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Modelling Regime-Dependent Price Volatility Transmissions Between China and U.S. Agricultural Markets: A Normal Mixture Bivariate GARCH Approach

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Abstract

Agricultural trade amongst and between the United States and China dominates world markets and has been complicated by rapid growth, significant changes in domestic farm policy, intermittent periods of considerable volatility, and, most recently, trade tensions. It is unlikely that a single GARCH process can adequately accommodate this vacillation. Not surprisingly, past literature has shown conflicting results depending on the period considered. We use mixture methods which let the data define the number of possibly heterogeneous volatility regimes. We model the price volatility transmissions for five commodities: soybeans, wheat, corn, sugar, and cotton. Specifically, we estimate, test, and find the presence of multiple regimes using a normal mixture multivariate GARCH model. We identify different economic structures across the regimes. While we find that the U.S. tends to play a leading role over China in terms of spillover effects, when the market state is unstable or highly volatile, we tend to find greater bidirectional volatility spillovers. Most importantly, we show that the standard approach of modelling spillover volatilities as a single regime is not valid.

Key Words: mixture models, multivariate GARCH, volatility transmission
JEL *Classification*: G17, Q14

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1 Introduction

Agricultural trade between the United States and China comes with complications: rapid growth, trade tensions and intermittent periods of considerable volatility. China and the U.S. are the world's two dominant food-producing countries which dominate international food trade. In an era where economies are closely related through trade, investments, and market integration, volatility transmission across borders is vital for understanding the causes, patterns, impacts of price volatility, and measures available to mitigate the problems associated with this volatility. Since China's 2001 accession to the World Trade Organization (WTO), both markets have become more integrated, which has lead to closer pricing relationships and the potential that price volatility can be transmitted between markets.

Price volatility — or the variability of prices around a central tendency — has been measured, decomposed, and predicted with a number of different approaches. Volatility transmission between markets is frequently measured with a Multivariate Generalized Autoregressive Conditional Heteroskedastic (MGARCH) model (Assefa, Meuwissen, and Oude Lansink, 2015). Understanding the source and direction of price volatility flows is important for all sectors of the economy. The risk associated with the volatility affects investment decisions, reduces supply response and food consumption, and impacts the welfare of households (Naylor and Falcon, 2010). Moreover, price volatility may have a negative impact on growth and thereby contribute to increased poverty (Ramey and Ramey, 1995). Finally, food price volatility causes planning problems for policy makers and is disruptive to the food supply chain.

Understanding the trading relationship between China and the U.S. is particularly informative in understanding the formation and transmission of volatility. Rapid initial trade growth in the years immediately following WTO accession increased U.S. agricultural exports from $3 billion to more than $9.5 billion in 2007 (FAS-USDA, 2019). This rapid growth was followed by agricultural price surges from 2006 to 2008. Trade continued to grow and peaked at $29.4 billion in 2012, again adding pressure to agricultural prices. Rapid trade growth leads to not only price surges but also trade tensions. After China became the U.S.'s top agricultural export market outside of North America in 2009, a number of trade disputes began to develop. In that year, China initiated an anti-dumping investigation of U.S. broiler chicken products. In 2018, in reaction to U.S. trade actions against solar panels and washing machines, China responded by initiating an anti-dumping investigation on U.S. sorghum. These minor skirmishes, driven by concerns about hidden subsidies and theft of intellectual property, resulted in disputes that evolved into a trade war. In the summer of 2018, President Trump followed through on threats to impose sweeping tariffs on China. The resulting showdown between the world's two biggest economics resulted in a tit-for-tat game of escalation, with China imposing tariffs on soybeans, beef, pork, fruits, and whiskey. A December trade truce failed to find a resolution and, by May 2019, a new round of tariffs was imposed. Shocks associated with prohibitive tariffs or border closures stifle price transmission, make supply and demand more inelastic, and, in turn, increase volatility (Rude and An, 2015). The interaction between these shocks creates complex dynamics in the transmission of volatilities, with unobservable states of the market complicating the measurement of the evolution of risk.

Previous research has assumed a single state of volatility interactions despite the changing nature of the trading relationship. In general, this research has found spillovers into China originating from the U.S. market (see Jiang et al. (2017) for a review). Exceptions include Jiang et al. (2017), who found bidirectional volatility transmission for wheat and sugar over the period 2005 to 2016, and Hernandez, Ibarra, and Trupkin (2014), who found bidirectional cross-volatility spillovers for daily soybean futures from 2004 to 2009. However, with the rapid development and growing importance of China in global agricultural markets and the volatile nature of the trading relationship between China and the U.S., the pricing relationship may very well be state-dependent. The objective of this manuscript is to estimate and test for the existence of multiple regimes using a mixture of multivariate GARCH models. The normal mixture univariate GARCH model, unlike standard GARCH models, explicitly allows the evolution of risk to depend on unobservable states of the market. This model was applied to U.S. agricultural commodity prices and was found to better capture the underlying volatility dynamics (Li et al., 2017). In terms of mixtures of multivariate GARCH processes, the multivariate innovation term is assumed to follow a mixture of joint normals, each having a regime-specific conditional variance–covariance structure.

Bauwens, Hafner, and Rombouts (2007), and Haas, Mittnik, and Paolella (2009) use this computationally intensive approach to examine financial markets.

