + \sum_{i=1}^{k} \pi_{11}^{usa}\ \Delta P_{t-i}^{usa} + \sum_{i=1}^{k} \pi_{12}^{j}\, \Delta P_{t-i}^{j} + \gamma^{usa} + \varepsilon_t^{usa}$$

$$\Delta P_t^{j} = \alpha^{j}\left(P_{t-1}^{usa} - \beta P_{t-1}^{j} + c\right) + \sum_{i=1}^{k} \pi_{21}^{usa}\ \Delta P_{t-i}^{usa} + \sum_{i=1}^{k} \pi_{22}^{j}\ \Delta P_{t-i}^{j} + \gamma^{j} + \varepsilon_t^{j}$$

where ΔP_t^{usa} and ΔP_t^{j} represent the daily change in U.S. and country *j*'s commodity prices (returns), respectively. The long-run relationship between the U.S. and country *j*'s commodity prices are captured by the long-run error term, u_{t-1}, which is equal to the expression $\left(P_{t-1}^{usa} - \beta P_{t-1}^{j} + c\right)$. The coefficients on that residual in each equation, α^{usa} and α^{j}, represent adjustment rates measuring the speed of the adjustment toward the long-run equilibrium in response to a short-run deviation of the system (Adämmer, Bohl, and Gross 2015), and can be used to estimate the price discovery weights, which are also known as factor weights. If, for instance, α^{j} is statistically significant, but α^{usa} is not, the results are supportive of a leading role of the U.S. market in the price discovery process, since only the prices in country j adjust to shocks. In other words, if $\alpha^{usa} = 0$ or close to zero, the price discovery occurs entirely or substantially in the U.S. market. The U.S. price discovery weight, ω^{usa}, can be calculated using $\omega^{usa} = \frac{\alpha^{j}}{\alpha^{j} - \alpha^{usa}}$; the weight for country *j*'s price is calculated using a similar procedure (Yan and Zivot 2010). The country with the larger price discovery weight is the leader in the system; its prices adjust less to short-run deviations. The cointegrating parameter is represented by

coefficient, β, which—if significant—indicates the existence of a long-run equilibrium relationship between prices in the U.S. and country j.

Wavelet Framework

A wavelet $\psi(t)$ is a continuous, real- or complex-valued square integrable function that is composed of scale S, which controls the frequency or length of the wavelet and time parameter τ, a proxy for the wavelet location (Vacha and Barunik 2012; Vacha et al. 2013; Rösch and Schmidbauer 2014). It is specified as

$$(2) \qquad \psi_{\tau,\mathrm{S}}(t) = \frac{\psi(\frac{t-\tau}{\mathrm{S}})}{\sqrt{\mathrm{S}}}.$$

Once the assumptions about the wavelet function are met[6], a time series $x(t)$ that undergoes a Morlet wavelet transformation can be represented using a function of two variables as

$$(3) \qquad W_x(\tau,\mathrm{S}) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{\mathrm{S}}}\psi^*(\frac{t-\tau}{\mathrm{S}})dt,$$

with * marking the complex conjugate operator so that there is no information loss by the transformation. The application of Morlet wavelets dates back to early-1980s and the decomposition of a signal into its frequency and phase contents as time evolves. Unlike the Fourier transformation, the Morlet wavelet provides a good balance between time and frequency localization (Kristoufek, Janda, and Zilberman 2016).[7]

[6] Rua and Nunes (2009) states these conditions. For instance, wavelet has zero mean, integrates to unity, and has admissibility condition.

[7] This section heavily builds on the works of Vacha and Barunik (2012), Vacha et al. (2013) and Rösch and Schmidbauer (2014).

The scale parameter s controls how the wavelet is stretched or compressed. For instance, if the scale is lower, the wavelet is more compressed and therefore detects higher frequencies, and vice versa. We obtain the wavelet coefficient by first performing a continuous transformation on the time series data of finite length $x(t), t = 1, \dots, N$ using the Morlet method. This method helps to preserve the basic information of $x(t)$. Then, we obtain a matrix of wavelet coefficients with $\tau = 1, \dots, N$ rows, and $\mathrm{s} = 1, \dots, k$ columns, where k is a maximum number of scales used for the wavelet decomposition. Each wavelet coefficient $W_x(\tau, \mathrm{s})$ represents local energy (variance) at a specific scale s at position τ.

To study the relationship between domestic and international prices, we use a bivariate framework called wavelet coherence that requires cross-wavelet transformation. Coherence provides appropriate tools for comparing the frequency contents of two time series $x(t)$ and $y(t)$. Their cross-wavelet transformation is defined as

(4) $$W_{xy}(\tau, \mathrm{s}) = W_x(\tau, \mathrm{s}) W_y^{*}(\tau, \mathrm{s}),$$

where $W_x(\tau, \mathrm{s})$ and $W_y(\tau, \mathrm{s})$ are continuous wavelet transformations of $x(t)$ and $y(t)$, respectively.

It is widely recognized that wavelet coherence can detect regions in the time-frequency space, where the examined time series co-move. On the other hand, the series do not necessarily have a common power. To overcome this challenge, we follow the approach of Torrence and Webster (1999) and define the squared wavelet coherence coefficient as

(5) $$R^2(\tau, \mathrm{s}) = \frac{|S(\mathrm{s}^{-1} W_{xy}(\tau, \mathrm{s}))|^2}{S(\mathrm{s}^{-1}|W_x(\tau, \mathrm{s})|^2)\, S(\mathrm{s}^{-1}|W_y(\tau, \mathrm{s})|^2)},$$

where S is a smoothing operator. The coefficient of the squared wavelet coherence is in the range of $0 \leq R^2 \leq 1$. Similar to the squared correlation coefficient in linear regression, the squared wavelet coherence coefficient measures the local linear correlation between two stationary time series at each scale, and can be efficiently represented in time-frequency space by a color map. Coefficient values close to zero indicate weak correlations and are represented by cooler (e.g., blue) colors, while strong correlations are represented by warmer (e.g., red) colors (Vacha and Barunik 2012). The frequency, that is the "run" of a relationship, is depicted in the map along the vertical axis—lower locations equate to a lower frequency, or longer run; location along the horizontal axis indicates the time for which the relationship is represented. We use Monte Carlo simulation methods to test the coefficients against the null hypothesis of autoregressive, AR(1), noise at the 5% level; statistically significant relationships are shown as areas bordered by a black thick contour. Because wavelet analysis is sensitive to boundary conditions, estimates at the beginning and end of the period of interest are less reliable (particularly at lower frequencies). Therefore, we overlay the chart with a cone of influence to distinguish between reliable (bright) and less reliable (pale) regions (Kristoufek, Janda, and Zilberman 2016).

