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This research evaluates the extent of market integration and direction of price transmission among major cotton trading countries before and after the COVID-19 pandemic. We hypothesize that supply and demand linkages among major production and consumption countries are significantly affected by the COVID-19 pandemic necessitating a closer look at market integration and price co-movements. To test this hypothesis, we collected average monthly spot prices in U.S., India, China, Brazil, Turkey, and Pakistan and daily futures data of U.S., India, and China for cotton from May 2015 to December 2022 and investigate price movements before and after the pandemic. We test separately for the price co-movement and the integration in the futures markets, and between spot and futures markets. Results revealed that market integration increased among all nations after the pandemic. Improved cotton market integration has welfare implications for not only the producers, but also the global public, who are the major consumers.

Key words: Cotton, COVID 19, spot and futures prices, Integration

Introduction

Cotton is an important commodity serving one of the basic needs of life: clothing. The global textile industry primarily relies on cotton for its fiber. In the past few decades, interest in cotton has extended beyond the basic needs of clothing to animal feed, edible oil, and space suits. Cotton has a rich trading history dating back to 4000 B.C. and continues to account for a significant share of the global commodity trade. The global cotton supply chain and cotton trade are facilitated by local and international markets through spot markets and futures markets, which not only help allocate resources but also provide returns to key participants (producers, buyers, and intermediaries).

The major cotton-producing countries are China, India, the United States (US), and Brazil, which together account for about 71 percent of global production as shown in figure 1. In 2022, China produced an average of 29.5 million bales of cotton, making it the largest producer in the world (U.S. Department of Agriculture 2022). India, after China, is the second largest cotton-producing country, with production of 24.5 million bales. As the third largest cotton-producing country, the U.S. produced 14.6 million bales in 2022. Most of the crop cultivated in the U.S. is in the “Cotton Belt,” a region comprising 17 southern states, including Georgia, Virginia, Arizona, Mississippi, and Texas. Brazil produced 13.3 million bales of cotton in 2022 (U.S. Department of Agriculture 2022) due to the country’s fertile land and consistent rainfall, creating perfect cotton growing conditions. The global cotton market is valued at about $40 billion, but more importantly, the cotton and textile industries employ millions of people, and China’s cotton industry alone has nearly 10 million workers (Liu 2020). On the cotton consumption side, China, India, Pakistan, Bangladesh, and Turkey are the main users of cotton globally, accounting for 68 percent of global consumption in 2022 as shown in figure 1 (U.S. Department of Agriculture 2022). The textile industries in these countries source cotton fiber as one of the major inputs for clothes or home finishings to meet the demand for domestic markets or export to international markets. Concerns about sustainability and the environment continue to fuel global demand for comfortable, frequently-wearable, and environmentally responsible clothing, and thus, cotton fiber. This indicates that the global need for cotton is rising significantly, and that international trade will be crucial now and, in the future, (Lawrence Pines, 2022).

The COVID-19 pandemic has created a significant and systemic shock with widespread influence on financial (stock markets, derivative markets) and spot markets, and in particular, commodity markets. According to the World Bank (2020), prices for most agricultural commodities remained stable just before the pandemic. However, by the end of the first quarter of 2020, COVID-19 was beginning to impact markets through multiple channels: macroeconomic as well as microeconomic pathways, e.g., exchange rates, the shutdown of production, movement restrictions on labor and commodities, and safety protocols (Zhang et al. 2022). Some preliminary work done by Monge and Lazcano (2022) reveals that during the COVID-19 pandemic, commodity prices exhibited a mean-reverting tendency, indicating that they will likely return to their long-term projections.

For cotton, the pandemic severely disrupted trade, with a fall in consumption of 6.4 percent in 2020 when the outbreak occurred (Liu 2020). COVID-19 severely disrupted the global cotton supply chain, which links producers to consumers worldwide. The enforced global lockdown restrictions to combat COVID-19 compelled the global closure of ginning mills and retail stores. As a result, large cancellations, and suspensions of orders by significant western textile retail companies occurred during the lockdown period, and cotton prices plunged during the early period of the pandemic due to decrease of consumption. Global production of cotton in also decreased in 2020 as shown in figure 2, which led to limited stocks and supplies. While the falling demand initially in the pandemic led to lower prices, limited supplies and disruptions to global supply chains reversed the price path. By early 2021, cotton prices skyrocketed above the pre-pandemic level. These high cotton prices forced overseas spinning mills to decrease the proportion of cotton in their spinning in favour of synthetic fibers (Liu 2021). Coincidental during the pre-pandemic years was the US-China trade war, which led to some market segregation and welfare losses to US producers and Chinese and global consumers (Gopinath 2021). Thus, it is necessary to understand cotton market integration before and after the pandemic, which as noted above, has implications for market efficiency, resource allocation and welfare of all producers and consumers.

Research on price transmission is a key pathway to understand market integration among different countries or between the spot/cash markets and the futures markets for a domestic country. This helps determine the nature of the interaction between distant markets globally and price transmission, as well as the impact of liberalization policies and identifying regions vulnerable to systemic shocks. The existence of a long-run link between geographically dispersed prices for the same commodity is crucial for determining the price discovery pricing of cash market transactions using future prices – among nations (Sehgal et al. 2012; Samal 2017). Even if prices momentarily diverge in the short term, the differentials should gradually converge in the long run towards each other, if markets are integrated. While international prices are more stable than domestic ones, it is anticipated that perfect market integration will improve social welfare (Ge et al. 2010; Susanto et al. 2008; Chinnadurai et al. 2019). Trade barriers and other domestic policies are the primary reasons keeping a market from becoming fully integrated into the world market.

