Commodity Price Comovement and Financial Speculation: The Case of Cotton

Joseph P. Janzen, Aaron Smith, and Colin A. Carter

Recent booms and busts in commodity prices have generated concerns that financial speculation causes excessive commodity-price comovement, driving prices away from levels implied by supply and demand under rational expectations. We develop a structural vector autoregression model of a commodity futures market and use it to explain two recent spikes in cotton prices. In doing so, we make two contributions to the literature on commodity price dynamics. First, we estimate the extent to which cotton price booms and busts can be attributed to comovement with other commodities. Finding such comovement would be necessary but would not be sufficient evidence to establish that broad-based financial speculation drives commodity prices. Second, after controlling for aggregate demand and comovement, we develop a new method to point identify shocks to precautionary demand for cotton separately from shocks to current supply and demand. To do so, we use differences in volatility across time implied by the rational expectations competitive storage model. We find limited evidence that financial speculation caused cotton prices to spike in 2008 or 2011. We conclude that the 2008 price spike was driven mostly by precautionary demand for cotton, and the 2011 spike was caused by a net supply shortfall.

Key words: Commodity prices, index traders, financialization, speculation, cotton, comovement, structural VAR.

JEL codes: C32, G13, Q11.

The world economy has experienced two recent commodity price booms and busts. Between 2006 and 2008, prices for agricultural, energy, and metal commodities all rose sharply. The prices of cotton, silver, and copper approximately doubled, while the prices of wheat and crude oil virtually tripled. After they rose together, commodity prices then fell together in late 2008 before commencing a second boom and bust in 2010 and 2011. The magnitude and breadth of these booms raises the question of attribution: Is there some fundamental reason why so many commodity prices moved together?

If any commodity might have avoided the 2006–2008 price boom and bust, it was cotton. Unlike other crops at the time, large quantities of cotton were held in storage. Figure 1 shows that the U.S. stocks-to-use ratio was above 50% at the end of the 2007–2008 crop year, a level higher than any year since the mid-1980s, when U.S. government policy encouraged higher cotton stocks. Nonetheless, cotton prices increased from \$0.50 per pound in mid-2007 to almost \$0.90 in March 2008 before dropping back to \$0.50 in the ensuing six months. It appears cotton prices comoved with other commodities in spite of contrary supply and demand fundamentals.

Several empirical papers suggest that commodity price comovement is characteristic of the presence of financial speculators who may be disconnected from current and expected supply and demand for a particular commodity. Pindyck and Rotemberg (1990)

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Amer. J. Agr. Econ. 100(1): 264–285; doi: 10.1093/ajae/aax052
Published online September 29, 2017

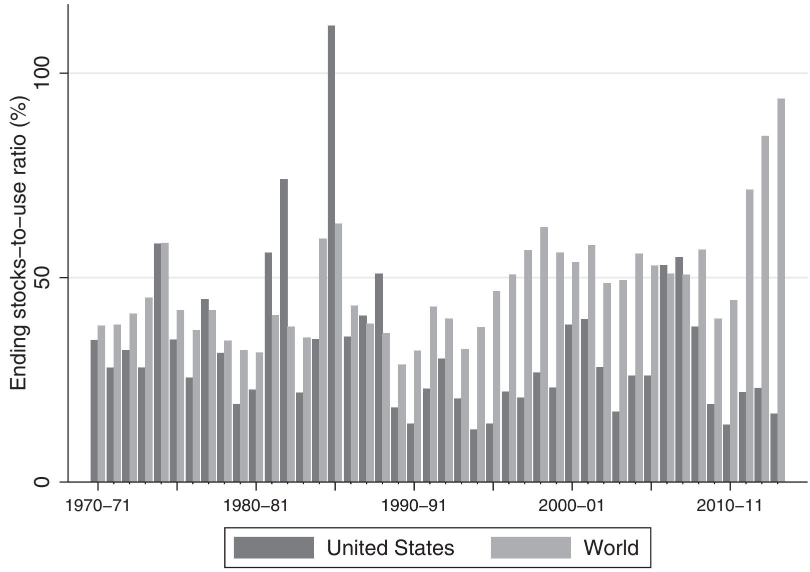

Figure 1. U.S. and world crop-year ending cotton stocks-to-use, 1970–71 to 2013–14

Source: United States Department of Agriculture, Foreign Agricultural Service (2015).

estimated that commodity prices, including cotton, move together more strongly than can be explained by fundamentals. They attributed this phenomenon to financial flows driven by changing trader sentiment common across a range of commodities. More recently, Tang and Xiong (2012) showed how the effects of commodity index trading may be revealed in similar comovement across commodity prices.

Comovement of commodity prices could be caused by coincidental shocks to consumption and production or by macroeconomic factors rather than by financial flows. Moreover, it is easy to conflate speculation by financial traders with rational speculation in physical or futures markets by storage firms that act to balance supply and demand across time. A study of comovement and speculation requires that both types of speculation be considered and separately identified. If the financial speculation effect highlighted by Pindyck and Rotemberg (1990) and Tang and Xiong (2012) exists, then we expect to find significant comovement with other commodities after controlling for changes in economic activity that drive demand for all commodities.

We make two contributions to the literature on commodity price dynamics and speculation using a structural vector autoregression (SVAR) model with cotton as a case study. First, we estimate the extent to which recent cotton price booms and busts can be attributed to comovement with other commodities suggested to be characteristic of financial speculation. Our model does not attempt to measure the presence of financial speculators, only whether their predicted impact through comovement with external markets is significant. We use Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI) as the external market price in our main analysis, but we also report results using the price of crude oil and a common factor derived from non-agricultural commodity prices. Throughout, we control for the global level of economic activity using the Kilian (2009) index.

After controlling for the components of prices related to real economic activity and external markets, we are left with cotton-specific price shocks. We decompose these fundamental shocks into two components: (*a*) precautionary demand for inventories, and (*b*) current-period demand and supply. The method for doing so is our second contribution. We exploit the fact that price volatility is higher when inventories are low than when inventories are high, which allows us to apply the "Identification through Heteroskedasticity" technique developed by Rigobon (2003). We motivate this heteroskedasticity using the canonical rational expectations competitive storage model (e.g., Williams and Wright 1991) and confirm it using statistical tests. The competitive storage model plausibly suggests the presence of tranquil and volatile price regimes that generate additional moment conditions to give exact identification of the SVAR model parameters. In contrast, previous studies of commodity pricing obtain only partial identification through sign restrictions and/or inequality constraints on short-run elasticities (Lombardi and Van Robays 2011; Kilian and Murphy 2014; Juvenal and Petrella 2015; Carter, Rausser, and Smith 2017).

We apply our model to the cotton market using data from 1970 through 2014. Contrary to Tang and Xiong (2012), we find that comovement characteristic of financial speculation plays only a minor role in cotton price fluctuations. During recent boom and bust cycles, cotton prices would have been at most 11% lower in the absence of comovement shocks and this maximum impact does not coincide with the 2008 or 2011 cotton price spikes. Other fundamental factors were responsible for a greater proportion of observed price changes: precautionary demand led to higher prices in 2008 as cotton plantings were reduced in light of higher prices for other crops, whereas supply shortfalls drove prices to record highs in 2011.

In general, we find that cotton futures prices, while volatile, have reflected cotton supply-and-demand fundamentals rather than the machinations of financial speculators. The significance of precautionary demand shocks in 2008 highlights the importance of expectations about future supply and demand for agricultural commodity price dynamics. This factor has been conflated with financial speculation in some analyses of recent price spikes (e.g., Tadesse et al. 2014). Our results provide limited support for claims that financial speculation causes cotton booms and busts.

Cotton as a Case Study

Cotton represents 40% of global fiber production, with 30–40% of cotton fiber crossing borders before processing (Meyer, MacDonald, and Foreman 2007). The United States is the third-largest producer after China and India, accounting for 14% of global supply over the period 2005–2014 (USDA, Foreign Agricultural Service 2015). Because cotton processing has largely moved from the United States to lower-cost areas such as China, most U.S. production is exported. After initial local processing separates cotton fiber from cottonseed, the U.S. exports about 2.8 million metric tons of cotton fiber annually, or 34% of global trade (USDA, Foreign Agricultural Service 2015).

Futures markets generate price discovery and serve as global price benchmarks. Cotton futures are traded at the Intercontinental Exchange (ICE), formerly the New York Board of Trade. The market has a relatively small trading volume compared to other commodities, which makes it potentially susceptible to spillover effects from other markets due to financial speculation. In 2014, approximately 5.7 million cotton futures contracts were traded at the ICE, representing approximately 131 million metric tons with a notional value of $220 billion. By comparison, the notional value of 2014 trading volume in West Texas Intermediate crude oil futures, the largest U.S. commodity futures market, was $13.5 trillion, or 61 times ICE cotton trading volume (Acworth 2015).