The square coherence in Eq.(5) loses complex information about direction. To recover this information, we apply a wavelet coherence phase difference using the following specification

(6) $$\phi_{xy}(\tau, s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(\tau,s))\}}{\Re\{S(s^{-1}W_{xy}(\tau,s))\}}\right) \phi_{xy} \in [-\pi, \pi],$$

where $\Im$ an imaginary and $\Re$ a real part operator. Phase is represented by arrows on the wavelet coherence plots. A zero phase difference means that the examined time series move together. The arrows points to the east (west) when times series are positively (negatively) correlated with no series as a leader. In addition, arrows pointing southward means that the first time series leads the second one by $\frac{\pi}{2}$, whereas northward pointing one shows the opposite. Combinations of these effects are depicted by arrow rotation: for instance, an arrow pointing up and to the right means the two series are positively correlated with the first time series following the second one.[8]

Results and Discussion

Error Correction Models

In this subsection, we share the results of traditional time series methods that search for evidence of co-movement with respect to a linear long-run relationship. According to corn's ECM results in table 3, there is a statistically significant cointegration between U.S. and Japanese corn. Adjustment rates in the table indicate that Japanese prices adjust more quickly to disequilibrium than U.S. prices. The adjustment rates can also provide information about the price discovery weights, as empirically presented in Arnade and Hoffman (2015). It is estimated that the U.S. corn price is responsible for about 70 percent of the price discovery weight, hence it is considered as

[8] A similar interpretation can be presented using the location where the value of ϕ_{xy} falls within the domain. For instance, the time series are positively correlated (are said to be in phase) if $\phi_{xy} \in (0, \frac{1}{\pi})$, with the first series leads the second (see Chang and Lee 2015).

a leader in corn price discovery process, compared with Japanese corn price that has only a discovery weight of around 30 percent.

The cointegration parameters for U.S.-Japanese for soybean prices are also statistically significant, supporting the cointegration test shown in Table 2. The adjustment rates indicate that the U.S. soybean price does not respond to any change in the corresponding markets as shown in Table 3. On the other hand, average soybean prices in Japan quickly adjust toward U.S. levels. Furthermore, the U.S. soybean price carries a price discovery weight of more than 91 percent, and is therefore judged to be a leader in the price discovery process.

The cointegration parameters for U.S.-Brazil, U.S.-Chinese and U.S.-Indian for cotton price pairs are likewise statistically significant, and match the results of cointegration tests in table 2. The adjustment rates indicate that when the U.S. cotton price is too high, it falls back to all the three cotton prices, but only the average cotton price in Brazil and India adjusts toward the U.S. price level. Although the Chinese cotton market shares a long-term relationship with the U.S. cotton market, its prices do not adjust to the change in the U.S. cotton prices. This is confirmed by evaluating the price discovery weight, where the U.S. cotton price is responsible for only 23 percent of the cotton price discovery weight relative to the Chinese market, and, therefore, lags Chinese cotton market shocks. It is noticeable that even though China is the largest export market for U.S. cotton, on average importing 913 thousand metric tons of cotton and cotton products in 2011-15 out of 2611 thousand metric tons of U.S. exports, Chinese cotton futures prices do not follow U.S. futures price dynamics (USDA/FAS 2016). This indicates that the Chinese domestic cotton policies insulate Chinese cotton prices from economic fundamentals transmitted by global

prices. On the other hand, U.S. cotton prices represent around 24 and 53 percent of the price discovery weight compared to Brazilian and Indian cotton prices, respectively, indicating that U.S. cotton prices are marginal leaders for that relationship. Most recently, both Brazil and India have become important competitors of the United States in Asian and European cotton markets (Kiawu, Valdes and MacDonald 2011).

Wavelet Analysis

Figures 5-7 show bivariate wavelet coherences between daily U.S. and international corn, soybeans, and cotton returns, respectively. The most striking finding from these results is that the relationships between U.S. and international prices are, in many cases, not stable. Quite distinct from the findings of our ECMs—which force domestic and international prices into a linear relationship, more flexible wavelet coherence shows that U.S. and international agricultural markets often appear to alternate between periods of integration and non-integration. In the short run (under one month= 20 trading days), U.S. and international prices bear no consistent, significant relationship for any commodity. Temporary correlations, which may last for about season appear and disappear rapidly. At longer horizons, though, the data do reveal some clearer correlations.

Corn returns exhibit the greatest level of consistency for any commodity; its pairs in figure 5 for U.S.-Brazil (2-6 month level) and U.S.-Japan (1.5-12 month level) are significantly correlated at lower frequencies, indicating a longer-run relationship. Moreover, phase arrows indicate that U.S. returns often lead those for Brazil, a major export competitor, and sometimes Japan, a major import market, at low frequencies (long run). On the other hand, at certain times—and at higher

frequencies—international corn market shocks lead those measured in Chicago, like during the US drought of 2012. As a result of structural changes that have occurred in the last decade, Brazil has started boosting corn exports from September to January, months traditionally dominated by U.S. and other Northern Hemisphere exporters (Canada and the EU). Recently, Brazil currency has weakened relative to the U.S. dollar, and transportation costs have declined substantially due to lower global energy prices, boosting Brazil's ability to compete with U.S. corn prices (Allen and Valdes, 2016).

We find that corn prices between the U.S. and China bear no consistent long-run relationship from 2010-present, however. This is unsurprising given the divergence between their price series displayed in figure 4. Over the limited period they do display a coherence 2011-2013 (3-6 month frequency), phase arrows point upwards, indicating that Chinese corn shocks generated a response in U.S. prices for a time. Chinese corn trade policy fluctuates with little relationship to the country's production, making China's corn trade difficult to predict (USDA/ERS 2016c).

In the case of soybeans, as shown in figure 6, wavelet coherences demonstrate that price relationships that had existed from the beginning of the sample in 2011 changed abruptly by the beginning of 2013. This is clearest for U.S.-Brazil, U.S.-India, and U.S.-South Africa, which displayed significant correlations at a range of frequencies up to the close of 2012. A similar finding is indicated by the U.S.-China pair. The U.S.-Brazil and U.S.-India for soybean price pairs are found to follow a low frequency, long-run relationship over the entire period, but higher frequency correlations ceased following the U.S.-drought year of 2012. Soybean prices in the U.S. and South Africa also exhibit a significant long-run relationship over the period of

observation, with some evidence of a temporary disconnect towards the end of 2014. Since 2015, South Africa has become a net exporter of soybeans in the global market and planted a record area to the crop (Mokhema 2015). U.S.-China and U.S.-Japan price pairs do not demonstrate consistent relationships across the period of interest, at any frequency: their prices are not well-integrated. For U.S.-China, this contrasts with the findings of Liu and An (2011), who found a significant relationship between soybean futures prices in these two countries; but, their data series ended in 2009, before our data series begins. The clearest demonstration of directionality is offered by the U.S.-South Africa pair, indicating that U.S. soybean market shocks lead changes in South African prices at low frequencies from 2012-2013.