A considerable amount of research has emerged studying the patterns of pricing behaviour across different geographic areas and attempting to make inferences about the structure of the underlying market from this behaviour (Sehgal et al. 2012; Samal 2017). Economists generally see price-based market integration tests as more conclusive and trustworthy than quantitybased tests as the price-based have clear interpretations (Volosovych 2011). On the other hand, the absence of market integration might lead to erroneous price signals, which can create uncertainty and influence production and marketing decisions (Fackler and Tastan 2008). Despite the wide use of cotton and the intensity of cotton trade globally, the extent of cotton market integration has received limited attention in the literature. This study will contribute to the literature by considering market integration of major cotton producers and consumers in futures market as well between spot and futures markets. In addition to examining the functioning and interactions of major markets, this study explores the potentially different integration pathways before and after the Covid-19 pandemic. The hypothesis of our study is that cotton market integration was weaker pre-pandemic, also aided by trade wars (e.g., Brext, US-China trade war). However, post-pandemic, the emergence of supply chain issues in international shipment, and the labor shortage in ginning and classing of cotton fiber have created shortages of cotton fiber across countries leading us to expect stronger market integration.

The rest of the paper is organized as follows. The next section describes the methodologies employed in assessing market integration followed by details on data used. The following section presents the empirical results, compares them to earlier results from the literature, and discusses the implications of our findings. The final section provides conclusions and implications.

Methodology

Johansen's cointegration test:

As an alternative to OLS processes, we applied Johansen's method to detect multiple cointegrating vectors using maximum likelihood estimation. It is a statistical procedure used to test correlation between two or more non-stationary series in the long-run or for a specified period, as in this study. That is, co-integrated series are linear combinations of two or more non-stationary series (Singh & Soni, 2021). This is followed by implementing various models based on the results of this test.

Vector Auto Regressive model (VAR):

This VAR model is used if the concerned time series do not exhibit cointegration, to identify price relationships usually with first differencing (Hudson et al.1996).

$$\boldsymbol{\Delta Y_t = \theta + \alpha_1 \Delta Y_{t-n} + \beta_1 \Delta X_{1(t-n)} + \beta_2 \Delta X_{2(t-n)} + \ldots\ldots + \beta_p \Delta X_{p(t-n)} + \varepsilon_t} \qquad (1)$$

t = time period, Y = Vector of prices of selected nation (dependent variable) , ΔY = Vector of first difference of prices (independent variables), Y_{t-1} = Vector of lag of prices, $\Delta X_1, \Delta X_2, \ldots X_p$ = Vector of prices of remaining countries (independent variables), n = optimum no of lags, p = no of countries – 1(country used as dependent variable), α, θ, β = short- run coefficients of parameters. The significant coefficients describe how the changes in independent variables will have effect on shifts in dependent variables. For instance, the coefficient (β_1) is significant then the if X_1 changes by one unit, it will have a significant effect on Y by a factor of β_1, all else constant (Hudson et al.1996).

Vector-error correction model (VECM):

VECM models are a specialized application of VAR or Vector Autoregressive Models. In order to specify VECM models, error correcting terms must be incorporated into VAR models. If the variables in model have a long-run connection, i.e., they are cointegrated, VECM method is employed (Hall et al. 1992).

$$\mathbf{\Delta Y_t = \theta + ECT_r + \alpha_1 \Delta Y_{t-n} + \beta_1 \Delta X_{1(t-n)} + \beta_2 \Delta X_{2(t-n)} + \ldots\ldots + \beta_p X_{p(t-n)} + \varepsilon_t} \quad (2)$$

t = time period, Y = Y = Vector of prices of selected nation (dependent variable), ΔY = Vector of first difference of prices , $Y_{\mathbf{t-1}}$ = Vector of lag of spot prices, $\Delta X_1, \Delta X_2, \ldots X_p$ = Vector of prices of remaining countries (independent variables), p = no of countries – 1(country used as dependent variable), ε_t = Vector of distributive error term, n = optimum no of lags, α_1 , θ, β = coefficients of parameters, r = rank (no of cointegrated vectors) , ECT = error correction terms. The significant error correction terms (ECT) represent the long-run equilibrium relationship exists dependent and independent variables. And the remaining coefficients describes the short-tun equilibrium relations between the variables. Example, the coefficient (β_1) is significant then the if X_1 changes by one unit, it will have a significant effect on Y by a factor of β_1, all else constant.

Granger Causality Test:

When there is a no cointegration between two variables, the Granger Causality Test (Granger, 1969) used to determine the direction of this co-movement relationship. The causality test determines if a link is unidirectional or bidirectional.

$$\mathbf{Y_t = \theta + \alpha_1 Y_{t-n} + \beta_1 X_{1(t-n)} + \beta_2 X_{2(t-n)} + \ldots\ldots + \beta_p X_{p(t-n)} + \varepsilon_t} \quad (3)$$

t = time period, Y = Spot prices of selective nation, $Y_{\mathbf{t-1}}$ = Vector of lag of spot prices, $X_{\mathbf{1}}, X_2 \ldots\ldots Xp$ = Spot prices of remaining nations, ε_t = distributive error term, n = optimum no of lags, α , θ, β = coefficients of parameters, p = no of countries – 1(country used as dependent variable) Theoretically, variable Y is said to Granger-cause another variable X if the present value of Y is dependent on the previous value and the history of X (Sehgal et al., 2012).