The 2008 and 2011 price spikes had a serious impact on the cotton industry, which provides a further reason to study them. In 2008, margin calls on futures positions forced several cotton merchants to exit the industry (Carter and Janzen 2009). The Commodity Futures Trading Commission (CFTC) responded to the 2008 price spike with an inquiry into potential market manipulation; they found no evidence suggesting any trader group had an outsized impact on prices (Commodity Futures Trading Commission 2010). Price swings in 2011 (in absolute terms much larger than in 2008) caused further large losses for some physical cotton traders. The 2011 losses were large enough to spur a lawsuit against Allenberg Cotton, the world's largest cotton trader, alleging market manipulation (Meyer 2013). The sum of this volatility prompted commentators to label cotton futures as the "widow maker trade" of the commodities world (Meyer and Blas 2011).

Commodity-Specific Price Variability: Net Supply and Precautionary Demand

For storable commodities such as cotton, equilibrium prices reflect contemporaneous supply and demand as well as the incentive to hold inventory in storage in anticipation of future supply and demand conditions. Williams and Wright (1991), Deaton and Laroque (1992, 1996), and Routledge, Seppi, and Spatt (2000) and others developed the modern framework for pricing storable commodities, known as the rational expectations competitive storage model. These researchers added supply, demand, and market-clearing conditions to the basic no-arbitrage relationship governing the relationship between prices for delivery in the current period t and future periods, and solved for a dynamic equilibrium. Use of the commodity in period t is governed by a downward-sloping inverse demand function, denoted $P_t = f(D_t)$ where P is the equilibrium price and D the quantity demanded for current consumption. Production in each period, S_t, is drawn from a distribution over which stockholding firms form rational expectations. These firms maximize expected profit from holding inventories, I, between periods. In equilibrium, the quantity available at t, $(S_t + I_{t-1})$, equals consumption demand plus stocks carried into the next period, $(D_t + I_t)$, and the futures price equals the expected spot price, that is, $F_{t,t+1} = E_t(P_{t+1})$. The final important feature of the model is a zero lower bound on inventories, $I_t \geq 0$, as stocks cannot be borrowed from the future.

The solution to the stockholding firm's problem implies a negative relationship between precautionary demand and P_t. The higher the spot price, the less inventory storage firms are willing to hold. Thus, the total demand curve in any period may be represented as the horizontal sum of the current-use demand function, $P_t = f(D_t)$, and this precautionary demand relationship, $P_t = g(I_t)$. The supply function, $h(S_t + I_{t-1})$ represents the outcome of the current period production shock plus inventories carried in from the previous period. Panel A of figure 2 illustrates equilibrium in price-quantity space.

Three functions—supply, consumption demand, and precautionary demand—underlie the equilibrium price solution illustrated in panel A of figure 2. The precautionary demand component can be considered a form of speculative demand since it is based on the speculative expectations about future supply and demand conditions. We can rearrange these functions to more clearly highlight the dichotomy between current and expected future supply and demand conditions. The net supply of the commodity available to be stored at t is the horizontal difference between the supply curve, $P_t = h(S_t + I_{t-1})$, and the current-use demand function, $P_t = f(D_t)$. Call this net supply function $P_t = j(S_t + I_{t-1} - D_t)$ or $P_t = j(I_t)$. The intersection of the net supply function and the precautionary demand function generate an equilibrium in price-inventory space in panel B of figure 2, corresponding to the equilibrium in price-quantity space in panel A of figure 2.

Relating Inventories to Calendar Spreads

In our empirical analysis, we aim to estimate the net supply and precautionary demand functions in panel B of figure 2. This task is complicated by the dearth of high-frequency information about inventory levels. However, the futures market calendar spread provides a good proxy for inventory (Fama and French 1987; Ng and Pirrong 1994; Geman and Ohana 2009). The validity of this proxy stems from the supply of storage curve, also known as the "Working curve" (Working 1933). We plot this curve in panel C of figure 2. It is upward-sloping because the marginal cost of storage increases with the level of inventory. At low inventory levels, the cost of storage in the figure is negative because a convenience yield provides a benefit to holding stocks.

The Working curve relationship implies that information from the term structure of futures contract prices may help infer the origin of observed price shocks when relevant quantity data regarding production, inventories, and consumption cannot be observed at high frequency. For example, price increases accompanied by rising inventories and an increasing calendar spread suggest an increase in precautionary demand for inventories. In contrast, a temporary shock to current supply due to poor growing-season weather would raise prices, decrease the calendar spread, and be associated with declining inventory.

Heteroskedasticity

It is a well-known empirical regularity that commodity futures prices are "characterized by volatile and tranquil periods" (Bollerslev 1987). The competitive storage model explains such heteroskedasticity. Williams and Wright (1991) show how price volatility depends on the presence of inventories. Extensions of the competitive storage model that include a convenience yield generate

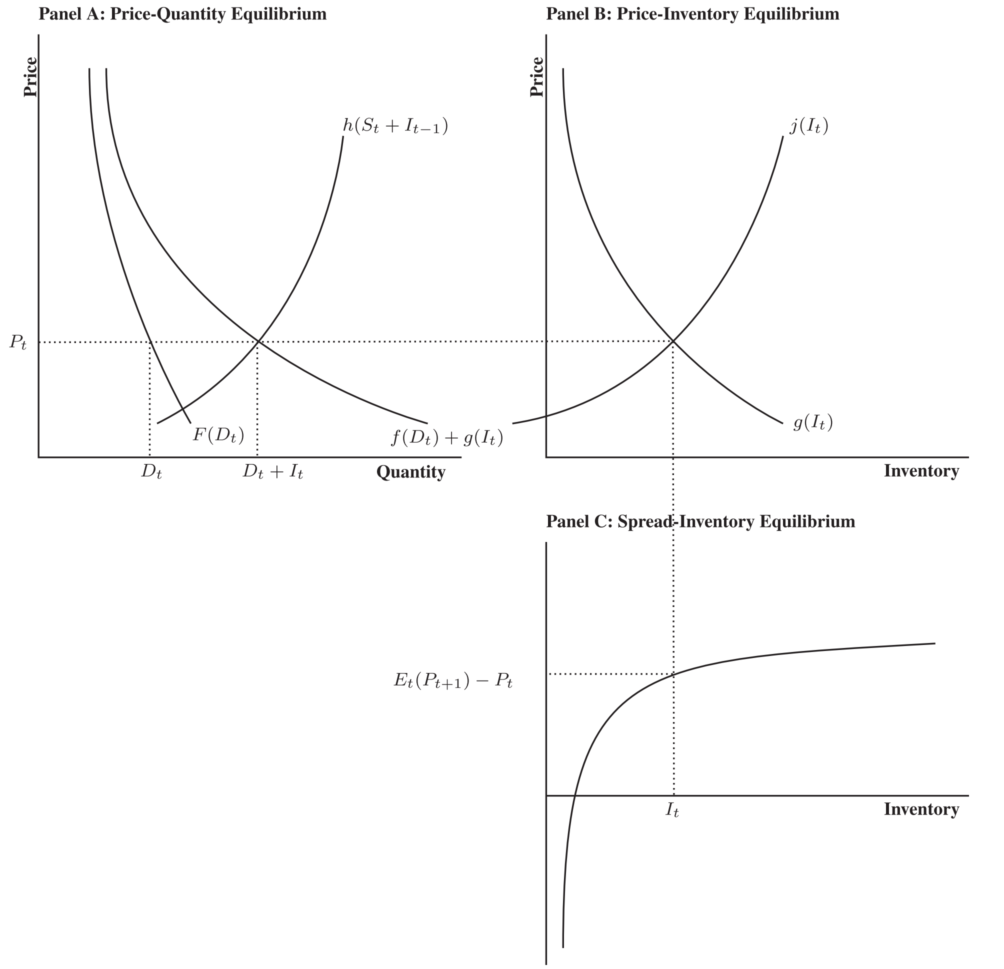

Figure 2. Price, spread, and inventory determination in a stylized single-period representation of the competitive storage model

similar inventory-dependent heteroskedasticity in calendar spreads (e.g., Peterson and Tomek 2005). The nonlinear Working curve relationship between price spreads and inventories suggests that spreads may be more volatile when inventories are low; Fama and French (1988) verified this conjecture empirically. We exploit this heteroskedasticity to identify the cotton-specific price shocks in our econometric model.