In this manuscript, we test if normal mixtures of multivariate GARCH processes improve the measurement of the direction and magnitude of bilateral volatility spillovers for agricultural daily nearby futures prices between Chinese and the U.S.. A normal mixture GARCH model has the flexibility of allowing for more than one multivariate GARCH component. This flexibility can improve the model performance by allowing time-varying conditional skewness and kurtosis. Furthermore, this flexibility makes it easy to understand the interdependence of agricultural futures markets at different market states, such as a usual state with low to moderate price movement and a "crisis" state with high price volatility.[1] The study spans the period from 2004 to 2018, focusing on five key agricultural commodities: soybeans, wheat, corn, sugar, and cotton. This manuscript makes two contributions to the literature. First, the normal mixture multivariate GARCH model offers a more complete examination of possibly regime-dependent volatility spillovers and cross-market dependence between the U.S. and Chinese futures markets. Second, this manuscript is the first empirical application to use formal statistical criteria to evaluate the goodness-of-fit of the normal mixture multivariate GARCH model in comparison to the standard one-component GARCH model.

The structure of the paper is as follows. Section 2 addresses the market background of the commodities of interest, along with the literature on volatility spillovers between the U.S. and China for those commodities. Section 3 presents the empirical approach while section 4 outlines the data. Diagnostic testing results are reported in section 5. The empirical results are discussed in Section 6. Section 7 presents our conclusions.

[1] Moreover, the normal mixture approach can be considered a simplified version of the Markov switching GARCH model of Haas and Liu (2018) by assuming constant state probabilities. This simplification avoids the problem of path-independent conditional variance and makes estimation easier than with the Markov switching approach (refer to Alexander and Lazar (2009) for a discussion of the comparison of normal mixture and Markov switching GARCH models in the univariate setting).

2 U.S.-China Trade

U.S.-China agricultural trade has grown dramatically since China joined the WTO, and the two countries have become key trading partners in agricultural products. However, the trading relationship between the two countries has evolved through time. Since 2012, China has become the predominant market for U.S. agricultural exports. China imported 16% of the total value of U.S. agricultural exports in 2016 (Hansen et al., 2017). The annual total exports of agricultural products to China, however, plunged dramatically after China imposed retaliatory tariffs, from \$21.6 billion in 2016 to \$9.3 billion in 2018, a level 24% less than 2008.

As reported by the Office of the United States Trade Representative (USTR, 2018), soybeans and cotton are among the leading export categories from the U.S. to China. Largely due to its expanding demand for livestock feed, China is now the world's largest soybean importer, while the U.S. is the largest soybean producing and exporting country. Calculated with data from Food and Agriculture Organization of the United Nations (FAO), on average, U.S. exports accounted for around 40% of China soybean imports between 2004-2016. Studies generally consistently demonstrated volatility spillovers from the U.S. to the Chinese agricultural futures market, but more recently, a few (e.g. Han, Liang, and Tang (2013); Hernandez, Ibarra, and Trupkin (2014)) have found that the volatility spillovers could be bidirectional.

As for cotton, in addition to being a major importer, China is the largest textile producing and exporting country. In 2017, Chinese textile exports accounted for 37.2% of the global market share (WTO, 2018). In the same year, China bought approximately 16% of U.S. cotton exports (Liu, Robinson, and Shurley, 2018). Among the limited research on the interrelation between U.S. and Chinese cotton futures markets, Liu (2009) found bidirectional volatility spillover, whereas Ge, Wang, and Ahn (2010) found mutual price transmissions.

Unlike the soybean and cotton markets, as the largest global producer of wheat and second largest producer of corn, China imports only a small portion of overall domestic consumption (USDA, 2019). Between 2000 and 2014, the U.S. exported about 30% and 80% of the total Chinese wheat and corn imports, respectively. In recent years, however, the U.S. exports to China have dropped considerably given issues related to the use of genetically modified seed that was not yet approved in China. Beginning in 2014, Ukraine replaced the U.S. as the major exporter of corn to China (Hansen et al., 2017). Empirical results regarding the interaction between the U.S. and China for wheat and corn are divergent. Using price data between 1998 and 2001, Hua and Chen (2007) found no significant linkage between the U.S. and China's wheat futures prices, while another study on wheat covering the period 1996 to 2001 documented bidirectional volatility spillover (Fung, Leung, and Xu, 2003). For both wheat and corn, Hernandez, Ibarra, and Trupkin (2014) found unidirectional volatility spillover from the U.S. to China, while Jiang et al. (2017) found significant bidirectional volatility spillover between the two markets. Not surprisingly, the time frame matters significantly, as volatility spillovers can change as market structures change. This represents one of the primary contributions of our manuscript, as we formally test for the possibility of changing volatility spillover structures.

China is the top importer of raw sugar, while the U.S. ranks third (USDA, 2018). While there is not much trade of sugar between the two countries, significant bidirectional volatility transmission was detected for the period spanning 2006 to 2016 (Jiang et al., 2017). They found the volatility spillover from the U.S. to China was only significant in the sub-sample between 2012-2016, while the impact from China to the U.S. was only significant during the global financial crisis period (2008-2011). Again, the changing structure of the market dynamics is not surprising and can be modelled with a mixture of possibly different bivariate GARCH processes.

Another driver of volatility regimes and market dynamics is Chinese government pricing policies (Yu, 2017). China's price intervention policies have changed over the estimation period. The basic instrument involves minimum procurement prices that ensure a price floor where government intervention purchases are triggered when market prices fall below pre-established levels. China's domestic price policies typically differ from commodity to commodity and the process of policy reform also varied across time. First in 2015, China replaced intervention procurement prices, for cotton and soybeans, with a new system of target prices where the target is achieved as a combination of market prices and deficiency payments. In 2016 corn procurement and intervention prices were replaced by market prices and direct subsidies. At the end of 2017 China reduced wheat minimum procurement prices for the first time on over a decade. Again these market and policy dynamics can be modelled with a mixture of possible different bivariate GARCH processes.