Wald test:

When there is cointegration between two variables, the Wald test is used to determine the direction of a cointegration relationship between two variables. Although the finite sample distributions of Wald tests are often unknown, the test has an asymptotic $\chi 2$ distribution under the null hypothesis. If the test statistic points to statistical significance, price transmission occurs between the independent and dependent variables (Haug 2002).

Data

Spot Prices

We collected the spot price data for the United States, India, China, Turkey, Brazil, and Pakistan from May 2015 to December 2022, as these nations account for a significant portion of cotton production and consumption in 2022 (U.S. Department of Agriculture 2022). There are specifications differences of fiber qualities among these nations for the base value of the upland cotton prices. In the U.S., the specifications of the base quality upland cotton are colour 41, leaf 4, staple 34 and in India the upland cotton, and its medium staple fibers are Shankar-6 quality (grade 29-3.8-76). In Brazil, cotton type 41 colour strict low middling (previous type 6, fiber 30/32 mm, characteristic-free), China cotton representing the 3128 B variety (grade 3, length 28 mm, Micronaire B) whereas the specifications of the Turkey cotton are ICE Colour grade 41, TB – 41 and Pakistan cotton is of base grade 3, 1-1/16 -inch staple length, and a Micronaire value between 3.8 and 4.9 are the cotton specifications. However, despite the difference in the specifications of the base quality of upland cotton, they all reflect the same type of upland cotton. As a result, the differences of fiber qualities have minimal influence on our analysis of price transmission.

The national average monthly spot rates for the United States are collected from the USDA's World Trade and Cotton Outlook (U.S. Department of Agriculture 2022). The monthly spot prices for India were obtained from Cotton Association of India (Gujcot Trade Association 2022), which reflects the average of all 346 marketplaces (approximately) located across various Indian states. The Brazilian monthly data is taken from the Centre for Advanced Studies in Applied Economics (CEPEA) (CEPEA 2022), which is the arithmetic mean of all spot market prices in the major cotton producing and consuming areas in Brazil. China monthly cotton spot prices were collected from China Cotton Association (China Cotton Association 2022), which reflects the national weighted average of cotton. The Turkey monthly spot prices are obtained from Turkey Cotton Association (Izmir Ticaret Borsasi 2022), and it represents national average prices. Pakistan monthly spot rates are collected from the Pakistan Cotton Committee (Ministry of National Food Security and Research 2022). The rates committee has a quorum of five members and meets daily to decide the official Karachi Cotton Association (KCA) Spot Rate for local transactions in Pakistani Rupees, where the monthly statistics table shows the monthly average cotton price index. All monthly spot price data were converted to U.S. dollars per kilogram using International Monetary Fund (IMF) conversion rates (International Monetary Fund 2022).

The monthly cotton spot price data of the major cotton production and consumption countries shown in figure 3. Prior to the outbreak of Covid-19 during the spring of 2020, cotton prices are relative stable. Cotton prices declined in value for all nations of our dataset during the first quarter of 2020 due to COVID-19, followed by a huge price increase due to a rise in cotton demand after the pandemic. Thus, the sample were divided into two sub-samples representing before and after pandemic eras by Bai-Perron structural break test (Bai and Perron 1998). Pakistan prices deviate significantly from the others after pandemic which is due to the high exchange rate fluctuations over this time period. We hypothesize these variations will have an impact on the integration among these major players.

Futures Prices

United States, China, and India have a significant impact on the global cotton trade by virtue of their large futures market transactions. According to previous studies, U.S. has been the market leader during the pre-pandemic era and aided in the price discovery of other emerging countries (Singh and Soni 2021; Ge et al. 2010). To study futures price relationships before and after the pandemic, we obtained the cotton futures data for these three countries of U.S., China, and India from May 2015 to December 2022 as shown in figure 4. Cotton futures prices for the Multi Commodity Exchange (MCX) in India, the Intercontinental Exchange (ICE) in the United States were obtained from (Investing.com 2022, Investing.com 2022), and the Zhengzhou Commodities Exchange (ZCE) in China is from (Zhengzhou Commodity Exchange 2022), respectively. Local currency was converted to U.S. dollars per kilogram of cotton fiber using International Monetary Fund exchange rates (IMF) for India and China (International Monetary Fund 2022). Two structural breaks were identified from the graph, one is in 2017 which is due to drop of total number of futures traded on exchanges to 6.6% (FIA Market Voice 2017) and other one in 2020 due to the Pandemic. Thus, we divided the sample into three sub-samples in our analysis by performing the structural break tests using Bai-Perron methods (Bai and Perron 1998). Integration tests were performed to investigate the effects of integration during each of these structural break periods.

Results and Discussion

Futures Prices Analysis Results:

We identified two structural breaks in futures price data by using the Bai-Perron test which are on 2017 December 13th and 2020 April 21st and recall that the sample period is from May 2015 to December 2022. Therefore, we divided the sample into three subsamples to conduct all the tests, identify cointegration, and compare how the countries' degrees of integration have changed over time. Here the first sample represents the period from 2015 May 1st to 2017 December 12th and second sample goes from 2017 December 13th to 2020 April 20th whereas third sample ranges from 2020 April 21st to 2022 December 30th.