Types of Speculation: Precautionary Demand vs. Financial Speculation

Precautionary demand for inventories is an important component of a well-functioning commodity market in which prices reflect both current and expected future supply and demand. A second type, financial speculation, describes trading in a derivatives market for a given commodity by firms who trade simultaneously across many commodity markets. Financial speculation has been mainly associated with recent growth in commodity index funds, but includes speculative trading by financial firms like hedge funds, pension funds, and others in commodities as an asset class for benefits related to portfolio diversification or sector-wide expected risk premia. Such speculation is unrelated to market-specific fundamental factors affecting precautionary demand or to the traditional non-commercial firms who trade commodity futures based on fundamentally-motivated directional views about price. The increased presence of financial speculation, carried out mainly but not exclusively by financial firms, has been termed the "financialization" of commodity markets (Irwin and Sanders 2011).

Commodity index funds are a weighted average of futures prices for many commodities designed to provide investor exposure to commodities. Two industry benchmarks are the S&P GSCI, which is a production-weighted index, and the Dow Jones-UBS Commodity Index (DJ-UBSCI), a liquidity- or volume-weighted index. Financial firms have developed exchange-traded funds, swap contracts, and other vehicles to allow investors to add these and similar indexes to their investment portfolios and obtain potential portfolio diversification benefits or risk premia (Gorton and Rouwenhorst 2006; Bhardwaj, Gorton, and Rouwenhorst 2015). Firms using index-tracking trading strategies are referred to as commodity index traders (CITs).

The large presence of CITs in cotton and the negligible importance of cotton to major commodity indexes is a reason cotton may be vulnerable to spillover impacts from unrelated commodities due to financial speculation. Cotton is a small component of both indexes, reflecting the relatively small value of world cotton production and small size of the cotton futures market. Between 2006 and 2014, CITs held between 16% and 44% of long open interest in ICE cotton futures. This proportion had statistically significant contemporaneous correlation with the CIT proportion of open interest in nine of the other twelve commodity markets for which the CFTC reports CIT positions (Commodity Futures Trading Commission 2015). Although CITs are large players in the cotton market, cotton is a small component of the portfolios held by these traders. In 2014, 1.02% of the widely-followed GSCI was allocated to cotton, compared to 23.73% for West Texas Intermediate (WTI) crude oil futures, and an additional 23.14% for Brent crude oil futures (S&P Dow Jones Indices 2013).

Authors such as Soros (2008) and Masters (2010) claim that CITs have caused boom and bust cycles in commodity markets. Consistent with this claim, Singleton (2014) finds that increased CIT positions in crude oil futures markets are associated with subsequent increases in prices. However, a considerable body of evidence supports the opposite conclusion, namely that CIT futures market positions are not associated with futures price levels or price changes (e.g., Stoll and Whaley 2010; Buyuksahin and Harris 2011; Irwin and Sanders 2011; Fattouh, Kilian, and Mahadeva 2013).

Identifying Financial Speculation through Comovement

Although the weight of evidence suggests that CIT trading does not predict commodity prices, Tang and Xiong (2012) show how the effects of financial speculation of the type described in the previous section can be revealed in the cross-section. Correlations between many commodity prices and the price of WTI crude oil, the most widely traded commodity futures contract, have risen over the period in which CIT activity has become prevalent. Tang and Xiong (2012) tested the link between returns for many commodities and crude oil before and after the rising prevalence of CITs controlling for macroeconomic factors, and concluded that observed comovement among crude oil and other indexed commodity prices was caused by their inclusion into major indexes such as the GSCI and the DJ-UBSCI.

The "index inclusion" impact of financial speculators like CITs follows similar effects found in equity markets by Barberis, Shleifer, and Wurgler (2005), who argue that index inclusion allows trader sentiment removed from fundamental factors specific to individual stocks to be an important determinant of stock prices. In related work, Bruno, Büyükşahin, and Robe (2017) find that market fundamentals rather than correlations with equity prices remain the pre-eminent driver of agricultural commodity price dynamics. These authors do not explicitly test for cross-commodity comovement as in Tang and Xiong (2012).

Finding common movement in commodity prices and attributing it to financial speculators is not unique to the study by Tang and Xiong (2012) or the recent period of growth in commodity index trading. Pindyck and Rotemberg (1990) presented findings of "excess comovement" among seven commodity prices, and posited that correlation among fundamentally unrelated commodity prices that cannot be explained by macroeconomic factors is excess comovement, driven by speculative financial flows common across a range of commodities. To control for macroeconomic factors, these authors employed a seemingly unrelated regressions framework in which prices for cotton and other commodities were dependent variables and macroeconomic variables were controls. Significant cross-equation correlation of the residuals from these regressions suggested evidence of excess comovement. Pindyck and Rotemberg (1990) and Tang and Xiong (2012) essentially conducted similar tests of comovement across commodity classes. Each set of authors noted the importance of controlling for general economic activity that generates common shocks to all commodity prices.

Just as other researchers countered the claims of Masters (2010) and Singleton (2014) with respect to CITs, commodity price comovement found in Pindyck and Rotemberg (1990) was contested as an artifact of methodological flaws or omitted variables. Deb, Trivedi, and Varangis (1996) found that the excess comovement result was driven by the assumption of normal and homoskedastic errors in the seemingly unrelated regressions model of Pindyck and Rotemberg (1990). Ai, Chatrath, and Song (2006) proposed that the omission of production, consumption, and inventory information led to observed cross-commodity price correlation, and they showed that including these variables can explain comovement in agricultural commodities.

This earlier comovement literature potentially explains why Tang and Xiong (2012) found a CIT-induced comovement effect: they excluded consideration of market-specific fundamentals. However, Ai, Chatrath, and Song (2006) did not directly refute Pindyck and Rotemberg (1990) and Tang and Xiong (2012) because they did not consider a comovement effect among commodities that are not direct substitutes in production and consumption. Additionally, Ai, Chatrath, and Song (2006) could not test for CIT-induced comovement effects, which would have happened after their article was published, and they could not consider price changes at a frequency greater than quarterly due to limited inventory data. Our empirical analysis addresses these shortcomings.

Financial speculation-induced comovement may affect precautionary demand for inventories by altering both the spot price and the futures calendar spread, as suggested theoretically in Vercammen and Doroudian (2014) and Hamilton and Wu (2015). If financial speculation increases calendar spreads, the Working curve relationship implies an increase in the incentive to store, and therefore an increase in inventories. Thus, the calendar spread remains indicative of the level of inventory even if financial speculation affects spreads. Our econometric model is capable of measuring both spot and spread effects.

Data

We include four variables in our econometric model: real economic activity, an external commodity market price, the calendar spread in the cotton futures market, and the price of cotton. All variables are observed monthly and deflated using the U.S. Consumer Price Index (CPI). To measure real economic activity, we use the real economic activity index developed by Kilian (2009), which aggregates ocean freight rates as a proxy for global demand for goods. Because the freight rate index will rise if economic activity rises in any part of the world, it will not be biased toward any one country or region of the world.

We collect data on cotton and other commodity market prices from the Commodity Research Bureau (2014). The cotton price series is the logarithm of the monthly average nearby real futures price. External markets are represented by the GSCI, which is backdated to 1970 by the data provider, and West Texas Intermediate crude oil. For both series, we again calculate the logarithm of the real monthly average price. The cash price series for crude oil is used because crude oil futures only began trading in 1983.

To measure the incentive to hold cotton inventory, we use the cotton futures price calendar spread over a one-year time span.[1] This measure always spans a harvest, so it represents expectations about the scarcity of cotton relative to a future period that allows for some production response. As such, it measures the incentive to hold inventories until future supply and demand uncertainty is resolved by a forthcoming harvest. Cotton futures contracts mature five times per year, so we calculate the spread as the logarithmic difference between the sixth-most-distant and the nearby futures contract. The time difference between these contracts is always a year, so the spread represents the term

[1] Data on physical inventories would be an alternative to the calendar spread variable in our model, but consistent data on physical inventories are not available for our sample period. We assess the empirical relationship between calendar spreads and physical inventories in an online supplementary appendix.

structure of cotton prices over a constant period of time.

Figure 3 plots these variables for July 1970–June 2014, adjusting for a linear trend and seasonality. There are 528 monthly observations covering 44 marketing years for cotton, where the marketing year runs from July to June.[2] We use a linear trend to account for productivity improvements and other factors responsible for a long-run decline in real commodity prices. We also adjust for the impact of the 1985 Farm Bill on the cotton market.[3] The augmented Dickey-Fuller test fails to reject the null hypothesis of a unit root in the price variables (cotton, GSCI, and crude oil), however, stationarity is not necessary in this case. Sims, Stock, and Watson (1990) showed that a VAR estimated in levels produces consistent estimates of the true impulse responses even in the presence of some unit roots.