3 Normal Mixture Multivariate GARCH Model

To examine the interdependence and volatility transmission across agricultural futures markets between the U.S. and China, we estimate normal mixture bivariate GARCH models. The two-dimensional time series innovation, denoted by the random error vector ε_t, is assumed to follow a mixture of k-component joint normals:

$$\varepsilon_t|\Omega_{t-1} \sim \text{MNM}(p_1, \ldots, p_k, \mu_1, \ldots, \mu_k, \text{H}_{1t}, \ldots, \text{H}_{kt}),$$

where Ω_t is the information set at time t, and $p_i \in (0, 1)$, $i = 1, \ldots, k$ are the mixing weights for the components characterized by the joint density $\phi(\varepsilon_t|\mu_i, \text{H}_{it})$. Note that $\sum_{i=1}^{k} p_i = 1$ and we impose that $\sum_{i=1}^{k} p_i\mu_i = 0$ to ensure that ε_t has zero mean. As is commonly done, we additionally assume that the density of each component is symmetric with mean 0 for parsimony of the mixture model.

We follow Haas, Mittnik, and Paolella (2009) and Chung (2009) to apply the BEKK-GARCH approach of Engle and Kroner (1995) to specify the conditional variance–covariance matrix, H_{it} for each component i. The BEKK model is attractive since it is flexible enough to account for, in detail, the direction, magnitude of own- and cross-volatility spillover caused by market shocks (past negative or positive innovations), and persistence of volatility. In addition, this specification guarantees the positive definiteness of all estimated conditional covariance matrices. The bivariate BEKK-GARCH(1,1) component can be written as follows:

$$\text{H}_{it} = \text{C}_i\text{C}_i' + \text{A}_i\varepsilon_{t-1}\varepsilon_{t-1}'\text{A}_i' + \text{B}_i\text{H}_{it-1}\text{B}_i' \qquad \text{for } i = 1, \ldots, k, \tag{1}$$

where $\text{C}_i, i = 1, \ldots, k$ are 2×2 lower-triangular matrices with elements $c_{rj,i}$; the elements $a_{rj,i}$ of the 2×2 matrix A_i measure the *spillover effect* of a price change in market j on the conditional volatility of market r under component i, and the elements $b_{rj,i}$ of the 2×2 matrix B_i measures the direct dependence of the conditional volatility in market r on past volatility of market j (*persistence effect*).

We use Schwarz's Bayesian criterion (SBC) (Schwarz et al., 1978) to select the appropriate order M of the vector autoregression (VAR) model for log returns at time t, specified as follows:

$$Q_t = \gamma_0 + \sum_{q=1}^{M} \gamma_q Q_{t-q} + \varepsilon_t, \tag{2}$$

where $Q_t = log(P_t)/log(P_{t-1})) * 100$ is the vector of the logarithmic return expressed in percentages for the two markets, and γ_0 is a vector of constants. Finally, we estimate the bivariate NM-GARCH model using the expectation-maximization (EM) algorithm of Dempster, Laird, and Rubin (1977) with multiple starting values.

4 Data

We use daily closing prices of nearby futures contracts on soybean, wheat, corn, sugar, and cotton. For China, we use data from the Dalian Commodity Exchange (DCE) and the Zhengzhou Commodity Exchange (CZCE). For the U.S. we use data from the Chicago Board of Trade (CBOT) and the New York Mercantile Exchange (NYMEX). The data were obtained from the Commodity Research Bureau of Barchart.com. To account for the potential impact of the exchange rate on market interdependence and volatility transmission between markets, we converted all prices to U.S. dollars.

Given that the Chinese agricultural futures market is relatively new, for each commodity we choose the time intervals for which data for both markets are available. The end date of the sample is September 28, 2018, for all commodities. Among the five commodities considered, soybean futures have the largest sample size (T=3390), whereas wheat has the shortest sample period (T=1459). Table 1 presents descriptive statistics of the series of log returns. As shown, the average daily returns for soybean, corn, and cotton in both China and the U.S. are positive, while the average daily return for wheat is negative in both countries. Interestingly, the mean returns of the sugar futures have opposite directions in the two countries: negative in the United States (-0.010%), positive in China (0.005%). For each of the five agricultural commodities, it is evident that the U.S. futures market is more volatile than that of China. The covariance matrices indicate the two markets exhibit small correlation. Returns of all series exhibit skewness, with the exception of China's sugar. Excess kurtosis exists in all markets, indicating leptokurtic distributions.

[Table 1 about here]

Figure 1 shows the standardized price levels (divided by their own means) for each commodity in U.S. and China exchanges. While the price movement of soybeans, wheat, and cotton appear similar, the prices of corn and sugar appear to be less correlated. Over the sample, there are three price spikes: the first happened from January 2007 to December 2008, the second from December 2010 to December 2012, and the latest in 2017. The volatility of prices also varies over time and between the two markets.

[Figure 1 about here]

5 Diagnostic Checks

To assess the fit provided by the proposed model in relation to the usual MGARCH model, we apply several criteria. First, we report the Bayesian information criterion (BIC) of each model. Second, we test for the unconditional distributional fit of the model-simulated data against the original data. To maintain the precision of the simulated density, we use 50,000 replications to simulate returns based on the estimated parameters. For each simulation, 1,001 trials of ε values were generated. We only use the last simulated return while discard the results of the first 1,000 steps of prediction of each simulation to ensure that the returns are robust to starting values. Third, we perform two-dimensional Kolmogorov–Smirnov (KS) test generalized by Peacock (1983) with an efficient algorithm proposed by Xiao (2017).