First, futures prices of United States, India, and China are tested for integration. After the stationarity tests, the Johansen test for cointegration is used where the first step is to estimate the rank of integration. To select the order, we evaluated both the Trace test and the Maximum Eigen value test, and as they are less than critical values, we cannot reject the null hypothesis of cointegration of rider (r). The first sample indicates that the three countries are integrated at r=1, showing that there is a single linear combination that is integrated, implying that prices in geographically disparate markets respond to each other, all else constant. In the second sample both the test statistics reveal that the nations are integrated at rank (r) zero, which implies lack of co-integration, which may be the result of a shift in the trade dynamics, e.g., U.S. – China trade war during this period. These findings are consistent with the investigations conducted by Singh and Soni (2021). The third sample, which covers the post-pandemic period, demonstrates a strengthening of integration across countries, consistent with our hypothesis rank (r) at two, which states that two linear combinations are now integrated. The reason for this is because of tighter supplies and increased trade flow after the pandemic where the results are shown in table 1.

This is followed by regression analysis, since we detected co-integration in the first and third samples. For the first sample, we used error correction models, and for the second sample, we used autoregressive models, as indicated by previous research.(Ge et al. 2010; Wårell 2006; Chinnadurai et al. 2019)

Vector-error correction model (VECM) results

The error correction terms (ECT) is statistically significant in the U.S. equation in first sample, it represents the log-run relationship India and China to the U.S., where it measures the speed of correction when a deviation from equilibrium occurs. That is, previous day errors (or deviations from long-run equilibrium) are corrected for in the current day price realization with a convergence speed of 5.6%, demonstrating long-run causality. And the error correction terms (ECT) are statistically significant in all equations for third sample. For instance, in U.S. equation, the convergence speed is found to be 6.4%. This shows that the price transmission increased after pandemic, that is from the first to third sample which is shown in table 2 and table 4.

Vector auto regressive model (VAR) results

For the second sample, we applied the VAR model to determine the short-term price dynamics and results are shown in table 3. And the positive coefficient suggests that, for example, if the price of U.S. futures in the previous time period grows by 1 percent, then India price levels today increases by 0.15 percent point. And the negative significant coefficient suggests that, for example, if the price of India futures in the previous time period grows by 1 percent, the price of India futures in the current time period will decrease by 0.14 percentage point. In addition, we ran diagnostic tests, which revealed that all the samples are free from autocorrelation and errors are normally distributed.

Spot and Futures Prices Analysis Results:

The integration of the spot and futures markets of U.S., India, and China using monthly spot and futures prices is examined followed by interaction between the futures prices of those three nations with spot prices of Brazil, Turkey, and Pakistan. Based on Bai-Perron test, the data sample is divided into two subsamples, before and after the pandemic. Before the pandemic, samples were taken between April 2015 and March 2020, and after the pandemic, it ranges from April 2020 and December 2022.

Table 5 below shows the order of integration. For the United States, the spot and futures markets are cointegrated before and after the pandemic, however for India and China, spot and futures markets were not integrated before pandemic, while integration is observed after the pandemic. In addition, all cross combinations among the six countries show that the spot prices of Brazil, Turkey and Pakistan integrated with U.S futures after the pandemic. The trading volume of U.S futures is larger than other futures which also the reason to be more dominant futures market. This is followed by VAR and VECM models as similar to the analysis before.

All the results for VECM and VAR models represents the interaction between the spot and futures markets and the results were reported in table 6 to table 11 below. These results are consistent with the futures price analysis - stronger integration after the pandemic between the spot and futures as well.

Wald tests results:

In the futures analysis, the first and third samples were subjected to this test to determine the short-run causality and the results displayed in Table 12. For the initial subperiod, our findings revealed strong unidirectional causation from the U.S. to the Chinese and Indian markets, as well as from the Indian markets to the Chinese markets. During the third subperiod, which represents the post-pandemic period, the results demonstrated substantial bidirectional causality from the U.S. to the Chinese and Indian markets and unidirectional causality from the Indian markets to the Chinese markets which are similar to the findings that integration increased after the pandemic.

In the spot and futures analysis, we used this test after the VECM model for spot and futures prices and the results are shown in table 13 for the after-pandemic sample. The cross-combination analysis indicates that in the pre- pandemic sample, short-run causality from U.S. futures to Turkey and Pakistan spot markets exists, and there are bidirectional effects between Brazil spot and U.S. futures markets.

Granger Causality tests results:

In the futures analysis, this test was used on the second sample to assess the short-run causality after VAR model was applied to futures prices. During the second subperiod (Table 14), our results revealed strong unidirectional causality from the U.S. to the Chinese and Indian markets, as well as unidirectional causality from the Indian markets to the Chinese markets, which is identical to the first sub-sample and are consistent with the investigations conducted by Singh and Soni (2021).

In the spot and futures analysis, results of this test are presented in Table 15. Our results revealed strong unidirectional causality from Indian futures to spot markets, as well as bidirectional causality between the Chinese spot and futures markets. And analysis on cross combinations in the post-pandemic sample, due to the restricted number of lags, there is no short-run causation found for Brazil and Turkey prices, but U.S. futures do affect Pakistan spot market. In general, U.S. futures market appears to drive the cotton market pre- and post-pandemic.

Conclusions

Focusing on international cotton markets, we assessed the integration of daily futures prices in the United States, India, and China from 2015 through 2022. The Johansen co-integration approach was used to three subsamples due to the discovery of two structural breaks, one in 2017 and one in 2020. There is substantial evidence of a rise in the integration of price series following the pandemic in the third sample compared to the first sample, as well as an increase in causality across nations, according to the findings. Even after the pandemic, the U.S. futures market continues to drive those of India and China. There is no observable integration among the three nations in the middle sample (2017-2020). Potential reasons include U.S.-China trade war, a pilot target-price-based subsidy plan (TSP) in China which limited imports from other countries, and highly volatile Indian futures markets.