Econometric Model

We apply a SVAR model to disentangle the effects of real economic activity, comovement, precautionary demand, and contemporaneous net supply. The SVAR enables us to measure the contribution of these components to observed cotton prices throughout the study period. Moreover, the structural shocks identified by the model enable us to estimate counterfactual prices in the absence of one or more of the components.

Previous Literature on SVAR and Commodity Speculation

Kilian and Murphy (2014) use monthly data on crude oil prices, production, inventory levels, and an index of economic activity to estimate an SVAR that considers competitive-storage-model-related shocks. By adding inventory data and a precautionary demand shock (which they call speculative demand), Kilian and Murphy (2014) extend earlier work (Kilian 2009) that focused on current shocks to oil prices. The Kilian and Murphy (2014) model shows that precautionary demand is an important determinant of crude oil prices, although precautionary demand shocks were not an important driver of the 2006–08 oil price boom.

The model in Kilian and Murphy (2014) does not extend directly to cotton for three reasons. First, their approach captures consumption demand using the Kilian (2009) real economic activity index. We recognize that demand for cotton and substitute fibers may not coincide with general economic activity, so we interpret this variable as capturing the state of the global macroeconomy. In our model, cotton-specific demand is subsumed in a net supply component as depicted in panel B of figure 2. In this sense, our setup is similar to Carter, Rausser, and Smith (2017), who estimate a SVAR model of corn prices. These authors use the real economic activity index to capture aggregate commodity demand and show that it is sufficient to focus on net supply when modeling inventory dynamics. Other applications of SVAR to agricultural commodity price dynamics such as Bruno, Büyükşahin, and Robe (2017) also use this index to concisely capture general commodity demand effects.

Second, the annual production cycle and sparse inventory data limit the ability of the Kilian and Murphy (2014) model to capture competitive-storage-model-type shocks for seasonal agricultural commodities. Pirrong (2012) notes that it is difficult to solve for intra-annual prices in a competitive storage model in which production occurs once per year. Carter, Rausser, and Smith (2017) avoid this problem by using annual data in their corn price model. Annual data avoids the need to observe the effective inventory level at high frequencies, but decreases sample size and smooths over intrayear price spikes. Following the discussion above, we use the calendar spread to capture the incentive to hold precautionary inventories in expectation of future supply and demand shocks.

Finally, the Kilian and Murphy (2014) model does not address financial speculation separately from speculative precautionary demand. Two subsequent articles (Lombardi and Van Robays 2011; Juvenal and Petrella 2015) adapt the Kilian and Murphy (2014) model to capture the effect of financial speculation on crude oil prices. Both articles attribute a significant portion of crude oil price volatility to financial speculation, but Fattouh, Kilian, and Mahadeva (2013) explain that the sign restrictions required for

[2] The cotton marketing year runs from August to July. In our data, the marketing year runs from July to June since we roll from the old-crop July contract to the new-crop October contract in July of any year.

[3] See the online supplementary appendix for description of these controls.

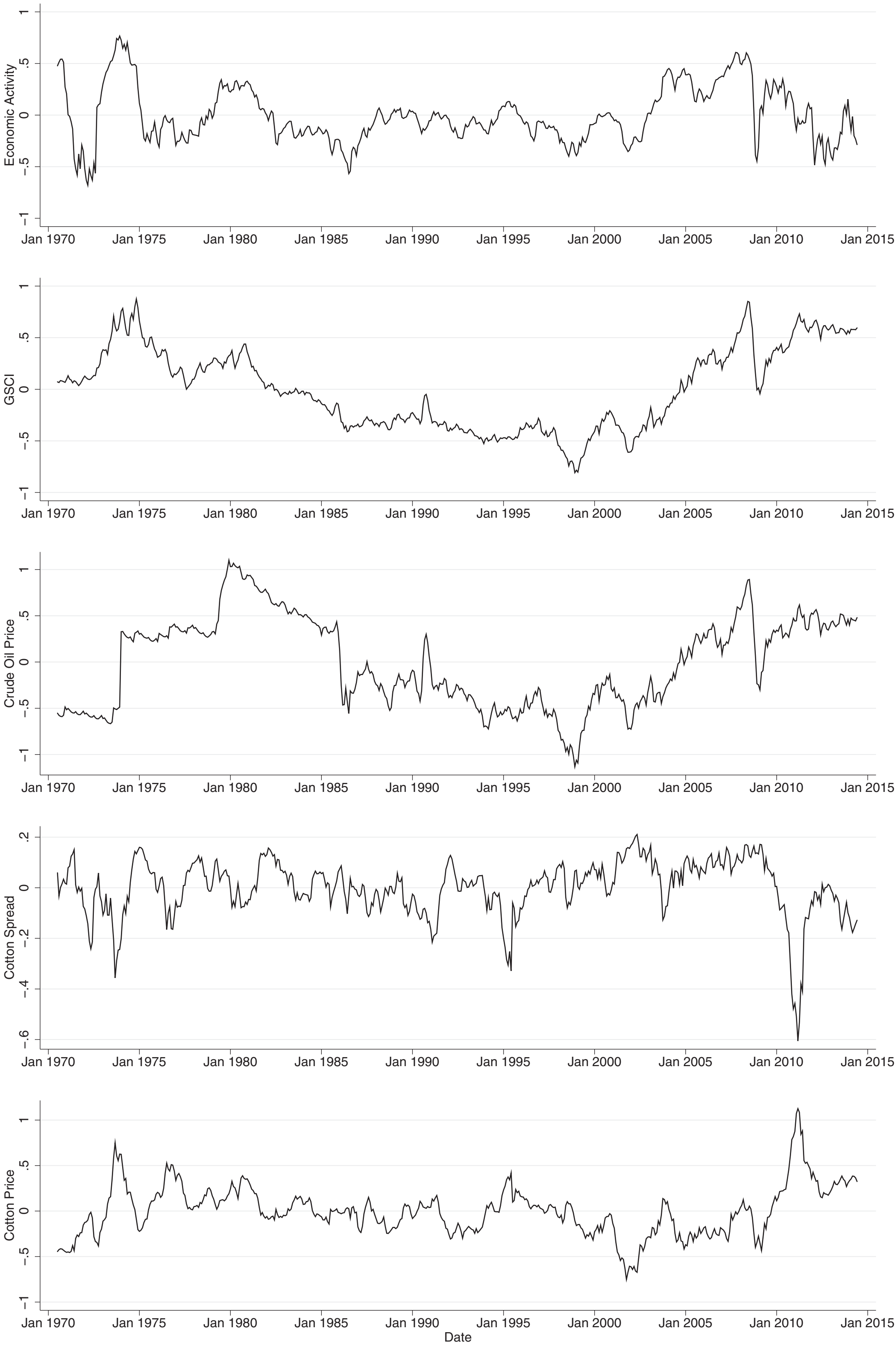

Figure 3. Data plot for variables in y_t, controlling for linear trend and seasonality, July 1970 to June 2014

identification in these articles are not credible. We model the effects of financial speculation differently by including the price of an external commodity in our model. If the financial-speculation effect highlighted by Pindyck and Rotemberg (1990) and Tang and Xiong (2012) exists, then we expect to find significant comovement with external commodity prices. Finding such comovement is not sufficient to prove a financial speculation effect, but it is necessary.

Identification

We include four variables in a vector $\boldsymbol{y_t}$: (*a*) real economic activity, *rea*, (*b*) the real price in an external market, *ext*, (*c*) the spread between distant and nearby futures prices for cotton, *spr*, and (*d*) the real price of nearby cotton futures, *pct*. A SVAR model for y_t is

$$(1) \quad A_0 y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + Cx_t + u_t$$

where x_t denotes a vector of deterministic components that includes a constant, a linear trend, and seasonal dummy variables. The structural shocks u_t are white noise and uncorrelated with each other. We label the four structural shocks (*a*) real economic activity, (*b*) comovement, (*c*) precautionary demand, and (*d*) current net supply. Multiplying through by A_0^{-1} produces an estimable reduced-form VAR

$$(2) \quad y_t = B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p y_{t-p} + Dx_t + \varepsilon_t$$

The reduced-form shocks, ε_t, are prediction errors and are a weighted sum of the structural shocks, where the matrix A_0 provides those weights, that is, $\varepsilon_t = A_0^{-1} u_t$. Identifying u_t requires making sufficient assumptions to enable consistent estimation of the elements of A_0.

Our identification approach is sequential. We use exclusion restrictions to identify the real economic activity and comovement shocks, and then we use Identification through Heteroskedasticity (ItH; Rigobon 2003) to separate the precautionary demand and net supply shocks. Lanne and Lutkepohl (2008) use a similar combination of recursion assumptions and ItH in an application to monetary policy.

