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

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Abstract

The United States historically played a dominant role in global agricultural commodity trading, and therefore price formation, for major food, feed and fiber commodities. But the share of U.S. agricultural commodity export has recently declined, and international supply and demand fundamentals likely play a larger role in setting commodity prices. Using wavelet coherence methods, this paper examines the price discovery process between the U.S. and international prices for corn, soybean, and cotton. The wavelet analyses reveal that short-run (around 20 trading days) relationship between the U.S. and international prices is, in many cases, not stable. The two major agricultural commodity exporters, the US and Brazil, experience long-run relationships in corn and soybean prices. Unlike Japan, Chinese commodity prices share little or no relationship with the U.S. prices even though China is one of the biggest export market for the US.

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

The behavior of market participants is shaped by price signals. Although in a free market the price in a given region is a reflection of local (current and expected) supply and demand fundamentals, the fact that important agricultural commodities are often traded internationally means that regional prices are also affected by the prices—and therefore the fundamentals—of their trading partners. 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 likely 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 first studying the relationship between the U.S. and major international markets for several commodities, and then identifying any structural changes in the importance and 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 India.

In addition to applying traditional time series methods, we use 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 estimate the bivariate wavelet coherence between the U.S. and international corn, soybean, and cotton price series for the commodities under study. Wavelet coherence analysis reveals that the relationship between U.S. and international prices is far from 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 US - Brazil and US - Japan for corn, US - Brazil and US - Indian for soybean, and US - Indian for cotton prices. However, U.S. and Brazilian soybean cash prices do share a positive short-run relationship at the 2-4 month level from mid-2011 through the end of 2013. After that, the short-run correlation disappears. One possible explanation is that the 2012/13 U.S. drought, short crop, and tight supplies made international prices more responsive to common fundamentals. The 2013/14 crops in both countries may have had the reverse affect, allowing prices to drift apart. 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. But both the wavelet and traditional cointegration analyses show long-run relationships between the U.S. and Japanese corn prices.

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 US 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 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 market share experienced a relative expansion, 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, Indian exports have represented more than 15 percent of global cotton market share.

In terms of technological changes, rising shares of the U.S. corn crop devoted to ethanol production have directly 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. crop production 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 export market share, and domestic feed use.[1]

Background

Commodity futures commodity markets, when they exist, are commonly accepted as strong facilitators of the price discovery process (Figuerola-Ferretti and Gonzalo, 2010). For storable commodities, futures and spot markets are intimately connected via arbitrage. 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 futures 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).

[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 prices in perfectly competitive markets. (Chang and Lee, 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 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 presumably 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 the greater the informational disparity between cash and futures prices (Covery and Bessler, 1995). On the other hand, Yang, Bessler, and Leatham (2001) found that asset storability may not affect the long-run relationship between cash and futures prices and challenged some previous empirical results such as Covey and Bessler (1995). Recently, Adämmer et al. (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 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 discovery. Bessler et al. (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 works that failed to find evidence of significant price leadership in the US and Canada using a cointegration and error correction approach (Mohanty, Meyers, and Smith, 1999).

Some of the potential limitations of the cointegration models include: the analyses only work for testing the unbiasedness of the price discovery process (Yang et al., 2001), or that their findings only account for the immediate (one-period) responses of market prices, 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 et al., 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).

Wavelet analyses offer 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.[3] 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). Indeed, avoiding the linear restrictions imposed by cointegration-based models affords

[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).

wavelets more flexibility in modeling heterogeneity in financial and economic time series data, and studying price co-movement and the price discovery processes (Joseph et al., 2015).

Wavelet tools are relatively new to economics, and the study of financial data. Some of the first few applications of such methods to these disciplines 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 preferable in revealing the comovement and causal relationships between oil spot and futures prices than the vector error correction framework. Joseph et al. (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 US. 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 US and sugarcane in Brazil) lead the prices of ethanol.