Followed by this we evaluated the integration between monthly futures and spot prices of United States, India, and China for the same sample period. The prices show greater shifts after the pandemic, while they were stable before the pandemic. Thus, co-integration was tested using the Johansen method on samples from before and after the pandemic. The results show evidence of integration between the U.S. futures and spot markets both before and after the epidemic, whereas for China and India spot and futures markets were integrated only after pandemic. Post- pandemic, Granger causality test indicates there was also a strengthening of the price transmission across global markets. Major reasons impacting the increase in integration are China's position as the major producer and consumer of cotton following the pandemic as well as the "Phase one trade arrangement" with the United States.

Cointegration was not observed exclusively in spot markets likely due to trade barriers and other transaction costs. However, futures markets are driving price movements in spot markets. Hence, we assessed the integration of spot markets of Brazil, Turkey, and Pakistan with futures prices of the United States, India, and China. All cross-combinations of the six countries are considered, and the results shows that all countries' spot markets have been integrated with the U.S. futures, which is often the first mover. This study provides decision-makers, traders, and investors with insightful information about price setting behaviour in the cotton market, which is useful in decision-making by stakeholders.

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Table 1: Order of Integration for futures prices

Country	Sample	Rank (R)	Trace Statistic < Critical value	Max eigen value < Critical value
US, India, China	First sample	1^{**}	9.40 < 15.41	7.58 < 14.07
	Second sample	0^{**}	23.00 < 29.68	16.99 < 20.97
	Third sample	2^{*}	5.55 < 6.65	5.55 < 6.65

Notes: * 10% significance, ** 5% significance, and *** 1% significance.

Table 2: VECM results for first sample of futures prices.

	D_lus_t (US)	D_lindia_t (India)	D_lchina_t (China)
Error Correction terms			
$\theta_{1(t-1)}$	$-.056^{***}$(.014)	.004 (.013)	-.016 (.011)
US lags			
D_lus_{t-1}	.068* (.041)	.213***(.038)	.277***(.032)
India lags			
D_lindia_{t-1}	.041 (.044)	-.043 (.041)	.069** (.033)
China Lags			
D_lchina_{t-1}	-.051 (.047)	-.074* (.043)	.105 (.036)
Constant	.000 (0.000)	.000 (0.000)	-.000 (0.000)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y* 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 3: VAR results for second sample of futures prices

	D_lus_t (US)	D_lindia_t (India)	D_lchina_t (China)
US lags			
D_lus_{t-1}	.029 (.049)	.147*** (.037)	.327***(.035)
India lags			
D_lindia_{t-1}	-.095 (.064)	-.142*** (.049)	.097** (.046)
China Lags			
D_lchina_{t-1}	.028 (.055)	.052 (.042)	.091** (.039)
Constant	-.000 (.001)	-.001 (.001)	-.001 (.001)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y, * 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 4: VECM results for third sample of futures prices.

	D_lus_t (US)	**D_lindia_t (India)**	**D_lchina_t (China)**
Error Correction terms			
$\theta_{1(t-1)}$	-.064 ***(.016)	-.028 *(.016)	.020 **(.009)
$\theta_{2(t-1)}$	.020 ***(.008)	.003 (.007)	-.015 ***(.004)
US lags			
D_us_{t-1}	.102 **(.043)	.159 ***(.037)	.287 ***(.024)
D_us_{t-2}	.056 (.048)	.046 (.046)	-.024 (.027)
D_us_{t-3}	.101 ** (.047)	.061 (.046)	-.005 (.026)
D_us_{t-4}	.077 (.047)	.037 (.046)	.016 (.026)
D_us_{t-5}	.135 ** (.047)	-.008 (.046)	.015 (.026)
D_us_{t-6}	-.067 (.048)	-.039 (.046)	-.036 (.026)
D_us_{t-7}	-.086 ** (.047)	.039 (.046)	.019 (.026)
D_us_{t-8}	.058 (.048)	.052 (.046)	.003 (.026)
D_us_{t-9}	.085 ** (.047)	.232*** (.046)	.027 (.026)
India lags			
D_lindia_{t-1}	.037 (.044)	-.022 (.042)	.033 ** (.024)
D_lindia_{t-2}	.013 (.043)	-.051 (.042)	.054 (.024)
D_lindia_{t-3}	-.103 **(.044)	-.066 (.042)	-.015 (.024)
D_lindia_{t-4}	-.021 (.044)	-.032 (.042)	.045 (.024)
D_lindia_{t-5}	-.079 *(.044)	-.042 (.042)	.022 (.024)
D_lindia_{t-6}	.036 (.044)	.065 (.042)	.039 (.024)
D_lindia_{t-7}	.048 (.044)	.106 (.042)	.056 (.024)
D_lindia_{t-8}	.067 (.044)	.055 (.042)	.034 (.024)
D_lindia_{t-9}	-.082 * (.044)	-.099 (.042)	-.013 (.024)
China Lags			
D_lchina_{t-1}	.025 (.074)	-.107 (.072)	.054 (.042)
D_lchina_{t-2}	.024 (.075)	-.041 (.072)	-.049 (.042)
D_lchina_{t-3}	-.188 ** (.078)	-.112 (.072)	.017 (.042)
D_lchina_{t-4}	-.034 (.075)	.055 (.072)	.053 (.042)
D_lchina_{t-5}	-.037 (.075)	-.030 (.072)	.036 (.042)
D_lchina_{t-6}	.066 (.075)	-.009 (.072)	-.078 (.042)
D_lchina_{t-7}	.108 (.075)	-.015 (.072)	-.013 (.042)
D_lchina_{t-8}	-.089 (.074)	-.151** (.072)	-.108 (.042)
D_lchina_{t-9}	-.195 *** (.066)	-.033 (.072)	-.047 (.042)
Constant	-.000 (.001)	.000 (.000)	-.000 (.000)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y* 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 5: Order of integration for spot and futures prices