Taken together, some of the corn and soybeans charts do demonstrate relatively high frequency price correlations between the U.S. and international markets (Brazil and Japan for corn; Brazil, India, and South Africa for soybeans) during 2012. One possible explanation for this is that the 2012/13 U.S. drought, a short crop, and tight supplies made international prices more responsive to common fundamentals.

As with corn and soybeans, our cotton results in figure 7 show no consistent relationship between U.S. and Chinese prices. Price shocks between these countries do not translate at any level of frequency; their markets are not currently well-integrated. The same is true for U.S. and Brazilian cotton prices, which bear no consistent relationship. On the other hand, U.S. and Indian cotton prices are found to exhibit a long-run relationship over the sample period, with temporary (2013 and 2014) medium-run correlations. India is becoming an export competitor for the U.S. markets after extensively adopting the Bt cotton variety over 90 percent of the area it plants to cotton.

Since 2013, both markets exhibited medium-run relationship (for 2-4 months) with alternating lead roles in the transmission of price shocks, matching our ECM results as shown in Table 3.

For robustness, we display Johansen trace test results in table 4 for the same time series examined in table 2, alongside results for the time periods identified in the wavelets analysis as bearing no or weak relationships. Results confirm that during those periods with no wavelet coherence, the futures price series in our study are also not cointegrated. Even though original Johansen statistics identified U.S.-Japan for soybeans, and U.S.-China for cotton, as price pairs that could be described by a VEC, the same tests fail to reject the null of no cointegration once the selected periods are considered. These findings demonstrate the flexibility of wavelets to structural breaks, and their ability to identify them.

In addition, Table 5 reaffirms the wavelet results in such as a way that correlations between the U.S. and trading partner's commodity prices identified using wavelet methods can also be verified using cointegration tests, with the exception of U.S.-Brazil for soybean prices which experienced week cointegration. For instance, even though the U.S. and Brazilian corn prices do not have a long-run correlation from 2010-2015 according to table 2, a partial analysis for the period 2010-13 (which was found to be significant according to our wavelet analysis) reveals a strong cointegration. These two countries are the leading global producer and exporters of corn, and the VEC estimated in Table 5 finds that Brazil is responsible for more than 60 percent of the price discovery weights from 2011-2013, covering the 2012 drought and subsequent stocks drawdown in the U.S., and the 2012/13 global food crisis.

Conclusions

We assess the role that the United States plays in price determination for important agricultural commodities using both traditional and model-free time series methods by studying the relationship between the U.S. and major international markets for corn, soybeans and cotton, three commodities with different trade dynamics.

We identify structural changes to the integration of these markets, and the importance and direction of fundamental shock transmission. Daily shocks to the U.S. and international prices bear no significant relationship: short-run dynamics are not highly correlated, while temporary medium- run relationships appear and disappear regularly. Several long-run relationships are present in the data, but are not consistently established for some price pairs that one might expect based on the literature (e.g., U.S. and Chinese soybeans, as in Liu and An, 2011).

Both the wavelet and cointegration models indicate that the U.S. has a leading role in the Japanese corn and soybean markets, where the U.S. is the major supplier of Japanese feed imports. In addition, both analyses reveal that Chinese agricultural commodity markets are not well-integrated with their U.S. counterparts. Even though China is the largest import market for U.S. cotton, for instance, Chinese cotton futures prices do not closely follow U.S. price dynamics. This indicates that Chinese domestic commodity policies successfully insulate Chinese prices from international shocks. Figure 4 demonstrates that this insulation is accomplished at a cost: Chinese corn, soybean, and cotton prices were routinely higher—sometimes quite a bit higher—than prices elsewhere from 2009-2016.

There may be a number of additional factors for having or not having a long-run relationship in commodity prices among major exporters and importers. Among them, the effect of exchange rates, declining transportation costs, generous government subsidies and structural changes in agricultural production in major producing countries reduce the U.S. export market share, and make the U.S. commodities less influential in setting international commodity prices (Allen and Valdes 2016; Cooke et al. 2016). Future research will investigate the effect of these additional factors on the price discovery process.

References

Adämmer, P., Bohl, M.T., and C. Gross. 2015. Price Discovery in Thinly Traded Futures Markets: How Thin is Too Thin? *Journal of Futures Markets*. In Press.

Allen, E., and C. Valdes. 2016. Brazil's Corn Industry and the Effect on the Seasonal Pattern of U.S. Corn Exports. Washington DC: U.S. Department of Agriculture, Economic Research, AES-93.

Arnade, C., and L. Hoffman. 2015. The Impact of Price Variability on Cash/Futures Market Relationships: Implications for Market Efficiency and Price Discovery. *Journal of Agricultural and Applied Economics* 47(04): 539-559.

Aguiar-Conraria, L., Azevedo, N., and M. J. Soares. 2008. Using wavelets to decompose the time–frequency effects of monetary policy. *Physica A: Statistical mechanics and its Applications* 387(12): 2863-2878.

Baillie, R.T., Booth, G.G., Tse, Y., and T. Zabotina. 2002. Price discovery and common factor models. *Journal of financial markets* 5(3): 309-321.

Bessler, D.A., Yang, J., and M. Wongcharupan. 2003. Price dynamics in the international wheat market: modeling with error correction and directed acyclic graphs. *Journal of Regional Science* 43(1): 1-33.

Black, F. 1976. The Pricing of commodity contracts. *Journal of Financial Economics* 3(1): 167–179.

Boyd, M.S., and B. W. Brorsen. 1986. Dynamic price relationships for U.S. and EC corn gluten feed and related markets. *European Review of Agricultural Economics* 13(2): 199-215.

Chang, C.P., and C. C. Lee. 2015. Do oil spot and futures prices move together? *Energy Economics* 50(1): 379-390.

Carter, C.A. and Mohapatra, S., 2008. How reliable are hog futures as forecasts?. American Journal of Agricultural Economics 90(2):367-378.

Cooke, B., Nigatu, G., Heerman, H., Landes, M., and R. Seeley. 2016. Global Macroeconomic Developments Drive Downturn in U.S. Agricultural Exports. Washington DC: U. S. Department of Agriculture, Economic Research Service, AES-94.

Covey, T., and D.A. Bessler. 1995. Asset storability and the informational content of inter-temporal prices. *Journal of Empirical Finance* 2(2): 103-115.

Engle, R.F., and C.W. Granger. 1987. Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55(2): 251-276.