Data

We obtain daily domestic and international commodity futures prices for major grains and cotton from Futuresource. The data cover the period 2009-present for corn, and 2011-present for soybeans and cotton. Futures markets included in the analysis are those located in the US

(Chicago Mercantile Exchange for corn and soybeans; ICE for cotton), Brazil (BM&F Bovespa for corn), China (Dalian Commodity Exchange for corn and soybeans, and the Zhengzhou Commodity Exchange for cotton), Japan (Tokyo Grain Exchange for corn and soybeans), India (National Commodity & Derivatives Exchange for soybeans, and the Multi Commodity Exchange for cotton), and South Africa (South African Commodity Exchange for soybeans). We considered using Brazilian soybean futures prices from the BM&F as well, but because of very low trading volumes in that market, we instead chose to use the daily cash price index collected by the Center for Advanced Studies on Applied Economics. To control for the influence of macroeconomic factors that affect exchange rates, we convert all prices into the U.S. dollars before analyzing their relationships. Normalized price charts for each commodity are shown in figure 4a-c.

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.[4] One feature common to the commodity prices presented in figure 4a-c is a decline in commodity price by about 40 percent since the end of the 2011/12 food price crisis (Trostle et al., 2011; Plumer, 2012). A notable exception is Chinese corn and soybean prices, however, which remained relatively flat for much of the observed period.

[4] 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.

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, 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 can be said to be integrated since their prices share 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, 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 markets: China and India.

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 as the VECM

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

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

where ΔP_t^{usa} and ΔP_t^{j} represent the daily change in U.S. and country j's commodity prices, 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 et al., 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 the coefficient, β, which 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; Vacga 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[5], 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 the 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 et al. 2016).[6]

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

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

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

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 stronger 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 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 et al., 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

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

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.[7]

Results and Discussion

Vector Error Correction Models

According to corn VECM, there is a statistically significant long-run relationships between U.S. and Japanese corn prices for the year 2010-15 as indicated by cointegration coefficients shown in Table 3. 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 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 US-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 85 percent, and is therefore judged to be a leader in the price discovery process.

[7] 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).

The cointegration parameters for US-Chinese and US-Indian for cotton price pairs are likewise statistically significant, supporting the cointegration tests in table 2. The adjustment rates indicate that the when the U.S. cotton price is too high, it falls back to Chinese and Indian cotton prices, but only the average cotton price in 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. corn price is responsible for about 10 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 second biggest market for U.S. cotton, Chinese cotton futures prices do not follow U.S. price dynamics. This indicates that the Chinese domestic cotton policies could matter more to the change in Chinese cotton prices than the underlying economic fundamentals. On the other hand, U.S. cotton prices represent slightly more than 50 percent of the price discovery weight compared to Indian cotton prices, indicating that U.S. cotton prices are marginal leaders for that relationship.

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 relationship between U.S. and international prices are, in many cases, not stable. Quite distinct from the findings of our VECMs—which fit 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 US-Brazil (2-6 month level) and US-Japan (1.5-12 month level) are significantly correlated at lower frequencies, indicating a longer-run relationship. Moreover, phase arrows indicate that US returns lead those for Brazil and sometimes Japan at low frequencies (long run), but that at certain times—and at higher frequencies—international corn market shocks lead those measured in Chicago. Corn prices between the US and China bear no consistent relationship from 2010-present, however. This is unsurprising given the divergence between their price series displayed in figure 4a. Over the limited period they do display a coherence, between 2010-2011 (~1.5-3 month frequency) and 2011-2013 (3-6 month frequency), phase arrows point upwards and slightly upwards, respectively, indicating that Chinese corn shocks generated a response in US prices for a time.

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 ended quite abruptly by the beginning of 2013. This is clearest for US-Brazil, US-India, and US-South Africa, which displayed significant correlations at a range of frequencies that by the close of 2012. A similar finding is indicated by the U.S.-China pair. The US-Brazil and US-India for soybean price pairs are found to follow a long-run (12-month level) relationship over the entire period, but higher

frequency correlations ceased starting in 2013. Soybean prices in the US and South Africa exhibit a significant relationship between 2011 and the beginning of 2015, but the relationship ends there. U.S.-China and U.S.-Japan price pairs do not demonstrate consistent relationships across the period of interest, at any frequency. 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. Some additional evidence demonstrates that US returns lead those in Japan at a 1-2 month frequency in 2013.

Taken together, some of the corn and soybean 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.