In addition to the above, we apply a series of tests to check the distributional properties of the standardized residuals of the two models. As the standardized residuals of a mixture model would not be identically distributed even if the model were correctly specified, we proceed with a transformation previously applied to a univariate normal mixture-GARCH model testing by Haas, Mittnik, and Paolella (2004), Alexander and Lazar (2009), and Li et al. (2017). Specifically,

$$z_t = \Phi^{-1}\left(\hat{F}(\varepsilon_t|\Omega_{t-1})\right), \tag{3}$$

where Φ^{-1} is the inverse normal probability distribution function and $\hat{F}(\cdot)$ is the conditional cumulative distribution function of the error vector ε_t. Since $\hat{F}(\varepsilon_t|\Omega_{t-1})$ returns the cumulative probability, we project the original two-dimensional residuals to a series of one-dimensional random variables. The transformed residuals z_t's should be independently and identically distributed standard normal, provided that the model correctly specifies the underlying data generating process. As shown by Berkowitz (2001), inaccuracies in the specified density will be preserved in the transformed residuals. Therefore, in principle, one can use Equation (3) to check correct specification of moment features such as skewness and kurtosis. Specifically, if z_t's are normally distributed, then we use the following test statistics $m_1 = Tg_1^2/6$ and $m_2 = T(g_2 - 3)^2/24$, where T is the sample size, g_1 denotes the sample skewness of z_t and g_2 the sample kurtosis, and both m_1 and m_2 are $\chi^2(1)$ distributed under the null.

We also test the normality and serial correlation in the transformed series z_t. To check the normality, we implemented the Jarque and Bera (1987) (JB) test ($JB = m_1 + m_2 \overset{asy}{\sim} \chi^2(2)$), and the energy-test of normality proposed by Székely and Rizzo (2005), which was shown to be very sensitive against heavy-tailed alternatives. The energy test statistic is based on Euclidean distance between sample moments. The stationary bootstrap of Politis and Romano (1994) with 10,000 replicates is used to construct the p-values of the energy test. The block length of the stationary bootstrapping was randomly chosen from a geometric distribution with mean 20. To test if the conditional volatility is accurately captured by the specified model, we use the Lagrange Multiplier ARCH test of Engle (1982) to fit a linear regression model for the squared transformed residuals and examine joint significance.

Table 2 reports the results of the diagnostic tests. The NM-MGARCH model is always preferred over the usual MGARCH model when using the BIC criterion. Moreover, the improvement of the NM-MGARCH model is considerable. As for the unconditional density fit, neither model passed the bivaraite KS test for any commodity. However, the smaller test statistics showed a clear preference for the NM-MGARCH models. Tests based on transformed residuals also confirmed better performance of NM-MGARCH model. While both models passed the energy test, the NM-MGARCH model always reported substantial smaller statistics suggestig a much better fit. Furthermore, the one component MGARCH model failed every single one of the skewness, kurtosis, JB normality, and Engle's ARCH tests. Conversely, the NM-MGARCH model passed the skewness test for all commodities except cotton. The NM-MGARCH model also passed the kurtosis test and JB normality test for corn. Most importantly, for tests that both models failed, the NM-MGARCH always had much smaller statistics, indicating a better fit.

[Table 2 about here]

In summary, our results indicate that an NM-MGARCH model fits much better than the generic MGARCH model. The outcome reflects the fact that the normal mixture models have additional flexibility. The NM-MGARCH model can capture time-varying skewness and kurtosis and the possibility that the heteroskedasticity generating process is driven by more than one GARCH component.

6 Estimation Results

Table 3 reports the estimated parameter matrices and standard errors of the parameters. As expected, the NM-MGARCH model identifies two regimes with distinctly different volatility dynamics. The unconditional covariance matrix for each regime (H_i) is in Table 3. For wheat, corn, and sugar, the NM-MGARCH model captures a highly unbalanced occurrence of the two market regimes. The lower probability market regime (regime 1) occurs, respectively, 29.5%, 10.1%, and 13.9% of the time. Conversely, for soybean and cotton, the occurrence of the two market regimes was close to even over time. Regime 1 (lower occurrence) and 2 (higher occurrence) are featured by high- and low-volatility, respectively, except for the cotton market where high-volatility regime occurred slightly more frequently (51.7%). Another observation is that, except for cotton, the correlations between the U.S. market and Chinese market are greater during turbulent markets, i.e., in the high-volatility market. This result is similar to the case of the return of stock market index as investigated by Haas, Mittnik, and Paolella (2009). Note that these effects cannot be accommodated by the traditional multivariate GARCH model. As for the cross-effects between markets, the estimated off-diagonal coefficients in table 3 identify direct spillover (a_{rj}) and persistence or dependence (b_{rj}) effects.

[Table 3 about here]

For soybean, the unconditional volatility in regime 1 is double and triple that in regime 2 for the U.S. market and Chinese market, respectively. We find significant volatility spillovers from price shocks originating in the U.S. soybean market to that of China in both the low-volatility and the high-volatility market regimes. In addition, we find significant direct dependence of the conditional volatility in China on that of the U.S. in the high-volatile market regime. Though volatility transmission happened in both regimes, the magnitudes are very different. For example, the magnitude of the persistence effect that occurred in the volatile state ($0.526, SE = 0.022$) is significantly bigger than that in the low-volatility state ($0.138, SE = 0.027$). While these findings confirm volatility spillover from the U.S. to China for soybean futures (consistent with the literature see Jiang et al. (2017) for a review), these results also suggest, the cross-market interdependence of volatility increases during turbulent market regime, a phenomena found in major stock markets (see Kasch and Caporin (2013), among others). Such dynamics of the conditional variances cannot be uncovered by a simple single component or the usual bivariate model, where the estimates (see Appendix) show significant volatility spillover from the U.S. to China and bidirectional cross-market volatility persistence. Not surprisingly, the magnitude of volatility spillover is higher than that in the low-volatility regime and lower than the estimate in the high-volatility regime. The magnitude of volatility dependence of China on the U.S. is also in-between those in the low- and high-volatility regimes.