Etienne, X.L., Irwin, S.H. and Garcia, P., 2015. Price explosiveness, speculation, and grain futures prices. American *Journal of Agricultural Economics* 97(1), pp.65-87

Figuerola-Ferretti, I., and J. Gonzalo. 2010. Modelling and measuring price discovery in commodity markets. *Journal of Econometrics* 158(1): 95-107.

Gale, F., C. Arnade, and B. Cooke. 2016. Agricultural Price Transmission to China. *Working Paper.* USDA Economic Research Service.

Gonzalo, J., and C. Granger. 1995. Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics* 13(1): 27–35.

Goodwin, B.K., and T.C. Schroeder. 1991. Price dynamics in international wheat markets. *Canadian Journal of Agricultural Economics* 39(2): 237-254.

Hasbrouck, J. 1995. One security, many markets: Determining the contributions to price discovery. *The journal of Finance* 50(4): 1175-1199.

Johansen, S. 1995. *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

Joseph, A., Sisodia, G., and A.K. Tiwari. 2015. The Inter-Temporal Causal Nexus between Indian Commodity Futures and Spot Prices: A Wavelet Analysis. *Theoretical Economics Letters 5*(1): 312-324.

Just, D.R. and Just, R.E., 2006. Information exchange and distributional implications of price discrimination with Internet marketing in agriculture. *American journal of agricultural economics* 88(4): 882-899.

Kavussanos, M.G., Visvikis, I.D., and P.D. Alexakis. 2008. The Lead-Lag Relationship between Cash and Stock Index Futures in a New Market. *European Financial Management 14*(5): 1007-1025.

Kiawu, J., Valdes, C., and MacDonald, S. 2011. Brazil's Cotton Industry: Economic Reform and Development. Washington DC: U.S. Department of Agriculture, Economic Research, CWS-11d-01.

Kristoufek, L., Janda, K., and D. Zilberman. 2016. Comovements of ethanol-related prices: evidence from Brazil and the U.S.A. *GCB Bioenergy* 8(1): 346-356.

Lien, D., and K. Shrestha. 2014. Price discovery in interrelated markets. *Journal of Futures Markets* 34(3): 203-219.

Liu, Q., and Y. An. "Information transmission in informationally linked markets: Evidence from US and Chinese commodity futures markets."Journal of International Money and Finance 30.5 (2011): 778-795.

MacKinnon, J. G., Haug, A. A., and L. Michelis. 1999. Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. *Journal of Applied Econometrics* 14(1): 563-577.

Mohanty, S., Meyers, W.H., and D.B. Smith. 1999. A reexamination of price dynamics in the international wheat market. *Canadian Journal of Agricultural Economics* 47(1): 21-29.

Mokhema, T. 2015. S. Africa Plants Record Soybean Area as Oilseed Demand Rises. *Bloomberg News*. Febuary 2.

Plumer, B. 2012. As food prices spike, how close is the world to another crisis? *The Washington Post*, August 9.

Ramsey, J.B. 2002. Wavelets in economics and finance: past and future. *Studies in Nonlinear Dynamics & Econometrics* 6(3): 1-27.

Rösch, A., and H. Schmidbauer. 2014. *WaveletComp · Guided tour through Wavelet Analysis*. R package version 1.0. Available at: http://www.hs-stat.com/projects/WaveletComp/WaveletComp_guided_tour.pdf

Rua, A., and L.C. Nunes. 2009. International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance 16*(4): 632-639

Trostle, R., Marti, D., Rosen, S., and P. Westcott. 2011. *Why Have Food Commodity Prices Risen Again*? Washington DC: U.S. Department of Agriculture, Economic Research Service WRS-1103.

United States Department of Agriculture, Economic Research Service (USDA/ERS). 2016a. Agricultural Baseline Projections. Available at http://www.ers.usda.gov/topics/farm-economy/agricultural-baseline-projections.aspx

---(USDA/ERS). 2016b. U.S. Bioenergy Statistics. Available at http://www.ers.usda.gov/data-products/us-bioenergy-statistics.aspx

--- (USDA/ERS). 2016c. Corn Trade. Available at http://www.ers.usda.gov/topics/crops/corn/trade.aspx

United States Department of Agriculture, Foreign Agricultural Service, (USDA/FAS). 2016. Global Agricultural Trade System. Available at http://apps.fas.usda.gov/gats/default.aspx

Torrence, C., and P.J. Webster. 1999. Interdecadal changes in the ENSO-monsoon system. *Journal of Climate 12*(8): 2679-2690.

Vacha, L., and J. Barunik. 2012. Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics* 34(1): 241-247.

Vacha, L., Janda, K., Kristoufek, L., and D. Zilberman. 2013. Time-frequency Dynamics of Biofuel-Fuel-Food System. *Energy Economics* 40(2): 33-241.

Yan, B., and E. Zivot 2010. A structural analysis of price discovery measures." *Journal of Financial Markets* 13(1): 1-19.

Yang, J., Bessler, D. and D.J. Leatham. 2002. Asset storability and price discovery of commodity futures markets: A new look. *Journal of Futures Markets* 21(2): 279–300.

Yogo, M. 2008. Measuring business cycles: A wavelet analysis of economic time series. *Economics Letters* 100(2): 208-212.

Table 1. Augment Dickey and Fuller (ADF) unit root tests for prices and their first difference

Commodity	Market	Level	First difference
Corn			
	USA	-2.06 (18)	-10.24 (17) ***
	Brazil	-2.21 (8)	-9.80 (18) ***
	China	-1.75 (0)	-14.80 (9) ***
	Japan	-2.42 (4)	-24.67 (3) ***
Soybeans			
	USA	-2.31 (12)	-10.57 (11) ***
	Brazil	-2.50 (20)	-7.88 (19) ***
	China	-1.79 (3)	-23.79 (2) ***
	Japan	-0.71 (1)	-36.51 (0) ***
	India	-2.14 (0)	-37.67 (0) ***
	South Africa	-2.45 (8)	-12.85 (7) ***
Cotton			
	USA	-2.96 (1)	-12.76 (9) ***
	Brazil	-1.88 (21)	-7.53 (20) ***
	China	-1.77 (1)	-33.74 (0) ***
	India	-2.40 (0)	-26.25 (1) ***

Note: The null hypothesis that the price series, p, (in log form) has a unit root. ADF specification, $\Delta p_t = \alpha_o + \alpha_1 t + \beta_i \sum_{i=1}^{l} \Delta p_{t-i}$, has trend and drift (intercept) where, l (number in parentheses) is the lag order automatically selected on the basis of AIC, with Maximum lag = 24. *** denote rejection of the null hypothesis at the 0.01 level.