Our cotton models show no consistent relationship between U.S. and Chinese market prices, as presented in figure 7. Price shocks between these countries do not translate at any level of frequency; their markets are not currently well-integrated. Some evidence of a long-run relationship (as well as a 2-3 month frequency coherence) terminates by the beginning of 2013. 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 2014-2015) medium-run correlations. This finding is supported by India becoming a recent export competitor for the U.S. markets. The weak evidence we find for price leadership between US and India in figure 7 basically matches our VECM results as shown in Table 3.

In Table 4, we displays Johansen trace test results 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 those periods with no long-run relationships between the U.S. and international prices identified using wavelet coherence analysis are also not cointegrated. Even though original Johansen statistics identified US-Japan for soybeans, and US-China for cotton, as price pairs that could be described by a VECM, 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 US-Brazil for soybean prices. 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 exporter of corn, and the VECM 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 US, 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 export 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 price pairs that one might expect (e.g., U.S. and Chinese corn and cotton).

Both the wavelet and cointegration models indicate that the US has a leading role in the Japanese corn and soybean markets, where the US is the major supplier of Japanese feed imports. In addition, both analyses reveal a peculiar characteristics of Chinese agricultural commodity prices and its interaction with the U.S. commodity prices. Even though China is the second biggest market for U.S. cotton, for instance, Chinese futures cotton prices do not necessary follow U.S. price dynamics. This indicates that Chinese domestic commodity policies do matter more in determining Chinese future prices than the underlying economic fundamentals.

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

Commodity	Market	Level	First difference
Corn			
	USA	-1.74 (2)	-28.73(1)***
	Brazil	-2.05 (3)	-20.73 (2) ***
	China	-0.91 (8)	-15.04 (7)***
	Japan	-1.93 (2)	-31.07 (1) ***
Soybean			
	USA	-2.01 (0)	-35.28 (0)***
	Brazil	-1.56 (8)	-9.65 (7)***
	China	-1.00 (3)	-22.36 (2)***
	Japan	-2.56 (0)	-37.25 (0)***
	India	-2.69 (8)	-9.36 (8) ***
	South Africa	-1.84 (0)	-22.15 (0)***
Cotton			
	USA	-2.78 (1)	-12.31(8) ***
	China	-1.56 (0)	-32.41 (0)***
	India	-2.36 (0)	-34.14 (0)***

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 = 8. *** 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	Not cointegrated
	USA-China	Not cointegrated
	USA-Japan	29.05*** (None)
Soybean		
	USA-Brazil	Not cointegrated
	USA-China	Not cointegrated
	USA-Japan	19.08** (None)
	USA-India	Not cointegrated
	USA-South Africa	Not cointegrated
Cotton		
	USA-China	13.72 *(None)
	USA-India	19.47**(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 $\Delta p_t = \alpha(\beta p_{t-1} + c) + \sum_{i=1}^{l} \pi_i \ \Delta p_{t-i} \ + \ \gamma \ + \ \epsilon_t$.

Table 3. VECM results

Cointegrating parameter, β, for USA market with			Adjustment rate, α, for USA market with		
			Corn		
	Japan			Japan	
USA_{t-1}	1.000		$\Delta\ USA_{t-1}$	-0.014* /69/ (0.008)	
$Japan_{t-1}$	-1.268*** (0.051)		$\Delta\ Japan_{t-1}$	0.031*** (0.007)	
			Soybean		
	Japan			Japan	
USA_{t-1}	1.000		USA_{t-1}	-0.003 /86/ (0.003)	
$Japan_{t-1}$	-1.238*** (0.161)		$\Delta\ Japan_{t-1}$	0.021*** (0.005)	
			Cotton		
	China	India		China	India
USA_{t-1}	1.000	1.000	$\Delta\ USA_{t-1}$	-0.020*** /10/ (0.005)	-0.016** /56/ (0.008)
$China_{t-1}$	-0.590*** (0.097)		$\Delta\ China_{t-1}$	0.002 (0.003)	
$India_{t-1}$		-1.088*** (0.090)	$\Delta\ India_{t-1}$		0.020*** (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. 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	Trace statistic for selected period
Corn				
	USA-Brazil	Not cointegrated		
	USA-China	Not cointegrated	2013-2014	Not cointegrated
	USA-Japan	29.05***		
Soybean				
	USA-Brazil	Not cointegrated		
	USA-China	Not cointegrated	2013-2015	Not cointegrated
	USA-Japan	19.08** (None)	2014-2016	Not cointegrated
	USA-India	Not cointegrated		
	USA-South Africa	Not cointegrated		
Cotton				
	USA-China	13.72 *	2013-2015	Not cointegrated
	USA-India	19.47**		