The marginal difference in the volatility of wheat between regimes is much greater in China than in the U.S.. We find the cross-market conditional volatility dependency of the U.S. on China in the wheat market only occurring in the low-volatility market regime (the usual market regime). The mean magnitude of cross-market dependency is substantial but with a very wide confidence interval (0.757, SE=0.229). We also find that the conditional volatility of China dependence on that of the U.S. mildly statistically significant but economically negligible in magnitude (-0.094, SE=0.056). Although any volatility spillovers are surprising given the lack of wheat trade, volatility spillovers from China to the U.S. were also documented in Fung, Leung, and Xu (2003) and Jiang et al. (2017). Moreover, based on a sample spanning from 2005 to 2009, Hernandez, Ibarra, and Trupkin (2014) found unidirectional volatility spillover from the U.S. to China.

For corn, the magnitude of between-regime difference in volatility is large both in the U.S. market and in China. The volatility of the high-volatility component is nearly 6 times that of the low-volatility component in China, while the ratio is around 2.5 for the U.S.. We find, the volatility of corn futures prices in China's market was affected by past volatility in the U.S. market during both high-volatility and low-volatility states. The magnitude of the persistence effect, was again, much stronger in high-volatility state. In fact, the magnitude of cross-market volatility persistence in the low-volatility (usual) regime, though significantly different from zero, is economically very small (-0.244, SE=0.028). This makes sense in that imports only account for a very small percentage of corn consumption in China (Jiang et al., 2017). In addition, we observe bidirectional volatility spillovers between the two markets during the high-volatility regime. Considering that the low-volatility regime occurred most of the time, we can conclude that for corn the volatility transmission is mostly unidirectional flowing from U.S. to China except in a crisis where the spillover is bidirectional. This finding provides a more complete picture than the finding using the traditional multivariate GARCH model (results shown in Appendix), where only the overall bidirectional volatility spillover and persistence effects were captured. Note, the unidirectional volatility spillover for corn was also documented in Hernandez, Ibarra, and Trupkin (2014), while Jiang et al. (2017) found the bidirectional spillover between the two countries.

For sugar, the volatility in the high-volatility regime is over 2 times and around 3.5 times as high as in the low-volatility regime, in the U.S. and China, respectively. We found significant volatility spillover to the U.S. market from a shock originating in China and significant dependence of volatility in the China's market on that of the U.S.. However, both are small in magnitude and only occurred under the low-volatility (the usual) regime. The estimates of standard multivariate GARCH model suggest no significant volatility spillover between the two markets, while the volatility persistence effects are bidirectional but economically negligible in magnitude. Our finding of bidirectional volatility transmission between the two countries is consistent with Jiang et al. (2017). While China and U.S. trade very little sugar, China is among the leading consumers of sugar in the world. Considering, China's markets are highly regulated and that China imports a substantial amount of sugar from global growers, it is not surprising that the price decrease of sugar in 2018 and the subsequent tariff increase of China (Patton and Gu, 2018) would affect the international and U.S. markets.

Regarding cotton, for both the U.S. and China, the high-volatility regime is about 3 times as high as the low-volatility regime. Different bidirectional volatility transmission was found between the regimes. Significant dependence of volatility in the U.S. market on that of China was found in the low-volatility regime, while significant volatility spillover from the U.S. market to China was found in the high-volatility regime. All of those effects were small in magnitude except for the volatility spillover from the U.S. to China in the high-volatility regime (-0.708, SE=0.046). The estimates from the standard multivariate GARCH model suggest significant bidirectional volatility spillover and persistence between the two markets; the magnitude is negligible except for the volatility dependence of the U.S. on China (-0.326, SE=0.082). The spillover from China to the U.S. may be due to the fact that China is a major importer of cotton and the largest textile producing and exporting country. The substantially smaller magnitude may be due to the fact that China's cotton imports from the U.S. took up only a small proportion of U.S. cotton exports (Liu, Robinson, and Shurley, 2018). The research on volatility spillover between China and the U.S. is very limited, among which Liu (2009) also found bidirectional volatility spillover between the two markets.

Finally, we conducted Wald tests for pairwise equality of all cross-volatility coefficients in both market regimes, reported in the last row of table 3. These tests confirm distinct cross-market volatility transmissions under the two regimes. In all five commodities, we rejected the null hypothesis that the off-diagonal coefficients a_{rj} and b_rj are equal across components/regimes. In summary, our results reveal a number of interesting findings: (i) volatility spillovers are regime-dependent; (ii) our results are consistent with previous literature and, at the same time, explain previously incongruent empirical results; (iii) volatility spillovers tend to flow unidirectionally from the U.S. to China; and (iv) when market regime is highly volatile, cross-border volatility spillover and dependence tends to be larger and bidirectional.

7 Conclusion

While there is substantial literature on the transmission of commodity price volatility across countries, there is no research that addresses how this transmission changes as market and policy regimes change. We attempt to remedy this deficiency by applying a multivariate normal mixture GARCH model. The advantage of this approach is that it maintains the simple structure of a multivariate GARCH model but mixes components of normal distributions to accommodate the possibility of regime-specific covariance structure between markets. The model gives rise to rich dynamics, including time-varying skewness and kurtosis which would not be encountered, other GARCH models driven by innovations from fat-tailed asymmetric distributions. This approach allows us to measure the transmission of volatility for major agricultural prices across the two most important markets which are adjusting to an evolving relationship that is fraught with increasing tensions at the same time that each becomes more important to the other.