Table 2. Johansen's Cointegration test for U.S.-trading partners commodity prices

commodity	U.S.-trading partner combination	Trace statistics (No. of Coinetgrating null hypothesis rejected)
Corn		
	USA-Brazil	8.54 (Not cointegrated)
	USA-China	13.38 (Not cointegrated)
	USA-Japan	53.08 *** (None)
Soybeans		
	USA-Brazil	12.98 (Not cointegrated)
	USA-China	10.98 (Not cointegrated)
	USA-Japan	30.73** (None)
	USA-India	12.44 (Not cointegrated)
	USA-South Africa	10.34 (Not cointegrated)
Cotton		
	USA-Brazil	23.90 ** (None)
	USA-China	17.70 * (None)
	USA-India	23.61***(None)#

Note: *, **, and *** denote rejection of the null hypothesis at the 0.1, 0.05, and 0.01 level, respectively, based on Mackinnon, Haug and Michelis (1999) test. The cointegration test includes a linear deterministic trend (the level data have linear trends but the cointegrating equations have only intercepts) specified as $\Delta p_t = \alpha(\beta p_{t-1} + c) + \sum_{i=1}^{l} \pi_i \Delta p_{t-i} + \gamma + \epsilon_t$. # denotes that the Null is rejected at the 0.05 or 0.1 level and indicates the presence of 2 cointegrating equations.

Table 3. ECM results

Cointegrating parameter, β, for USA market with				Adjustment rate, α, for USA market with			
				Corn			
	Japan				Japan		
USA_{t-1}	1.000			$\Delta\, USA_{t-1}$	-0.018* /79/ (0.007)		
$Japan_{t-1}$	-0.905*** (0.031)			$\Delta\, Japan_{t-1}$	0.064*** (0.010)		
				Soybeans			
	Japan				Japan		
USA_{t-1}	1.000			$\Delta\, USA_{t-1}$	-0.004 /91/ (0.003)		
$Japan_{t-1}$	-0.945*** (0.101)			$\Delta\, Japan_{t-1}$	0.037*** (0.007)		
				Cotton			
	Brazil	China	India		Brazil	China	India
USA_{t-1}	1.000	1.000	1.000	$\Delta\, USA_{t-1}$	-0.024*** /24/ (0.006)	-0.019*** /23/ (0.005)	-0.014** /53/ (0.006)
$Brazil_t$	-0.790 *** (0.09)			$\Delta\, Brazil_{t-1}$	0.008* (0.004)		
$China_{t-1}$		-0.356*** (0.059)		$\Delta\, China_{t-1}$		0.006 (0.005)	
$India_{t-1}$			-1.061*** (0.113)	$\Delta\, India_{t-1}$			0.016*** (0.006)

Note: Standard errors are given in parentheses.*, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively. The number of lags, l=2 in our case, is determined using Akaike Information Criterion (AIC). // are percent of price discovery weights or common factor weights for the U.S. commodity, $\omega^{usa} = \frac{\alpha^j}{\alpha^j - \alpha^{usa}}$. The *j*'s country commodity weight can be calculated as $1 - \omega^{usa}$.

Table 4. Johansen's Cointegration test for no-relationship periods identified by wavelet coherences

commodity	U.S.-trading partner combination	Trace statistics for the entire period	Selected period of no cointegration identified using wavelet	Trace statistic for selected period[#]
Corn				
	USA-Brazil	8.54	2013-2014	8.88 (Not cointegrated)
	USA-China	13.38	2009-2011	7.18 (Not cointegrated)
	USA-Japan	53.08 ***	N/A	N/A
Soybeans				
	USA-Brazil	12.98	N/A	N/A
	USA-China	10.98	2013-2015	8.08 (Not cointegrated)
	USA-Japan	30.73 **	2014-2016	6.93 (Not cointegrated)
	USA-India	12.44	N/A	N/A
	USA-South Africa	10.38	2013-2014	5.34 (Not cointegrated)
Cotton				
	USA- Brazil	23.90 **	2013-2015	10.36 (Not cointegrated)
	USA-China	17.70 *	2013-2015	7.72 (Not cointegrated)
	USA-India	23.61 **	N/A	N/A

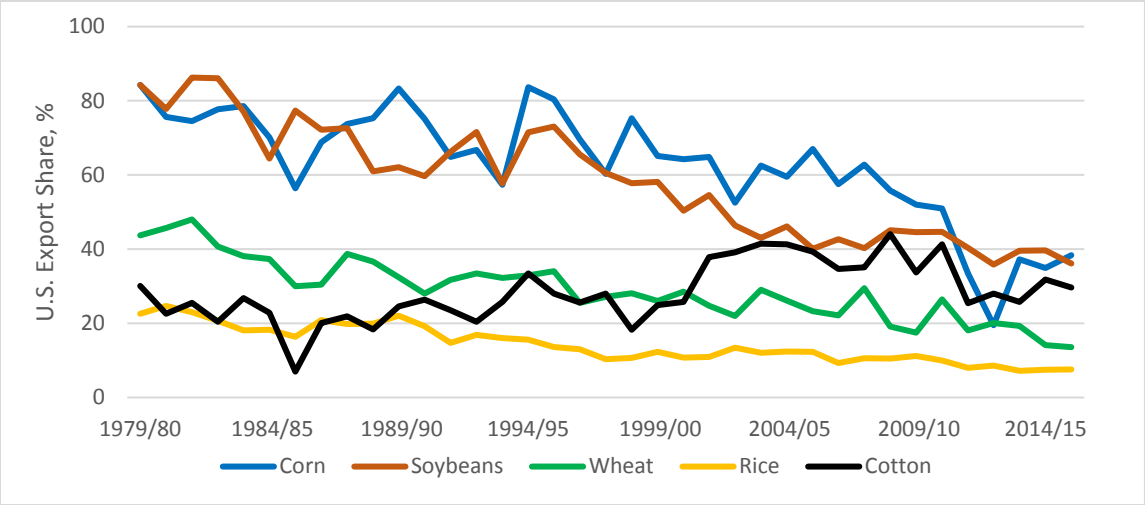
Note: *, **, and *** denote rejection of the null hypothesis at the 0.1, 0.05, and 0.01 level, respectively, based on Mackinnon-Haug-Michelis (1995). The cointegration test includes a linear deterministic trend. N/A refers not applicable that indicate wavelet identified no period of no relationship between the two prices. [#] 0.05 critical value for non-relationship for rejecting not cointegrated is 15.50.