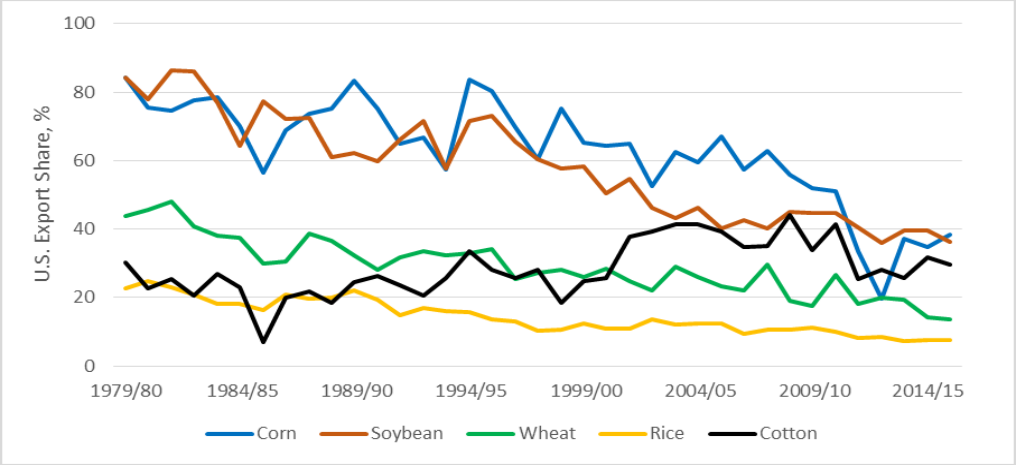
Note: *, **, and *** denote rejection of the null hypothesis at the 0.1, 0.05, and 0.01 level, respectively, based on Mackinnon-Haug-Michelis (1995). The cointegration test includes a linear deterministic trend.

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	2010-13	14.11*	37
	USA-China	2009-13	15.70**	67
	USA-Japan [#]	2011-13	19.50**	100
Soybean				
	USA-Brazil	2011-13	Not cointegrated	N/A
	USA-China	2011-12	14.15*	58
	USA-Japan[#]	2011-13	22.39***	90
	USA-India	2011-13	22.20***	32
	USA-South Africa	2011-13	14.80*	65
Cotton				
	USA-China[#]	2011-13	17.95**	26
	USA-India[#]	2012-14	28.27***	70

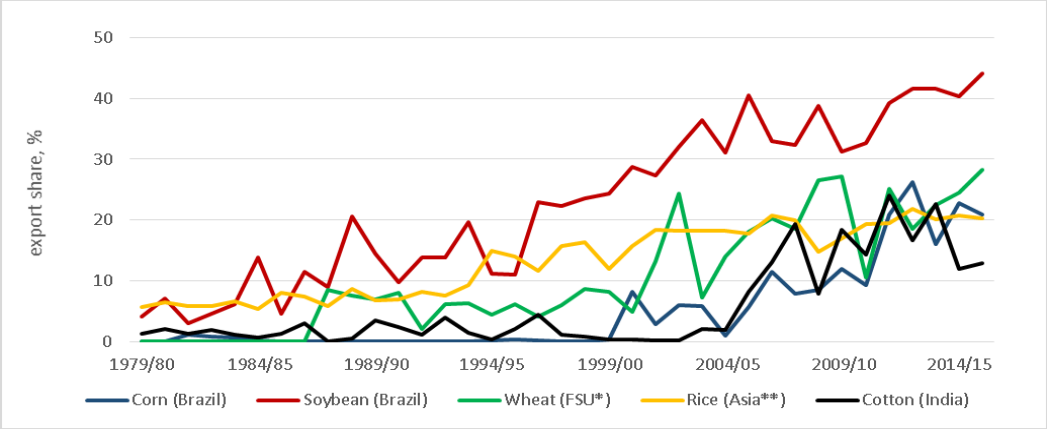
Note: *, **, and *** denote rejection of the null hypothesis at the 0.1, 0.05, and 0.01 level, respectively, based on Mackinnon-Haug-Michelis (1995). The cointegration test includes a linear deterministic trend. [#n] These are also cointegrated in whole period analysis as shown in Table 4. N/A not applied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