The most important finding is that while other studies have found spillovers that are transmitted from the U.S. to China, we find that as events change the marketing regime, the direction that the volatility flows changes. For most agricultural products, the U.S. is viewed as the market maker and volatility is transmitted from that market. However, China‘s increased importance changes the dynamics of pricing relationships. Changes in regimes affect the direction of the spillover from unidirectional to shared bidirectional. When markets become less stable highly volatile, they become highly interrelated and there are significant bidirectional volatility spillovers. Bidirectional flows reflect a more equal role in determining market disturbances and market power. We performed a battery of tests on the existence of regime specific volatility spillovers. The results overwhelmingly favored the multiple regime model over the standard MGARCH model. We also found that the probability of changing price transmission regimes is higher for soybeans and cotton than for sugar, corn, and wheat. For both soybeans and cotton, the U.S is the most important exporter and

China is the most important importer. However, while the U.S is the dominant exporter of corn and wheat, China is not a significant importer of these products. Furthermore, neither country exports sugar, and because TRQs insulate each market, their imports play a small role in international price volatility, so there is a smaller probability of regime shift.

The findings of this study are subject to several limitations. First, by only considering two normal distributions, we only allow for the possibility of two types of regimes. Second, we only make bilateral comparisons. Increasing the dimensionality of the model would be more realistic, but it would come at a cost of increased complexity with significantly more parameters and more complex interpretations. Certainly, China and the U.S. dominate agricultural commodity markets, and adjustments in these markets are fundamental to international price formation.

Price volatility remains a concern for policy makers, analysts, and the general public. The relationship between China and the U.S. is central to the policy debate and fundamental to understanding how markets will evolve under stress. Given that the two countries have not been able to reach a negotiated resolution to the current trade war, the transmission and amplification of shocks will have long-term implications for risk management policies.

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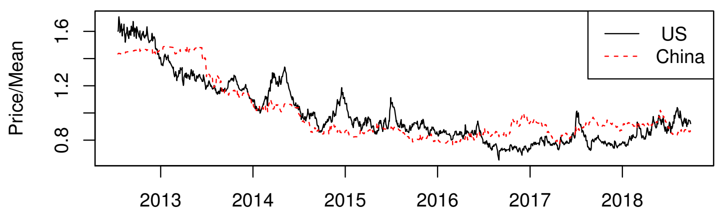
Table 1: Descriptive statistics of daily returns

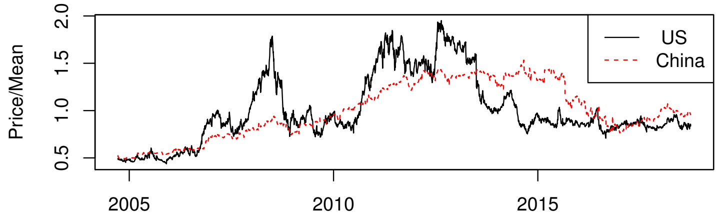
Futures	Market	Sample period	Sample Size	Mean	Covariance matrix	Skewness	Excess Kurtosis
Soybean	CBOT DCE	01/02/2004– 09/28/2018	3,390	0.002 0.008	$\begin{pmatrix} 3.007 & 0.401 \\ 0.401 & 1.283 \end{pmatrix}$	-1.386*** 0.100**	14.048*** 15.167***
Wheat	CBOT CZCE	07/16/2012– 09/28/2018	1,459	-0.038 -0.034	$\begin{pmatrix} 3.223 & 0.087 \\ 0.087 & 1.162 \end{pmatrix}$	0.483*** -0.114*	2.165*** 9.497***
Corn	CBOT DCE	09/22/2004– 09/28/2018	3,239	0.016 0.019	$\begin{pmatrix} 4.000 & 0.152 \\ 0.152 & 1.098 \end{pmatrix}$	-1.032*** -1.458***	15.906*** 53.394***
Sugar	NYBOT CZCE	01/06/2006– 09/28/2018	2,946	-0.010 0.005	$\begin{pmatrix} 4.976 & 0.305 \\ 0.305 & 1.434 \end{pmatrix}$	-0.263*** -0.024	7.124*** 12.101***
Cotton	NYBOT CZCE	05/09/2005– 9/28/2018	3,099	0.011 0.008	$\begin{pmatrix} 3.763 & 0.415 \\ 0.415 & 1.086 \end{pmatrix}$	-0.962*** -1.366***	14.964*** 31.872***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