Country/ Variables	**Pandemic**	**Rank (R)**	**Trace Statistic < Critical value**	**Max eigen value < Critical value**
US spot and futures	Before	**1**	1.52 < 9.42	1.53 < 9.24
	After	**1**	3.80 < 9.42	3.81 < 9.24
India spot and futures	Before	**0**	15.04< 19.96	13.97< 15.67
	After	**1**	4.40 < 9.42	4.40 < 9.24
China spot and futures	Before	**0**	14.45 < 19.96	13.63 < 15.67
	After	**1**	7.06 < 9.42	7.06 < 9.24

Notes: R=1 represents integration exists, R=0 represents integration does not exist.

Table 4:VECM results for after pandemic of U.S. spot and futures prices.

	D_lusf_t (US futures)	**D_lussp_t (US spot)**
Error Correction terms		
$\theta_{1(t-1)}$	1.073* (.599)	1.669***(.294)
US futures lags		
D_lusf_{t-1}	-.762 (.552)	-.686*** (.271)
D_lusf_{t-2}	-.925 *** (.377)	-.623*** (.185)
US spot lags		
D_lussp_{t-1}	.324 (.380)	.218 (.187)
D_lussp_{t-2}	.509*** (.223)	.258*** (.109)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y, * 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 5: VAR results for before pandemic sample of India spot and futures prices

	$D\_lindiaf_t$ (India futures)	**$D\_lindiasp_t$ (India spot)**
India futures lags		
$D\_lindiaf_{t-1}$	-.056* (.167)	.228***(.114)
India spot lags		
$D\_lindiasp_{t-1}$	.222 (.055)	.103 (.161)
Constant	-.004 (.007)	-.001 (.005)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y , * 10% significance, ** 5% significance, and *** 1% significance; t, t-n = Time periods and Lag of time periods.

Table 6: VECM results for before pandemic sample of U.S. spot and futures prices.

	D_lusf_t (US futures)	**D_lussp_t (US spot)**
Error Correction terms		
θ_{t-1}	-.158 (.168)	.741***(.141)
θ_{t-1}	-.158 (.168)	.741***(.141)

Notes: Standard errors are in parenthesis, *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 7: VAR results for before pandemic sample of China spot and futures prices

	$D\_lindiaf_t$ (India futures)	**$D\_lindiasp_t$ (India spot)**
India futures lags		
$D\_lindiaf_{t-1}$	.528*** (.192)	.513***(.114)
India spot lags		
$D\_lindiasp_{t-1}$	-.591** (.296)	-.318* (.176)
Constant	-.005 (.006)	-.003 (.004)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y* 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 8 : VECM results for after pandemic of US futures and Brazil spot prices

	D_lusf_t (US futures)	**$D\_lbrazilsp_t$ (Brazil spot)**
Error Correction terms		
$\theta_{(t-1)}$	.057 (.188)	.559***(.120)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y, *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 9: VECM results for after pandemic sample of US futures and Turkey spot prices

	D_lusf_t (US futures)	**$D\_lturkeysp_t$ (Brazil spot)**
Error Correction terms		
$\theta_{(t-1)}$	.005 (.159)	.509***(.090)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y, *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 10 : VAR results for before pandemic sample of US futures and Turkey spot price

	D_lusf_t (US futures)	**$D\_lturkeysp_t$ (Brazil spot)**
US futures lags		
D_lusf_{t-1}	-.0329 (.143)	.265***(.114)
Turkey spot lags		
$D\_lturkeysp_{t-1}$	.009** (.155)	.092 (.123)
Constant	-.004 (.008)	-.000 (.007)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y* 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods.

Table 11: VAR results for before pandemic sample of US futures and Pakistan spot prices

	D_lusf_t (US futures)	**$D\_lpakistansp_t$ (Brazil spot)**
US futures lags		
D_lusf_{t-1}	-.027 (.142)	.442 (.197)
Pakistan spot lags		
$D\_lpakistansp_{t-1}$	.057 (.090)	-.094 (.126)
Constant	-.005 (.008)	-.007 (.011)

Notes: Standard errors are in parenthesis, D_ly = Difference of log prices of country y* 10% significance, ** 5% significance, and *** 1% significance, t, t-n = Time periods and Lag of time periods

Table 12: Wald test results for first and third samples of futures prices

Country	**Sample**	**Chi square**	**Probability**	**Causality**	**Relationship**
US/India	First	0.910 (I)	0.341 (I)	India do not cause US.	(US → India)
		31.760 (U)	0.00*** (U)	US cause India.	
	Third	19.670 (I)	0.020** (I)	India cause US.	(US ↔India)
		42.480 (U)	0.00***(U)	US cause India.	
US/China	First	1.200 (I)	0.274 (I)	China do not cause US	(US → China)
		76.580 (U)	0.00*** (U)	US cause China	
	Third	20.080 (I)	0.017** (I)	China causes US	(US↔ China)
		149.600(U)	0.00*** (U)	US cause China	
India /China	First	4.260 (I)	0.039** (I)	India causes China	(India ↔ China)
		2.990 (C)	0.084* (C)	China causes India	
	Third	18.490 (I)	0.029** (I)	India causes China	(India → China)
		10.020 (C)	0.349 (C)	China do not cause India	

Notes: (U) indicates US, (I) indicates India, (C) indicates China, * 10% significance, ** 5% significance, and *** 1% significance, (→ Unidirectional, ↔ Bidirectional)

Table 13: Wald test results for post pandemic sample of spot and futures prices.