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



Source: USDA/ERS (2016a)

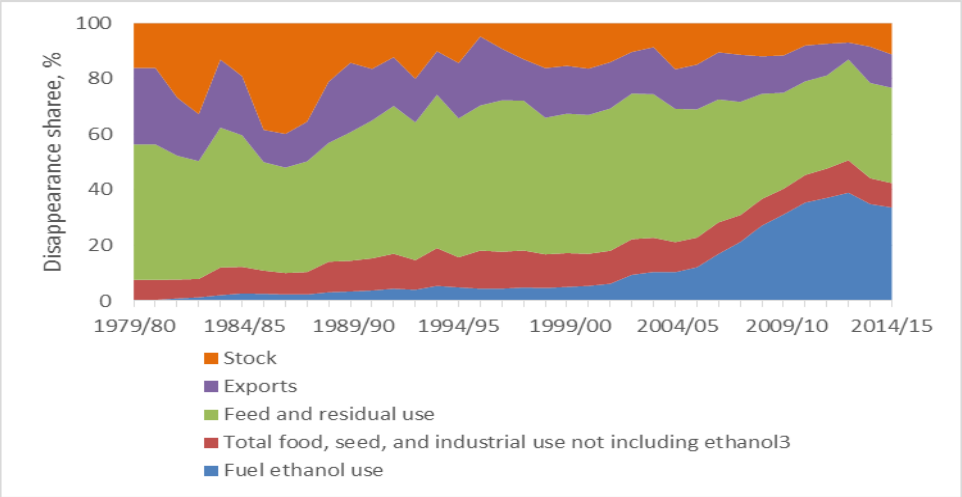
Figure 2. Export market share for selected commodities and countries, 1980-2015



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 4a. Normalized corn price, Feb. 2012=100