Table 5. Johansen's Cointegration test for relationship periods identified by wavelet coherences

commodity	U.S.-trading partner combination	Selected period when wavelet coherences exists	Trace statistic for the selected period	Price discovery weights in percent
Corn				
	USA-Brazil	2010-11	17.60 **	29
	USA-China	2011-13	16.82 **	60
	USA-Japan [#]	2011-13	48.24 **	79
Soybeans				
	USA-Brazil [#]	2014-16[&]	15.61 **	1
	USA-China	2015-16	13.64 *	65
	USA-Japan	2011-13	30.65 ***	89
	USA-India [#]	2011-13	24.70 ***	13
	USA-South Africa	2011-13	16.83 **	70
Cotton				
	USA-Brazil	2012-13	14.41 *	13
	USA-China	2011-13	14.09 *	32
	USA-India[#]	2012-14	27.97 ***	92

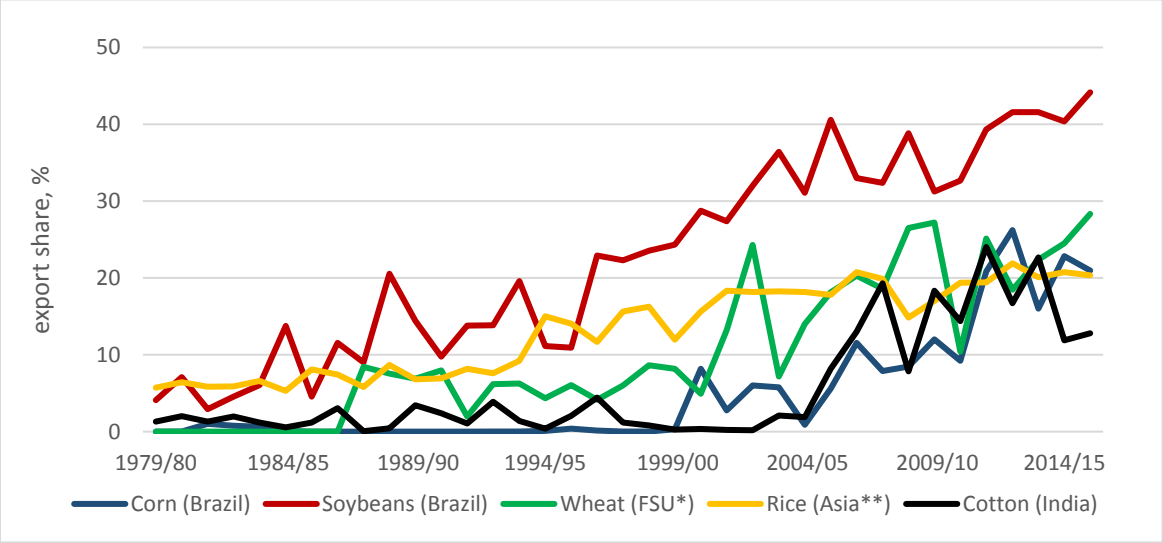
Note: *, **, and *** denote rejection of the null hypothesis at the 0.1, 0.05, and 0.01 level, respectively, based on Mackinnon-Haug-Michelis (1995). The cointegration test includes a linear deterministic trend. [#] These are also cointegrated in whole period analysis as shown in Table 4.N/A not applied since they are not cointegrated. [&] Indicates cointegrating at most 1 at 10 percent level.

Figure 1. U.S. export market share in world trade, 1980-2015



Source: USDA/ERS (2016a)

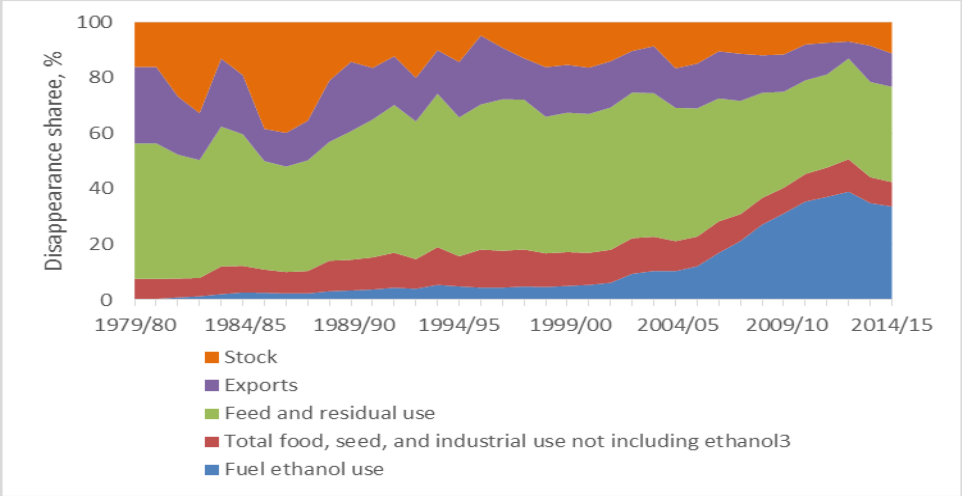
Figure 2. Export market share for selected commodities and countries, 1980-2015



Source: USDA/ERS (2016a)

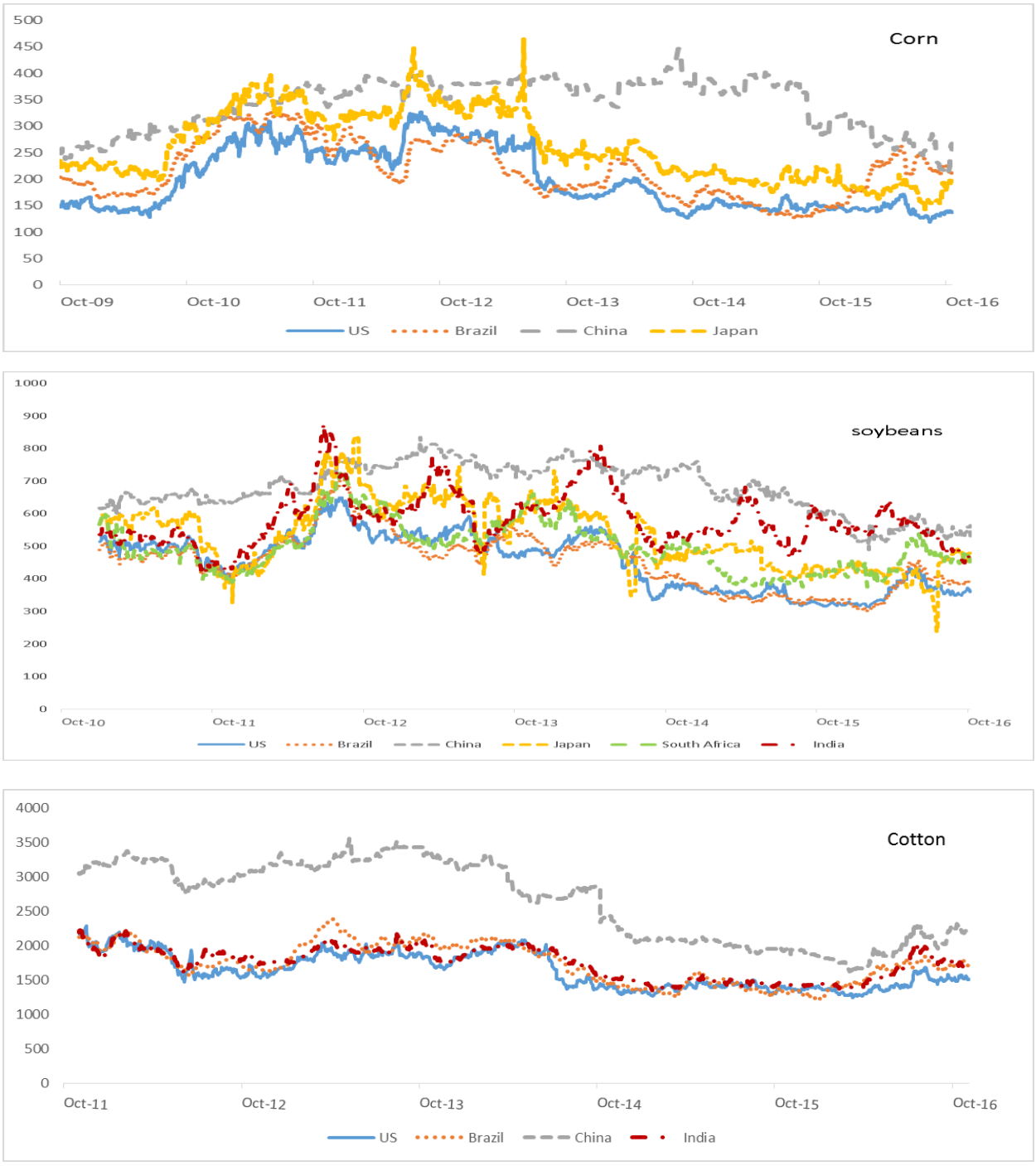
Note: FSU* includes Russian, Ukraine and 10 other FSU countries. Asia** includes India, Thailand, Vietnam, Pakistan, Burma, and Cambodia.