We specify real economic activity as exogenous to the other variables within a month, and we specify the external market as exogenous to the cotton market within a month. With these assumptions, the elements of the equation $A_0 \varepsilon_t = u_t$ are

$$(3) \quad \begin{bmatrix} 1 & 0 & 0 & 0 \\ A_{21} & 1 & 0 & 0 \\ A_{31} & A_{32} & 1 & A_{34} \\ A_{41} & A_{42} & A_{43} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{rea} \\ \varepsilon_t^{ext} \\ \varepsilon_t^{spr} \\ \varepsilon_t^{pct} \end{bmatrix} = \begin{bmatrix} u_t^{REA} \\ u_t^{CM} \\ u_t^{PD} \\ u_t^{NS} \end{bmatrix}.$$

This initial recursive ordering means that we interpret contemporaneous correlation between real economic activity and the other variables as an effect of real economic activity on those variables. Similarly, we interpret contemporaneous correlation between the external market and cotton as reflecting a comovement effect characteristic of financial speculation rather than an effect of events in the cotton market on the external market. That is, our model does not attempt to measure the presence of financial speculators, only whether their predicted impact through comovement is significant. Finding an insignificant relationship between comovement and cotton prices could be attributed to weak correlation in trading activity between cotton and other commodity markets, but we believe this is not the case based on the mechanics of major commodity indexes and the CFTC data on CITs.

Since the correlation between the external market and cotton (net of any common movement with real economic activity) may be due to spillovers related to both financial speculation and other factors such as production costs, this identification scheme estimates an upper bound on the influence of financial speculation on both cotton prices and cotton calendar spreads. Any association between the external market and cotton prices, as a measure of cotton scarcity, or cotton spreads, as a measure of the incentive to hold inventory, is attributed to the influence of the comovement factor. Finding a significant relationship between external market prices and cotton spreads or cotton prices does not prove this type of speculation exists since other unknown factors could conceivably explain the relationship, but an insignificant relationship indicates the absence of such an effect. The remaining variation in cotton spreads and prices after controlling for fluctuations in real economic activity and the external market price, akin to the residuals from regressions of prices or spreads on real economic activity and external market prices, is attributed to cotton-specific fundamental factors.[4] Thus, our model gives the maximum opportunity for a comovement effect to show itself in both cotton spreads and prices.

The parameters A_{34} and A_{43} in equation (3) represent short-run elasticities implied by the slopes of the precautionary demand and net supply curves in figure 2. Setting $A_{34} = 0$ would imply that the spread cannot respond contemporaneously to the net supply shock, that is, precautionary demand for inventory is perfectly inelastic within a month. Similarly, setting $A_{43} = 0$ would imply that net supply is perfectly elastic within a month. Neither assumption is credible in our case: the competitive storage model suggests that precautionary demand and net supply endogenously generate observed prices in equilibrium.[5]

Rather than assuming a recursive structure or using sign restrictions, we exploit the heteroskedastic nature of observed prices implied by the competitive storage model to identify the two components of the cotton-specific part of the model. The ItH relies on differences in the variance of the structural shocks across time to identify A_{34} and A_{43}; it requires the sample to be partitioned into (at least) two volatility regimes, where the relative variance of the structural shocks differs between regimes. In the case of two regimes, we refer to the high variance regime as volatile and the low variance regime as tranquil. We partition the sample into two regimes r, one volatile vl and one tranquil tr, to satisfy the following properties:

$$(4) \quad \begin{aligned} var(u_t | t \in tr) &= \Sigma^{tr} \\ var(u_t | t \in vl) &= \Sigma^{vl} \end{aligned}$$

where $\Sigma^{tr} \neq \Sigma^{vl}$. The parameters A_j remain the same across regimes, which implies that the variance of the reduced form errors Ω^r must also be heteroskedastic.

Defining Ω^{tr} and Ω^{vl} as the variance of the reduced form errors in the tranquil and volatile states, respectively, the equation $A_0\varepsilon_t = u_t$ implies two moment conditions:

$$(5) \quad \begin{aligned} A_0\Omega^{tr}A_0{}' &= \Sigma^{tr} \\ A_0\Omega^{vl}A_0{}' &= \Sigma^{vl} \end{aligned}$$

where the structural shock variance-covariance matrix in regime r is

$$(6) \quad \Sigma^r = \begin{bmatrix} \sigma_{REA} & 0 & 0 & 0 \\ 0 & \sigma_{CM} & 0 & 0 \\ 0 & 0 & \sigma^r_{PD} & 0 \\ 0 & 0 & 0 & \sigma^r_{NS} \end{bmatrix}$$

There are 13 free parameters in Ω^{tr} and Ω^{vl}. We have 13 parameters to be identified, 7 in the A_0 matrix, and 6 structural shock variances, so the model satisfies the order condition. To obtain identification, we also require that the relative variance of the structural shocks $(\sigma^r_{PD}/\sigma^r_{NS})$ differs across regimes (Rigobon 2003).

The condition that $(\sigma^r_{PD}/\sigma^r_{NS})$ differs across regimes provides intuition for how ItH works. A scatter plot of observed prices and calendar spreads makes a cloud of points from which we cannot immediately infer the shape of the precautionary demand or current net supply curves shown in the panel B of figure 2. If the net supply shock is relatively more volatile in the volatile regime, then the cloud of points drawn from the volatile regime stretches relatively more along the precautionary demand curve, which enables its slope to be identified.

Empirical Suitability of Model, Data, and Identification Assumptions

We use monthly data from July 1970 to June 2014. The reason we construct a long time series when our interest is in recent price spikes is because more data allows for more precise estimation of model parameters. More importantly, we aim to use periods of dramatic

[4] Though our model focuses on the relationship between external market price levels and cotton prices and spreads, we also explored the potential for speculative impacts on calendar spreads in other markets to affect cotton price spreads. We found no evidence of a significant relationship between calendar spreads in crude oil and cotton. We are unable to test for a similar relationship between the GSCI and cotton price due to the nature of the GSCI as an index of current commodity prices.

[5] Some SVAR applications to agricultural commodity price dynamics such as Bruno, Büyükşahin, and Robe (2017) use recursive identification of inventory demand shocks. This identification scheme may be credible in their case, where the variable of interest is the correlation among commodity prices and equity prices, but not when the variable of interest is the commodity price itself.

price volatility. Our time series contains arguably four general booms and busts in commodity prices centered around 1973, 1996, 2008, and 2011. A shorter time series excludes some of these periods. A shorter time series also reduces the number of volatile periods we can use to identify our econometric model using ItH.[6]

To employ ItH, we identify volatile and tranquil regimes using a rule suggested by the competitive storage model, namely that price shocks will be more volatile when stocks are low relative to use. This result follows from competitive storage model simulation results and empirical studies of prices discussed above. We declare as volatile any marketing year where the projected cotton ending-stocks-to-use ratio (as defined by USDA World Agricultural Outlook Board [2008, 2010] forecasts) was at least 25% less than long-term trendline stocks-to-use for at least three months. Ending stocks-to-use forecasts measure both current and future cotton scarcity pertinent to contemporaneous commodity pricing. Considering projected stocks-to-use relative to trend accounts for a long-run decline in inventory levels over our sample period. We thereby obtain ten volatile windows, including the 1973–74, 1976–77, 1979–81, 1983–84, 1989–91, 1993–96, 1997–98, 2003–04, 2009–2011, and 2013–14 marketing years[7].

To assess the suitability of a linear VAR model and an ItH identification scheme in this context, we generate scatter plots in figure 4 of the spread and price variables in both levels and logarithms. This scatter plot illustrates the data in a context similar to panel B of figure 2 (except with the spread rather than inventory on the horizontal axis). The data plotted in levels suggests a negative correlation between prices and spreads, implying that net supply shocks dominate precautionary demand shocks. Put another way, movements along the precautionary demand curve are more prevalent than movements along the net supply curve. However, the levels plot also appears quite nonlinear, suggesting that levels data are unsuitable for analysis using a linear VAR. Taking logarithms addresses this non-linearity, as shown in the right panel of figure 4.

Figure 4 also suggests that the relative variance of the structural shocks ($\sigma^r_{PD}/\sigma^r_{NS}$) varies across regimes. The slope of a regression line through each regime's data points remains relatively constant across regimes, in line with the ItH assumption of constant parameters in the A matrix. While the cloud of points generally traces out the shape of the precautionary demand function, data points from the volatile (red) regime appear to more closely follow the precautionary demand function and vary less in the direction of the net supply function. This implies that structural shocks to net supply are relatively larger in the volatile regime. The cloud of points in the tranquil regime appear more spherical, suggesting precautionary demand shifts are relatively more important in the tranquil regime. In the results section, we corroborate this visual evidence by comparing the estimated variances of the structural shocks (σ^r_{PD} and σ^r_{NS}) across regimes.