Figure 4b. Normalized soybean price, Feb. 2012=100

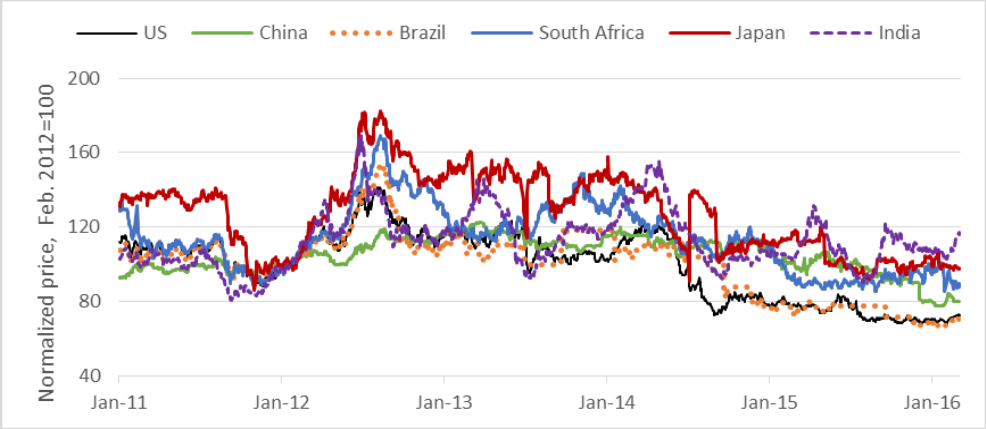
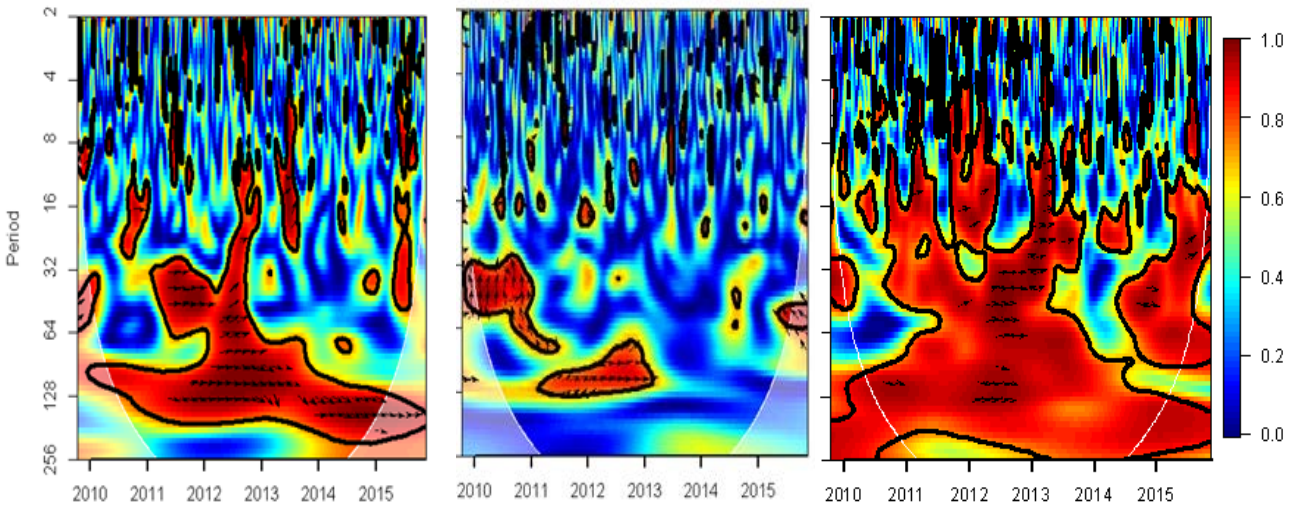