Figure 3. U.S. corn disappearance, 1980-2015



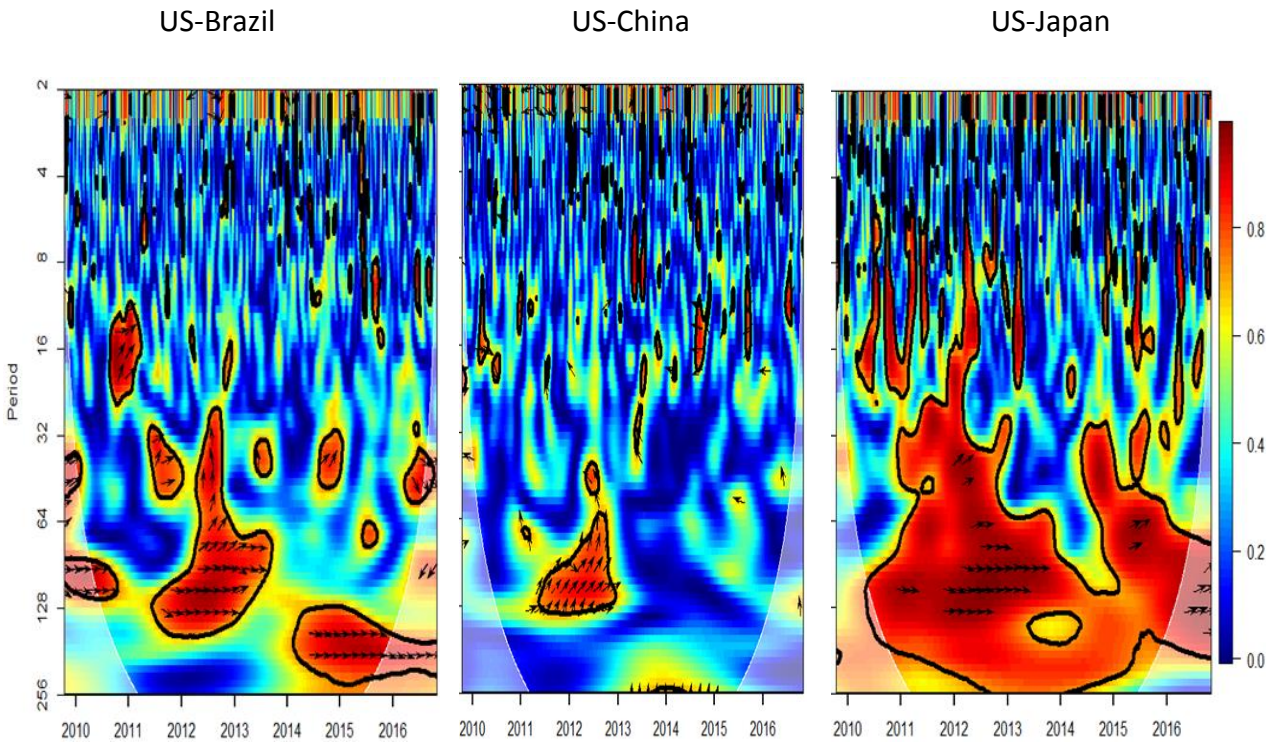
Source: USDA/ERS (2016b)

Figure 4. U.S. and international corn, soybean and cotton prices in $ per metric ton