Country	Chi square	Probability	Causality	Relationship
US spot-futures	11.340 (F)	0.003** (F)	US futures cause US spot	US futures ⟺ US spot
	5.800 (S)	0.055* (S)	US spot do not cause US futures.	
India spot - futures	13.500 (F)	0.001** (F)	India futures cause India spot	India futures ⟺ India spot
	14.060 (S)	0.00*** (S)	India spot cause India futures	
China spot - futures	14.300 (F)	0.014** (F)	China futures cause China spot	China futures ⟺ China spot
	10.060 (S)	0.073* (S)	China spot cause China futures	

Notes: * 10% significance, ** 5% significance, and *** 1% significance, (F) indicates futures, (S) indicates spot, (→ Unidirectional, ⟺ Bidirectional)

Table 14: Granger causality test results for second sample of futures prices

Country	Chi square	Probability	Causality	Relationship
US/India	2.175 (I)	0.140 (I)	India do not cause US.	(US → India)
	15.497 (U)	0.00*** (U)	US cause India.	
US/China	.260 (I)	0.610 (I)	China do not cause US	(US → China)
	85.683 (U)	0.00*** (U)	US cause China	
India /China	4.448 (I)	0.035** (I)	India causes China	(India → China)
	1.569 (C)	0.210 (C)	China do not cause India	

Notes: ** 5% significance, and *** 1% significance, (U) indicates US, (I) indicates India, (C) indicates China, (→ Unidirectional)

Table 15: Granger causality test results for pre- pandemic sample of spot and futures prices

Country	Chi square	Probability	Causality	Relationship
India spot - futures	3.988 (F)	0.046** (F)	India futures cause India spot	India futures → India spot
	.882 (S)	0.348 (S)	India spot do not cause India futures	
China spot - futures	20.303 (F)	0.00*** (F)	China futures cause China spot	China futures ⟺ China spot
	3.9768 (S)	0.046** (S)	China spot cause China futures	

Notes: * 10% significance, ** 5% significance, and *** 1% significance, (F) indicates futures, (S) indicates spot, (→ Unidirectional, ⟺ Bidirectional)

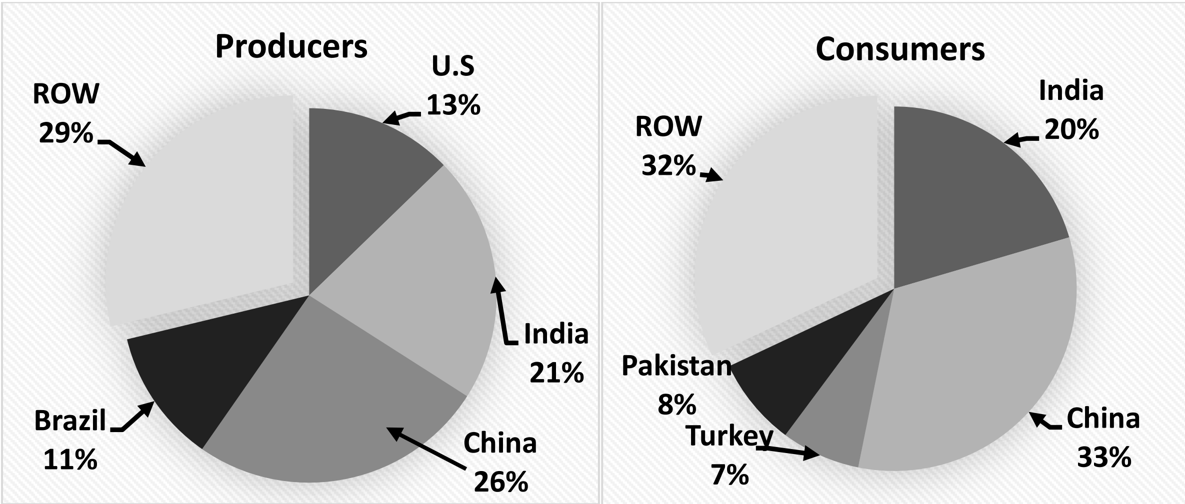

Figure 1: Major producers and consumers of cotton fiber (U.S. Department of Agriculture 2022)

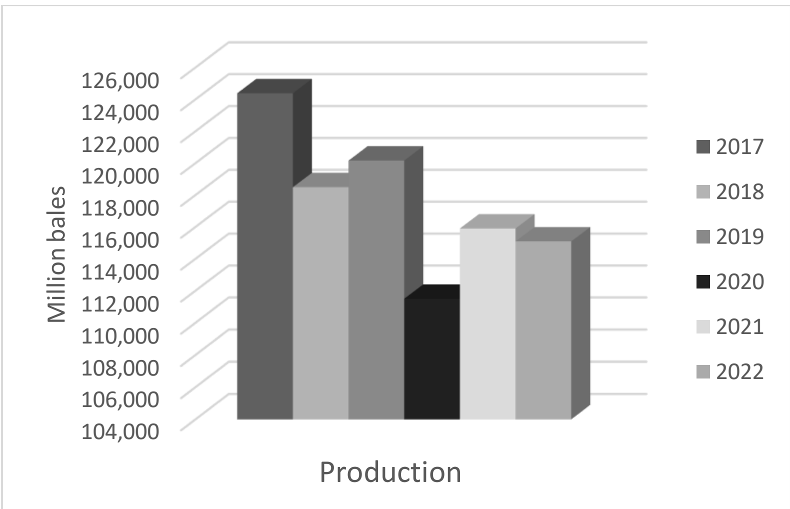

Figure 2: Global cotton production statistics (U.S. Department of Agriculture 2022)