Figure 4b. Normalized soybean price, Feb. 2012=100

Figure 5. Wavelets results for international corn market integration, 2010-2015

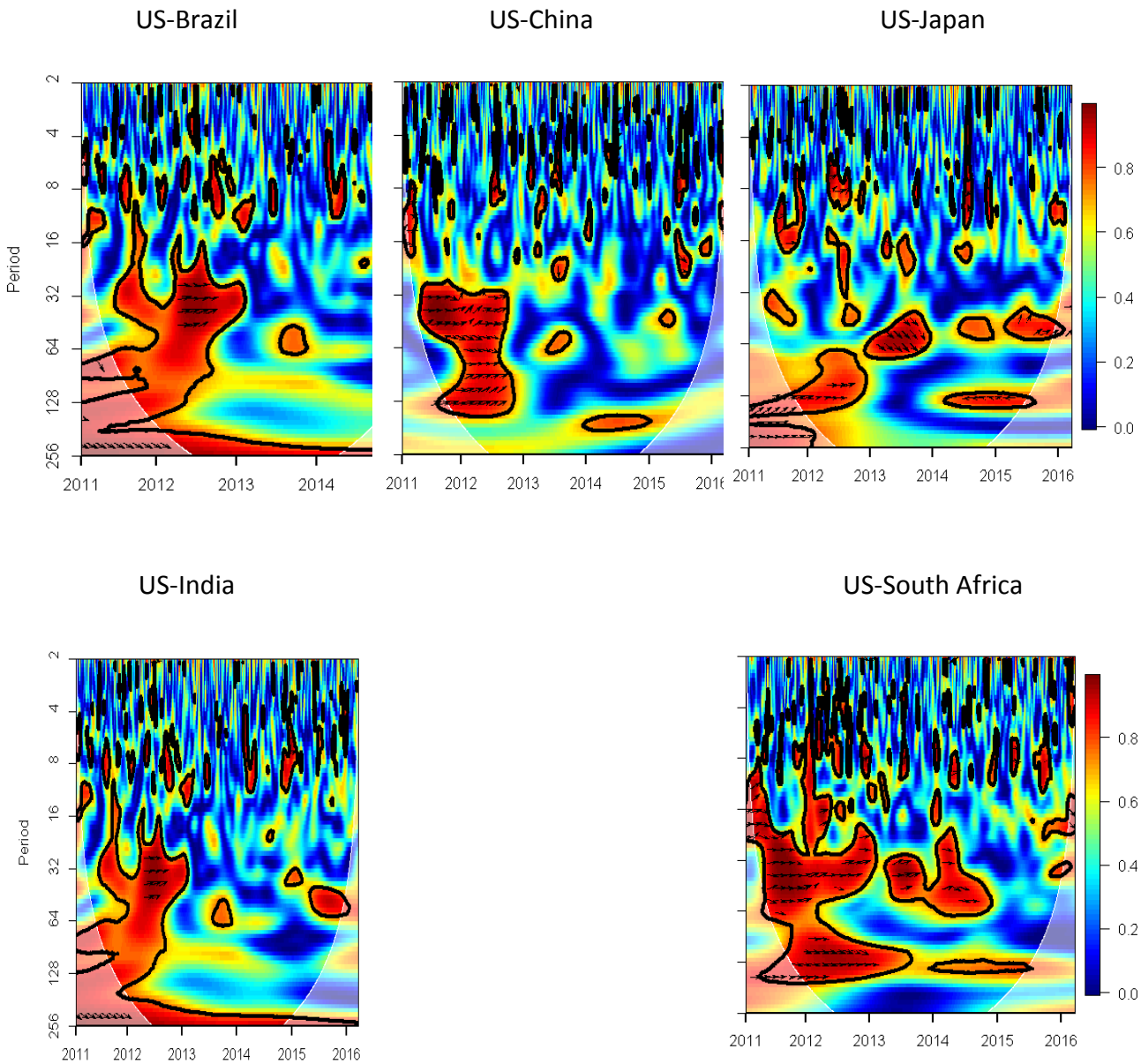
US-Brazil US-China US-Japan



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 stronger 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.

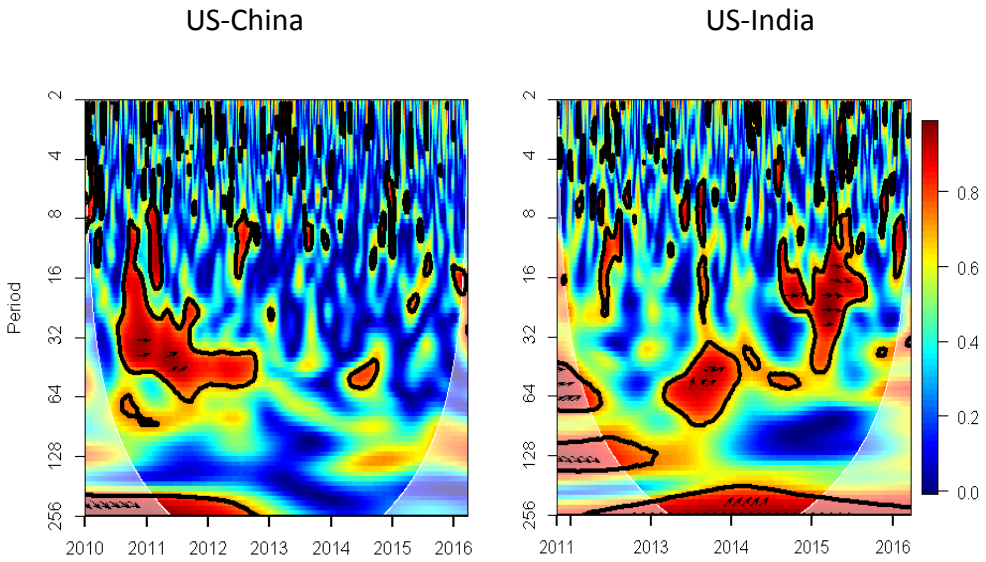
Figure 6. Wavelets results for international soybean market integration, 2011-2016

Soybean



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 stronger 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. soybean price leads the trading partner's price.

Figure 7. Wavelets results for international cotton market integration, 2010-2016



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 stronger 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. cotton price leads the trading partner's price.