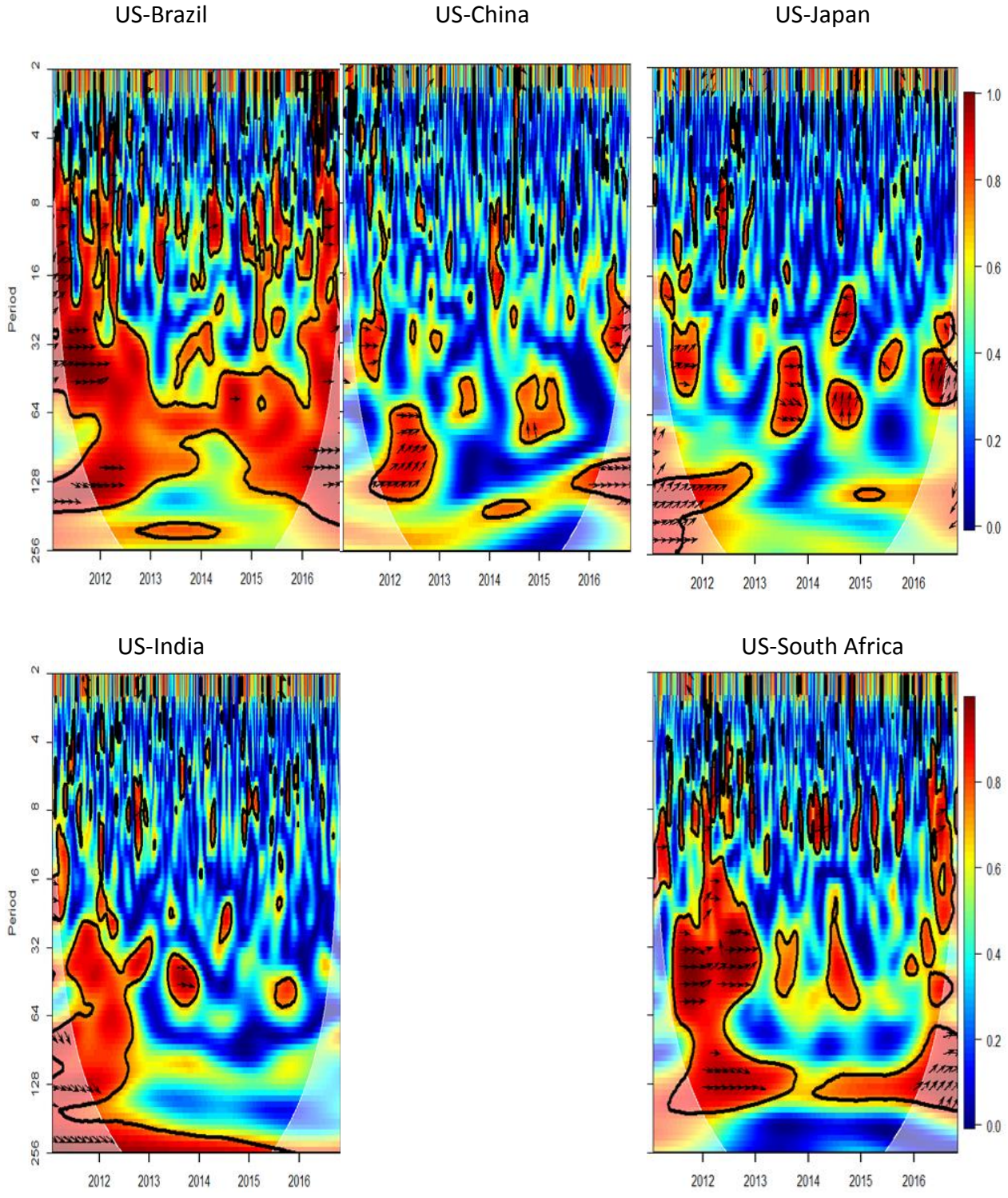
Source: The US: the Chicago Mercantile Exchange for corn and soybeans, and the Intercontinental Exchange (ICE) for cotton; Brazil:, the Center for Advanced Studies on Applied Economics for corn, soybeans, and cotton; China:, the Dalian Commodity Exchange for corn and soybeans, and the Zhengzhou Commodity Exchange for cotton; for Japan, the Tokyo Commodity Exchange for corn and soybeans; India: the National Commodity & Derivatives Exchange for soybeans, and the Multi Commodity Exchange for cotton; South Africa:, the South African Commodity Exchange for soybeans.

Figure 5. Wavelets results for the U.S. and international corn markets integration, 2010-2015



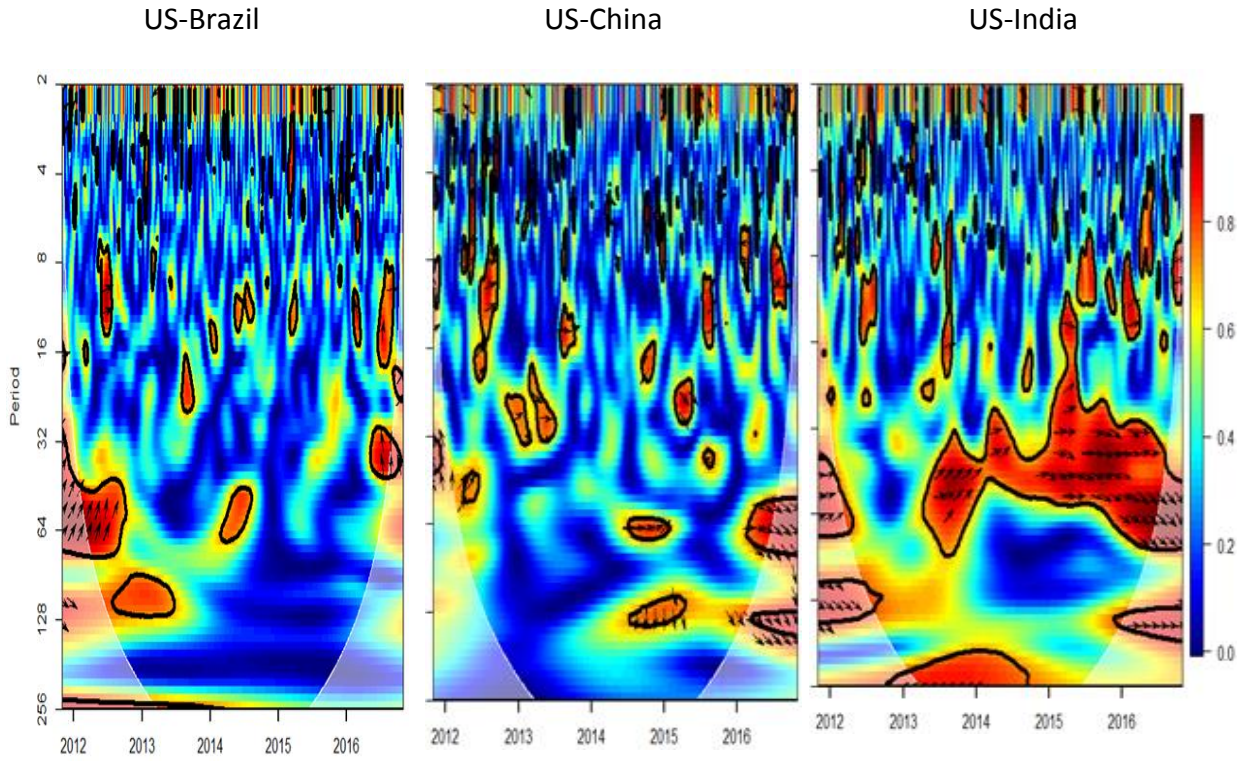
Note: The horizontal axis shows time in year, while the vertical axis shows the frequency in days. Weak correlations are represented by blue (cooler) colors, while strong correlations are represented by red (warmer) colors. A perfect positive (negative) correlation with no clear lead or lag relationship is represented by red (blue) color and right- (left) pointing arrows. Arrows pointing to downward directions indicate that the U.S. corn price leads the trading partner's price.

Figure 6. Wavelets results for the U.S. and international soybean markets integration, 2011-2016



Note: See Table 5.

Figure 7. Wavelets results for the U.S. and international cotton markets integration, 2010-2016



Note: See Table 5.