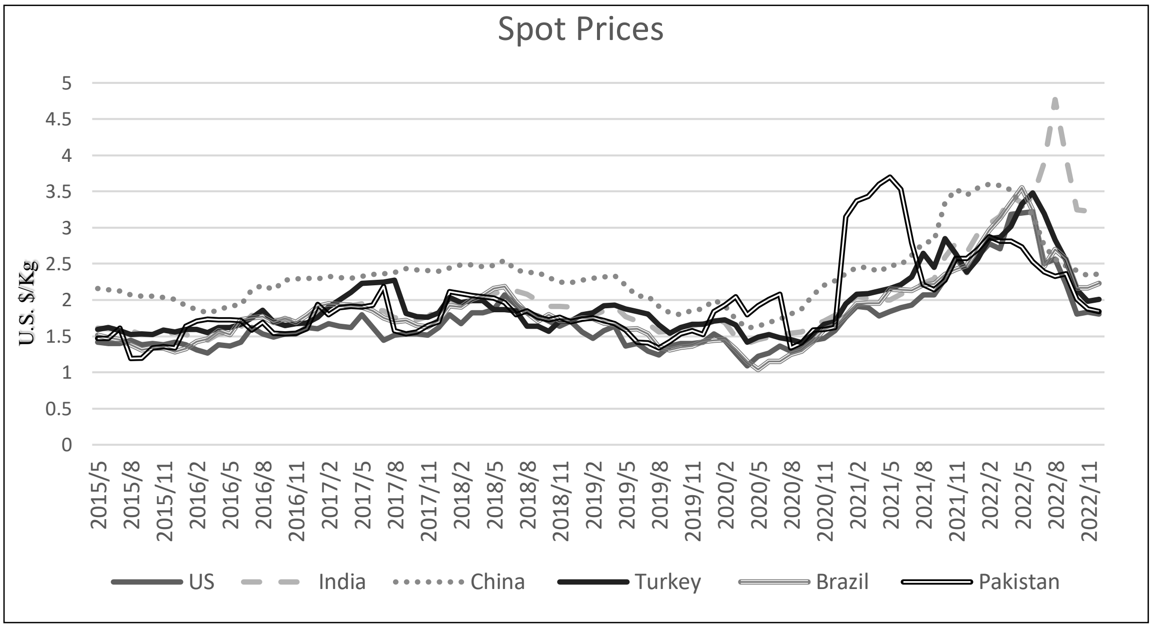

Figure 3: Monthly spot prices of cotton in different nations.

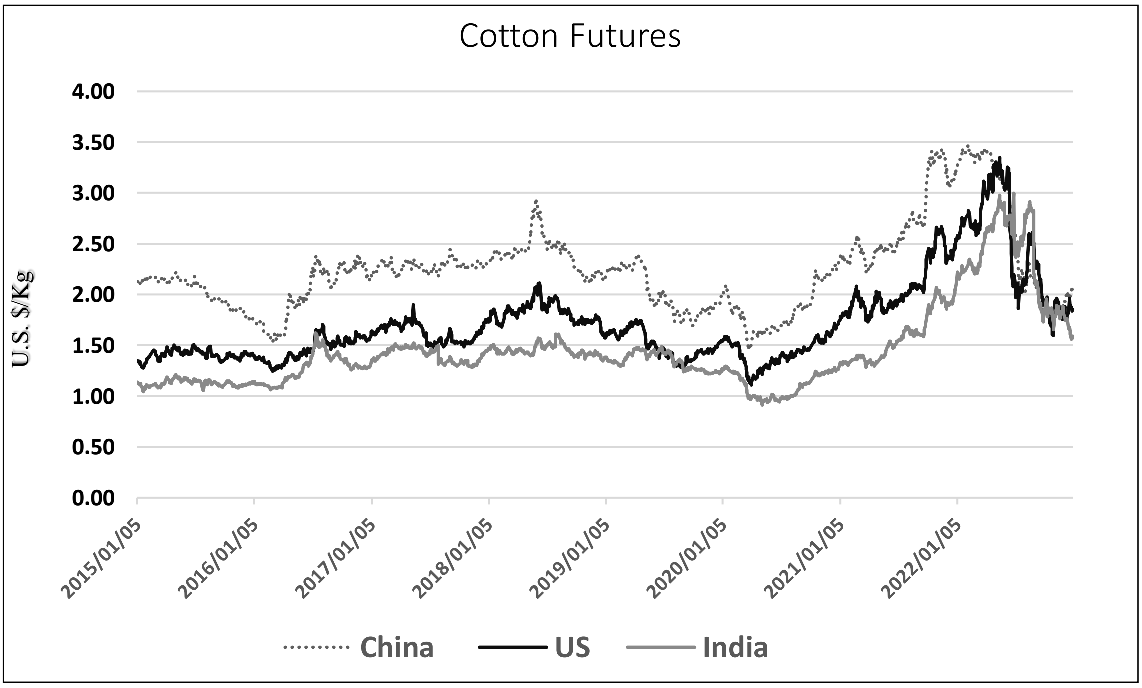

Figure 4: Daily futures prices of cotton in different nations.