Estimation and Results

We estimate the reduced-form VAR of equation (2) using ordinary least squares with two lags. Both the Akaike and Schwarz-Bayesian information criteria select a lag length of $p = 2$. The parameter estimates and their standard errors are presented in table 1. From the VAR estimates, we extract the reduced-form residuals, $\hat{\varepsilon}_t$ and divide them into two groups corresponding to the tranquil and volatile regimes.

From the estimated reduced-form residuals for each regime, we calculate the variance-covariance matrices, $\hat{\Omega}^{tr}$ and $\hat{\Omega}^{vl}$, as shown in table 2. Because we model heteroskedasticity only in the cotton-specific part of the model, we constrain the terms in the first two rows of $\hat{\Omega}^{tr}$ and $\hat{\Omega}^{vl}$ to be equal across regimes. Parameters in A_0 and Σ^r are computed by minimizing a distance function equal to the sum of the squares of each element of $\hat{A}_0\hat{\Omega}^r\hat{A}_0{}' - \hat{\Sigma}^r$ for each regime r. We report parameter estimates $\hat{\Sigma}^r$ and $\hat{A}_0$ in table 2.

The variances and covariance of the reduced-form residuals for the volatile regime from the *spr* and *pct* equations are 30% to 55% larger than in the tranquil regime (these are the parameters inside the boxes in

[6] In an online supplementary appendix, we test whether the model parameters are stable over time and find no evidence of a change in the parameters after 2004.

[7] We also tested similar rules for setting the regime windows based on relative and absolute stocks-to-use levels (e.g., choosing marketing years where the stocks-to-use ratio was below 20% for three months.) We found our results were robust to other regime selection methods.

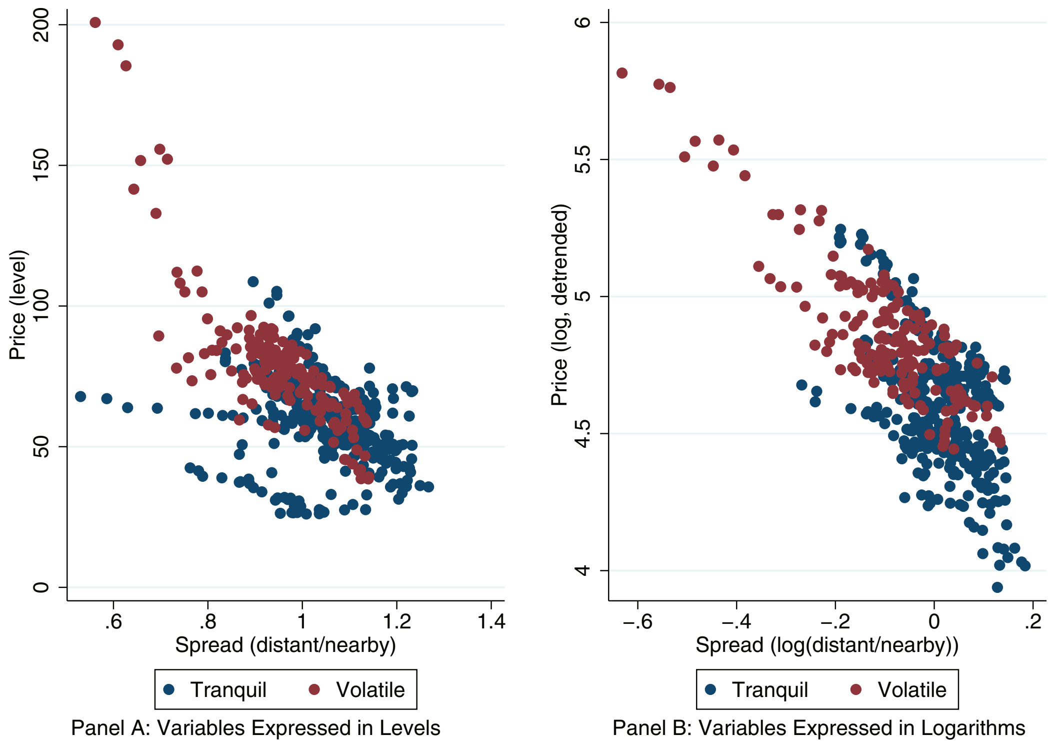

Figure 4. Scatter plots of *spr* and *pct* variables in levels (left) and detrended logarithms (right) by volatility regime

Table 1. Reduced-form VAR Regression Results

	Equation			
	rea	*ext*	*spr*	*pct*
Intercept	0.022	0.116**	0.062	0.099
	(0.101)	(0.046)	(0.049)	(0.072)
rea_{t-1}	1.102**	0.031	0.039	−0.017
	(0.069)	(0.027)	(0.027)	(0.044)
ext_{t-1}	0.183*	1.220**	−0.042	0.122*
	(0.092)	(0.052)	(0.043)	(0.071)
spr_{t-1}	0.2304*	0.214**	0.599**	0.569**
	(0.122)	(0.064)	(0.147)	(0.190)
pct_{t-1}	0.209*	0.195**	−0.228**	1.427**
	(0.093)	(0.055)	(0.068)	(0.099)
rea_{t-2}	−0.161**	−0.019	−0.026	0.006
	(0.068)	(0.028)	(0.027)	(0.044)
ext_{t-2}	−0.179*	−0.228**	0.041	−0.110
	(0.091)	(0.053)	(0.042)	(0.070)
spr_{t-2}	−0.250*	−0.264**	0.279*	−0.502**
	(0.121)	(0.067)	(0.143)	(0.188)
pct_{t-2}	−0.223**	−0.215**	0.212**	−0.456**
	(0.091)	(0.055)	(0.066)	(0.097)

Note: Heteroskedasticity-robust standard errors are in parentheses. Asterisks * and ** denote significance at the 5% and 1% levels. Coefficient estimates for seasonal indicators and linear time trend are not reported.

table 2). The associated structural shock variances, σ^r_{PD} and σ^r_{NS} also vary across regimes. The net supply shock has a variance 45% greater in the volatile periods than in the tranquil periods, whereas the precautionary demand shock variance is actually slightly smaller in the volatile period. This result strongly suggests the condition requiring the relative variance of the structural shocks to differ across regimes holds.

To formally test the heteroskedasticity assumption, we perform standard F-tests of equality across regimes for the variances σ^r_{PD} and σ^r_{NS}. These tests reject the null of constant variance (i.e., $\sigma^{vl} = \sigma^{tr}$) at the 5% level. We also test for differences in the entire variance-covariance matrix $\hat{\Omega}^r$ using Box's M-test (Box 1949). For our two regime model, the approximate null distribution of the test statistic is $\chi^2(10)$. The test rejects the null of equality of $\hat{\Omega}^r$ with a p-value of 5.2 $\times 10^{-6}$. Although these are parametric tests that may not have ideal small sample properties, the clear rejection of the null hypotheses suggests we are unlikely to attribute observed differences to small sample bias.

Table 2. Structural Vector Autoregression Model Parameter Estimates

Parameter								
$\hat{A}_0$	1	0	0	0				
	−0.084	1	0	0				
	−0.032	−0.026	1	0.711				
	−0.126	−0.107	−3.209	1				
	Regime							
Parameter	Tranquil				Volatile			
$\hat{\Omega}^r$	0.491	0.043	−0.009	0.034	0.491	0.043	−0.009	0.034
	0.043	0.183	0.003	0.040	0.043	0.183	0.003	0.040
	−0.009	0.003	0.156	−0.186	−0.009	0.003	0.221	−0.284
	0.034	0.040	−0.186	0.369	0.034	0.040	−0.284	0.479
σ^{REA}	0.491				0.491			
σ^{CM}	0.179				0.179			
σ^{PD}	0.073				0.054			
σ^{NS}	3.025				4.369			

Note: For ease of presentation, we report the estimated variance and covariance parameters multiplied by 100, and we include a box around the reduced-form parameters that vary by regime.

Having solved for the model parameters, we calculate a set of orthogonal structural shocks for each period. We estimate impulse response functions for all model variables with respect to each structural shock and generate confidence bounds for the impulse responses using the wild bootstrap procedure of Goncalves and Kilian (2004). Each variable in the model can be represented as a weighted sum of current and past structural shocks. We use this representation to create time series of the historical contribution of each structural factor to the observed innovations in each variable. We discuss our results for these impulse responses and historical decompositions below, first for the case where GSCI represents the external market, and then for alternative external markets.