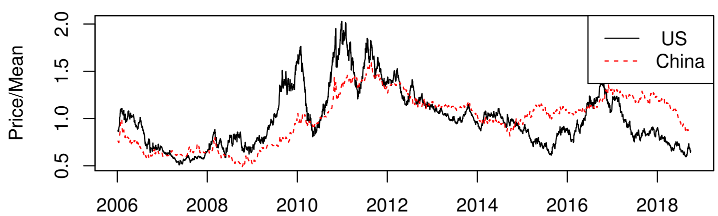
(a) Soybean



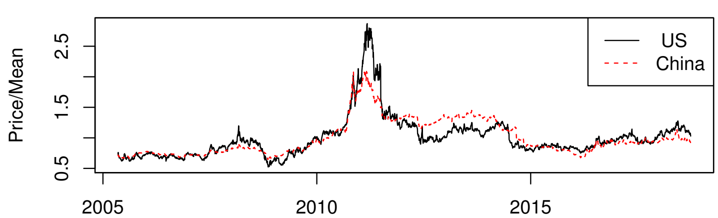
(b) Wheat



(c) Corn



(d) Sugar



(e) Cotton

Figure 1: Price movement of five commodities

Table 2: In-sample fit of MGARCH and NM-MGARCH models

	Soybean		Wheat		Corn		Sugar		Cotton	
	MGARCH	NM-MGARCH	MGARCH	NM-MGARCH	MGARCH	NM-MGARCH	MGARCH	NM-MGARCH	MGARCH	NM-MGARCH
BIC	22,566	22,287	10,125	9,528	22,450	20,227	21,544	20,996	20,516	20,448
Multidimensional K-S test	0.167***	0.113***	0.154***	0.069***	0.234***	0.062***	0.132***	0.051***	0.173***	0.107***
Skewness	-1.706***	-0.037	-1.521***	-0.087	-1.805***	-0.081*	-1.697***	-0.037	-1.294***	-0.190***
Kurtosis	18.932***	2.941***	6.825***	0.652***	14.906***	-0.039	12.003***	0.408***	5.546***	0.472***
JB	52,271***	1,222***	3,394***	27.683***	31,746***	3.719	19,098***	21.152***	4,836***	47.370***
Energy test	49.605	7.978	23.201	1.437	80.543	4.382	38.831	1.432	45.516	1.107
Engle's ARCH test (H_0: no ARCH effects)										
lag=4	7,709***	1,106***	1,428***	263.4***	5,513***	463.6***	4,654***	476.9***	2,979***	656***
lag=8	3,846***	552***	708***	130.1***	2,736***	226.9***	2,333***	231.9***	1,470 ***	304***
lag=12	2,559 ***	367***	467***	86.4***	1,811***	149.6***	1,557***	152.2***	975***	197***
lag=16	1,916***	274***	348***	63.6***	1,336***	109.7***	1,168***	111.1***	725 ***	146***
lag=20	1,527***	219***	275***	50.4***	1,057***	87.3***	898***	86.7***	572***	116***
lag=24	1,264***	181***	228***	41.5***	875***	71.8***	744***	71.5***	462 ***	96***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: NM-MGARCH Estimation results

	Soybean	Wheat	Corn	Sugar	Cotton
p_1	0.425 (0.044)	0.295 (0.030)	0.101 (0.009)	0.139 (0.015)	0.483 (0.025)
C_1^*	$\begin{pmatrix} 2.717 & 0 \\ (0.198) & \\ 0.156 & 0.603 \\ (0.056) & (0.025) \end{pmatrix}$	$\begin{pmatrix} 2.111 & 0 \\ (0.126) & \\ 0.077 & 1.764 \\ (0.132) & (0.115) \end{pmatrix}$	$\begin{pmatrix} 3.372 & 0 \\ (0.210) & \\ -0.15 & 1.585 \\ (0.310) & (0.132) \end{pmatrix}$	$\begin{pmatrix} 4.037 & 0 \\ (0.234) & \\ 0.321 & 2.148 \\ (0.164) & (0.161) \end{pmatrix}$	$\begin{pmatrix} 0.678 & 0 \\ (0.067) & \\ 0.242 & 0.361 \\ (0.021) & (0.023) \end{pmatrix}$
A_1^*	$\begin{pmatrix} 0.386 & 0.099 \\ (0.088) & (0.109) \\ -0.06 & -0.619 \\ (0.064) & (0.098) \end{pmatrix}$	$\begin{pmatrix} 0.197 & -0.184 \\ (0.204) & 0.181 \\ -0.031 & -0.542 \\ (0.147) & (0.148) \end{pmatrix}$	$\begin{pmatrix} 0.978 & -0.568 \\ (0.177) & (0.240) \\ 0.540 & -0.995 \\ (0.165) & (0.184) \end{pmatrix}$	$\begin{pmatrix} 0.026 & 0.260 \\ (1.375) & (0.605) \\ 0.054 & 0.657 \\ (0.317) & (0.248) \end{pmatrix}$	$\begin{pmatrix} 0.115 & -0.288 \\ (0.053) & (0.084) \\ -0.103 & -0.132 \\ (0.016) & (0.042) \end{pmatrix}$
B_1^*	$\begin{pmatrix} 0.131 & -0.450 \\ (0.310) & (0.914) \\ 0.526 & -0.664 \\ (0.022) & (0.040) \end{pmatrix}$	$\begin{pmatrix} 0.362 & -0.661 \\ (0.177) & (0.638) \\ 0.213 & -0.045 \\ (0.207) & (0.931) \end{pmatrix}$	$\begin{pmatrix} 0.469 & -0.051 \\ (0.388) & (1.452) \\ -0.833 & 0.161 \\ (0.133) & (0.394) \end{pmatrix}$	$\begin{pmatrix} 0.135 & -0.474 \\ (0.317) & (0.873) \\ 0.061 & 0.442 \\ (0.237) & (0.618) \end{pmatrix}$	$\begin{pmatrix} 0.443 & -0.228 \\ (0.045) & (0.053) \\ -0.002 & 0.073 \\ (0.009) & (0.013) \end{pmatrix}$
H_1	$\begin{pmatrix} 5.515 & 0.901 \\ 0.901 & 2.441 \end{pmatrix}$	$\begin{pmatrix} 6.000 & 0.346 \\ 0.346 & 3.501 \end{pmatrix}$	$\begin{pmatrix} 16.897 & 1.034 \\ 1.034 & 8.454 \end{pmatrix}$	$\begin{pmatrix} 15.883 & 1.921 \\ 1.921 & 6.354 \end{pmatrix}$	$\begin{pmatrix} 0.745 & 0.162 \\ 0.162 & 0.205 \end{pmatrix}$
C_2^*	$\begin{pmatrix} 1.110 & 0 \\ (0.034) & \\ -0.132 & 0.358 \\ (0.042) & (0.043) \end{pmatrix}$	$\begin{pmatrix} 1.190 & 0 \\ (0.059) & \\ 0.003 & 0.395 \\ (0.035) & (0.038) \end{pmatrix}$	$\begin{pmatrix} 1.438 & 0 \\ (0.028) & \\ 0.076 & 0.264 \\ (0.023) & (0.058) \end{pmatrix}$	$\begin{pmatrix} 1.489 & 0 \\ (0.121) & \\ 0.414 & 0.191 \\ (0.049) & (0.050) \end{pmatrix}$	$\begin{pmatrix} 2.342 & 0 \\ (0.118) & \\ 0.754 & 0.111 \\ (0.161) & (0.082) \end{pmatrix}$
A_2^*	$\begin{pmatrix} 0.162 & -0.170 \\ (0.183) & (0.203) \\ 0.156 & -0.054 \\ (0.036) & (0.058) \end{pmatrix}$	$\begin{pmatrix} 0.311 & -0.011 \\ (0.076) & (0.091) \\ -0.007 & -0.035 \\ (0.025) & (0.070) \end{pmatrix}$	$\begin{pmatrix} 0.018 & -0.043 \\ (0.043) & (0.097) \\ -0.020 & 0.210 \\ (0.019) & (0.059) \end{pmatrix}$	$\begin{pmatrix} 0.114 & 0.181 \\ (0.068) & (0.088) \\ -0.002 & -0.120 \\ (0.025) & (0.114) \end{pmatrix}$	$\begin{pmatrix} 0.463 & 0.038 \\ (0.050) & (0.083) \\ 0.193 & 0.138 \\ (0.044) & (0.101) \end{pmatrix}$
B_2^*	$\begin{pmatrix} 0.23 & 0.098 \\ (0.059) & (0.124) \\ 0.138 & 0.020 \\ (0.027) & (0.067) \end{pmatrix}$	$\begin{pmatrix} 0.252 & 0.757 \\ (0.071) & (0.229) \\ -0.094 & 0.069 \\ (0.056) & (0.207) \end{pmatrix}$	$\begin{pmatrix} 0.166 & -0.189 \\ (0.05) & (0.158) \\ -0.244 & 0.020 \\ (0.028) & (0.083) \end{pmatrix}$	$\begin{pmatrix} 0.591 & -0.135 \\ (0.082) & (0.185) \\ -0.243 & 0.185 \\ (0.031) & (0.071) \end{pmatrix}$	$\begin{pmatrix} 0.344 & -0.123 \\ (0.040) & (0.050) \\ -0.708 & 0.112 \\ (0.046) & (0.091) \end{pmatrix}$
H_2	$\begin{pmatrix} 1.150 & 0.037 \\ 0.037 & 0.216 \end{pmatrix}$	$\begin{pmatrix} 2.061 & -0.026 \\ -0.026 & 0.176 \end{pmatrix}$	$\begin{pmatrix} 2.541 & 0.047 \\ 0.047 & 0.255 \end{pmatrix}$	$\begin{pmatrix} 3.203 & 0.066 \\ 0.066 & 0.489 \end{pmatrix}$	$\begin{pmatrix} 6.561 & 0.584 \\ 0.584 & 1.712 \end{pmatrix}$
Wald joint test for equal cross-coefficients on each regime ($H_0 : a_{rj,1} = a_{rj,2}$ and $b_{rj,1} = b_{rj,2}\ \forall r \neq j$)					
Chi-squared	531,431***	10,606***	110,195***	6,304 ***	901,7894***