Impulse Response Functions

Figure 5 plots the dynamic response of each variable in our model to the economic activity, comovement, precautionary demand, and net supply shocks for the case where crude oil is the external market. The dashed lines represent the point-wise 90% confidence interval about the average response generated using 1,000 bootstrap replications. These graphs demonstrate, based on the average response observed in the data, how each variable in the model would respond to a hypothetical one-standard-deviation structural shock using the standard deviations for each structural shock across the entire sample. We normalize the shocks such that each causes an increase in the price of cotton. In particular, net supply shocks refer to a disruption that increases cotton prices.

The impulse response functions serve two purposes. First, they act as a check on the validity of our assumptions about the shocks we want to identify. The direction of the responses should be consistent with the theory that motivated our identification scheme. Second, the impulse response functions for the price of cotton can be compared to ascertain the magnitude and duration of the influence of each structural shock.

If a precautionary demand shock occurs, the price and the spread should increase to encourage stockholding by providing higher returns to storage. The bottom-right corner of figure 5 shows that this is the case. Similarly, a net supply shock (equivalent to a supply disruption) raises cotton prices and has a negative influence on the spread in order to draw supplies out of storage and place them on the market. The precautionary demand shock displays some evidence of overshooting: prices increase quickly in the months following the shock, before declining. Both the precautionary demand and net supply shocks have an impact on prices for at least a year, which is to be expected based on the annual harvest cycle.

Figure 5 shows real economic activity shocks have small and statistically insignificant price effects, on average. Comovement effects associated with the GSCI have a small, statistically significant, and long-lived impact on cotton prices. Comovement shocks

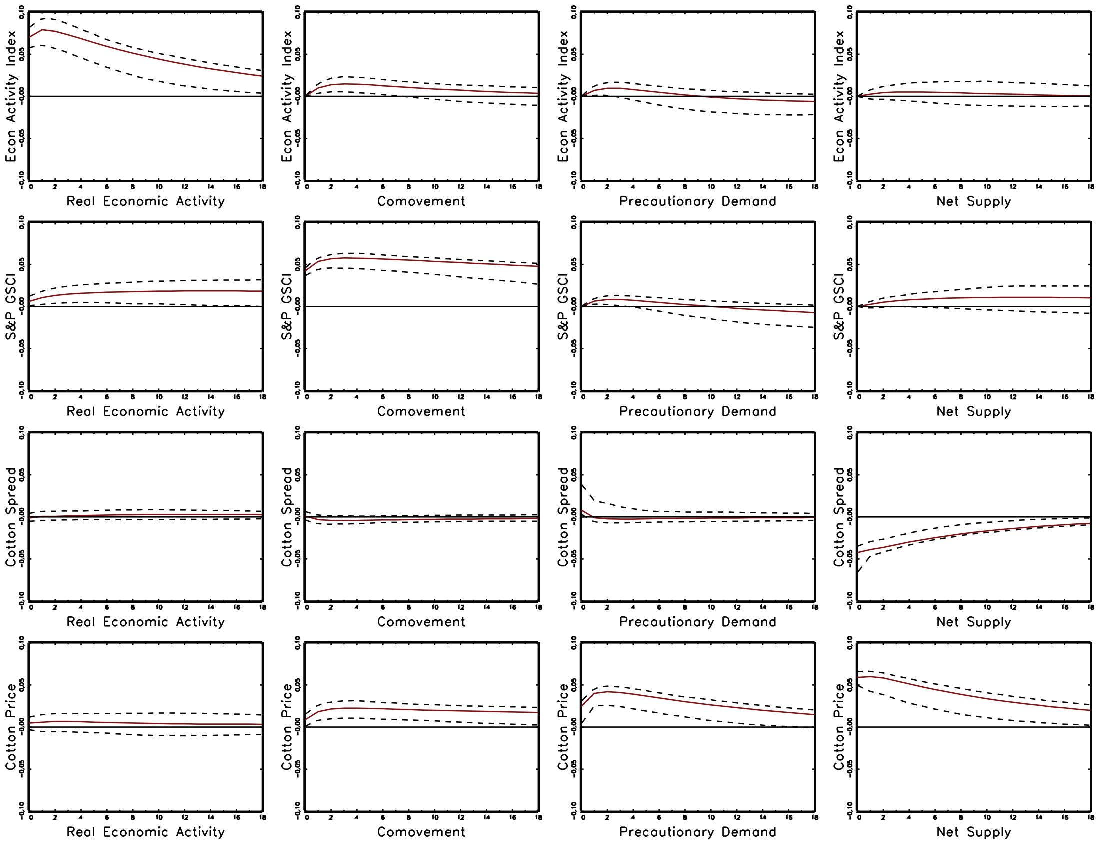

Figure 5. Impulse response functions generated from SVAR with GSCI as external market

do not affect cotton calendar spreads, indicating that in this case, comovement-induced financial speculation does not alter the incentive to store.

Historical Decomposition of Cotton Price Shocks

Impulse response analysis only allows us to assess the average response of cotton prices to one-standard-deviation structural shocks. The historical decomposition in figure 6 shows the accumulated contribution of each shock to the observed price at each point in time, which enables us to generate counterfactual prices. The series in figure 6 is constructed so the sum of the four series equals the realized price net of long-run linear trend and seasonality in any month (see, e.g., Kilian 2009).

Most of the observed variation in cotton prices throughout our sample is due to the two cotton-market-specific shocks; the precautionary demand and net supply shocks dominate these figures. Comovement shocks are periodically relevant to cotton pricing. Longer but considerably smaller swings in price are attributed to real economic activity. For example, the real economic activity component increases during the period from 2000 to 2008, likely tracking commodity demand growth from emerging markets. However, the effect is small relative to other shocks that occur over the same period.

The results of our decomposition analysis regarding real economic activity differ from analyses of crude oil prices by Kilian (2009) and Kilian and Murphy (2014) that used similar methods. These studies found that fluctuations in real economic activity related to the macroeconomic business cycle were the largest and most persistent driver of crude oil prices, particularly during the period of rising prices that ended in 2008. Similarly, Carter, Rausser, and Smith (2017) find that between its 2003 low and 2008 high, real economic activity generated an increase in corn prices of up to 50%. Our results for cotton suggest that real economic activity does not similarly impact the cotton market. Over the same

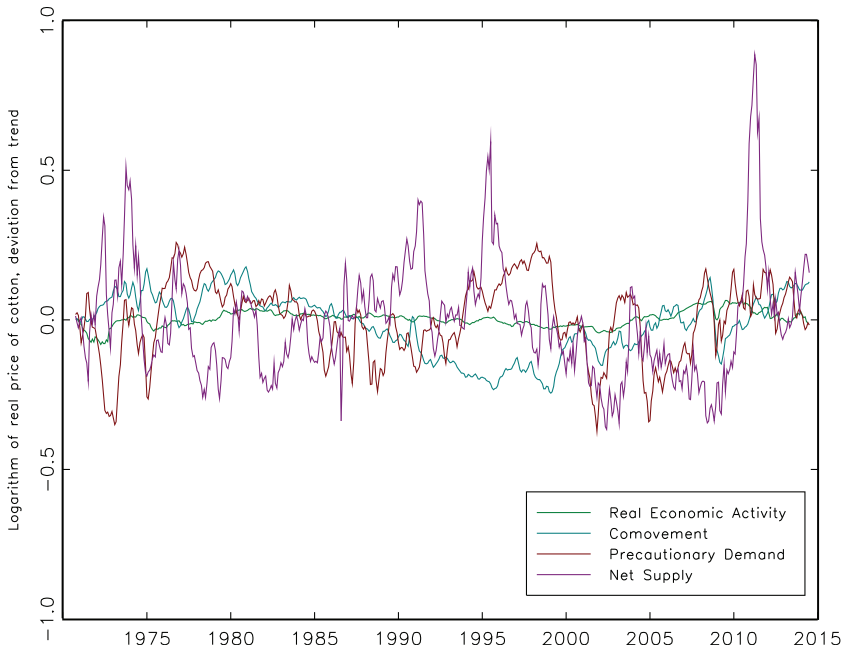

Figure 6. Historical decomposition of structural shocks with the GSCI as external market

period, real economic activity increased cotton prices by up to 6%.[8] This is not zero, but it is small relative to the contribution of other factors.

Throughout our sample period, major booms and busts in cotton prices have always been related most strongly to precautionary demand or net supply shocks. The net supply shock is the largest and most variable component of observed cotton futures prices over this period; it is the major driver of cotton price spikes in 1973–74, 1990–91, 1995–96, and especially the most recent spike in 2010–11. These are all periods of major supply disruptions. Each of these major positive net supply shocks is associated with lower U.S. and world cotton production.

The precautionary demand shock appears to have a significant role in cotton price increases in 2003–04 and 2007–08. In 2003–04, a price increase due to precautionary demand precedes a subsequent increase due to net supply. In contrast, the 2007–08 cotton price spike is not associated with major changes in the net supply shock.