Numbers in parentheses represent standard errors (SE)

Appendix

Table A.1: MGARCH Model Estimation results

	Soybean	Wheat	Corn	Sugar	Cotton
C_1^*	$\begin{pmatrix} 0.159 & 0 \\ (0.027) & \\ -0.018 & 0.682 \\ (0.409) & (0.041) \end{pmatrix}$	$\begin{pmatrix} 0.277 & 0 \\ (0.038) & \\ 0.283 & 0.749 \\ (0.279) & (0.108) \end{pmatrix}$	$\begin{pmatrix} 1.882 & 0 \\ (0.030) & \\ 0.101 & 0.003 \\ (0.065) & (0.415) \end{pmatrix}$	$\begin{pmatrix} 0.113 & \\ (0.029) & \\ 0.258 & 0.205 \\ (0.447) & (0.547) \end{pmatrix}$	$\begin{pmatrix} 0.097 & 0 \\ (0.033) & \\ -0.453 & 0.202 \\ (0.234) & (0.529) \end{pmatrix}$
A_1^*	$\begin{pmatrix} 0.222 & -0.021 \\ (0.013) & (0.019) \\ 0.113 & -0.471 \\ (0.024) & (0.033) \end{pmatrix}$	$\begin{pmatrix} 0.195 & -0.005 \\ (0.016) & (0.066) \\ -0.016 & -0.507 \\ (0.041) & (0.052) \end{pmatrix}$	$\begin{pmatrix} 0.333 & -0.174 \\ (0.034) & (0.078) \\ 0.065 & -0.801 \\ (0.011) & (0.043) \end{pmatrix}$	$\begin{pmatrix} 0.124 & 0.025 \\ (0.012) & (0.018) \\ 0.006 & 0.374 \\ (0.013) & (0.025) \end{pmatrix}$	$\begin{pmatrix} 0.163 & -0.072 \\ (0.012) & (0.039) \\ -0.067 & -0.681 \\ (0.014) & (0.035) \end{pmatrix}$
B_1^*	$\begin{pmatrix} 0.983 & -0.099 \\ (0.000) & (0.029) \\ 0.178 & -0.635 \\ (0.031) & (0.040) \end{pmatrix}$	$\begin{pmatrix} 0.970 & -0.023 \\ (0.000) & (0.084) \\ -0.002 & 0.483 \\ (0.027) & (0.065) \end{pmatrix}$	$\begin{pmatrix} 0.000 & 0.228 \\ (0.140) & (0.088) \\ -0.240 & -0.630 \\ (0.020) & (0.033) \end{pmatrix}$	$\begin{pmatrix} 0.987 & 0.056 \\ (0.000) & (0.025) \\ 0.125 & -0.888 \\ (0.018) & (0.015) \end{pmatrix}$	$\begin{pmatrix} 1.000 & -0.326 \\ (0.000) & (0.082) \\ 0.113 & -0.622 \\ (0.025) & (0.029) \end{pmatrix}$

Numbers in parentheses represent standard errors