Generally speaking, comovement shocks appear to have some influence on cotton prices but the timing of comovement shocks related to changes in the GSCI does not correspond with the timing of cotton price spikes. Rather, it accounts for some broad swings in prices. Figure 6 implies that comovement lowered cotton prices by about 20% in the late 1990s and raised prices by at most 18% in 1980, and 11% in 2008.

Counterfactual Analysis of the 2008 and 2011 Price Spikes

To focus attention on the two most recent cotton price spikes in 2007–08 and 2010–11, we eliminate individual orthogonal shocks from our historical decomposition and use the sum of the remaining shocks to construct the price series for a counterfactual scenario: what would have happened to cotton prices during this period in the absence of any one of the effects we identify? For example, how would the time series of observed cotton prices have differed if the external market comovement shocks did not affect cotton prices? The counterfactuals are plotted in figure 7. The five series shown are the observed cotton price and counterfactual cotton prices with each of the real economic activity, external market comovement, precautionary

[8] We measure this change as the log difference between prices with and without each of the shocks. These log differences approximate a percentage change, so we use percentage to refer to these log differences.

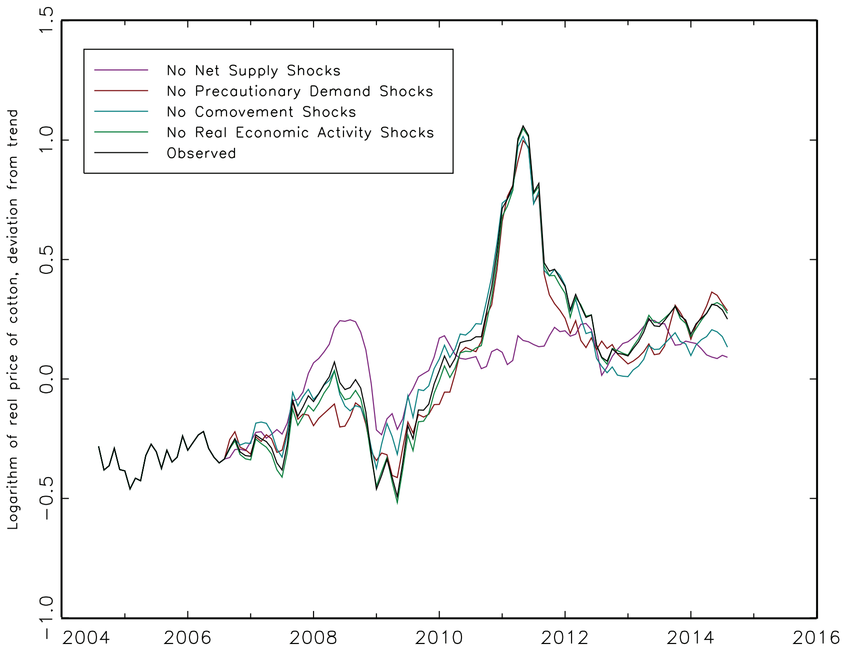

Figure 7. Counterfactual analysis of cotton prices, 2006–2014, for SVAR with GSCI as external market

demand, and net supply shocks set to zero for the period from 2006 to 2014.

During the 2006–2014 period, we find modest effects of comovement shocks. Cotton prices would have spiked even in their absence. Setting the comovement effect to zero during the 2010–2011 spike would not have changed the peak price. In 2007–08, comovement played no role in the price increase, but it did prolong the high prices somewhat. Cotton prices increased beginning in 2007 and peaked in March 2008. If we eliminate the comovement shocks, figure 7 shows that the increase in prices would have been the same. By July 2008, four months after the price peak, actual prices had dropped slightly, whereas prices would have dropped a further 11% in the absence of comovement. This is the maximum estimated impact of the comovement shock during this episode. In absolute terms, the impact of comovement shocks at this point was approximately $0.07 cents per pound. Relative to the price volatility observed over this period such an effect is small; average monthly cotton futures prices rose $0.30 per pound in 2007–08 and by more than $1.20 per pound in 2010–11.

The cotton price spikes in 2007–2008 and 2010–2011 had very different origins; elevated cotton prices in 2010–2011 were not a repeat of the events of 2007–2008 (figure 7 illustrates). The 2008 price spike would have been non-existent without shocks to precautionary demand. Specifically, the observed cotton price was 45% higher in March 2008 than in May 2007, the pre-spike low. In the absence of precautionary demand shocks, the cotton price would have been only 15% higher in March 2008 than it was in May 2007. However, if we set the net supply shocks to zero, the price change would have been about the same as observed—the estimated March 2008 price is 44% higher than the May 2007 price in that case. In contrast, the 2011 price spike originated with net supply. The log price in March 2011 was 0.90 higher than in May 2010. Without the net supply shock, the March 2011 price would have been only 7% higher than in May 2010. The precautionary demand shock played no role in this episode. Without precautionary demand shocks, log prices still would have increased by 0.88 in that year. Without comovement shocks, log prices would have increased by 0.82.

Market intelligence from early 2008 corroborates the precautionary demand explanation for the 2007–2008 spike. Early USDA projections for the 2008–2009 cotton marketing year called for “sharply lower production and ending stocks" in the United States. As projected plantings of other field crops were expected to increase, cotton-planted acres were expected to decline by 25%. Projections also called for "strong but decelerating growth in consumption" and increased exports to China in the coming marketing year (USDA, World Agricultural Outlook Board 2008). These expectations are consistent with price increases in early 2008 caused by a precautionary demand shock. Subsequent projections were considerably less bullish, consistent with falling prices later in 2008.

In contrast, a series of shocks to current net supply were behind the large price increases in 2010–2011. Global production for the 2009–2010 marketing year was approximately 13% below the previous five-year average, and usage rebounded from declines following the 2008 global financial crisis. The world ending-stocks-to-use ratio fell from 56% in 2009 to 39% in 2010 (USDA, Foreign Agricultural Service 2015). At the time, cotton prices were extremely vulnerable to further shocks. Unexpected events, highlighted by floods in Pakistan and periodic export bans in India, limited supplies during the 2010–2011 marketing year (Meyer and Blas 2011). Trade reports suggest that the market suddenly became aware of "shortages in (current) mill inventories" in late 2010 (USDA, World Agricultural Outlook Board 2010) that triggered steep price increases.

Assessing Robustness to Selection of the External Commodity

We consider two robustness checks of our findings with respect to the influence of financial speculation through comovement on cotton prices. First, we replace the GSCI variable in our SVAR model with two alternative measures of external market comovement associated with financial speculation. We consider crude oil prices, following the result of Tang and Xiong (2012), and an alternative index of non-agricultural commodity prices generated using principal components analysis, similar to the factor-augmented VAR approach to assessing commodity price comovement in Byrne, Fazio, and Fiess (2013).

The prominence of crude oil among commodity markets led Tang and Xiong (2012) to test whether financial speculation as related to the inclusion in a major index led indexed commodities to exhibit stronger comovement with crude oil prices than non-indexed commodities. Recall that our identification strategy attributes all comovement (net of shocks to real economic activity) to this financial speculation effect. When we consider the price of crude oil as the external market, the impulse responses look essentially the same as in figure 5, but the comovement shock is no longer statistically significant.

Figures 8–9 display similar historical decomposition and counterfactual analyses as those shown in figures 6 and 7, except crude oil is used as the external market. This model shows that cotton-market-specific precautionary demand and net supply shocks dominate the determination of cotton prices. The effect of the comovement shock is negligible. In the absence of speculative comovement shocks related to crude oil prices, the cotton price would have been 1.4% lower in March 2008 and 1.5% lower in March 2011. At its peak impact during the period of cotton price booms and bust between 2006 and 2014, the comovement shock raises cotton prices by about 2.5%. The impact of real economic activity in this model is larger than for the model with GSCI—approximately 5% to 10% during the most recent period.

As an alternative measure of comovement with non-agricultural commodity prices, we construct an alternative index using principal components analysis. We consider only non-agricultural commodities included in major commodity indexes to avoid intra-agricultural price relationships driven by substitution in production or other fundamental factors. These represent prices for energy and precious and industrial metals. Principal components analysis finds that two significant components (whose eigenvalues are greater than one) are responsible for 82% of variation in these prices over our sample period. We use the sum of these components as our index and include it as the external market variable in our SVAR model.

We generate historical decompositions and counterfactual analysis of the 2008 and 2011 price spikes using this factor-augmented VAR. Historical decompositions generated using this approach are very similar to the results in figures 8–9.[9] The factor-augmented VAR shows

[9] These figures are provided in an online supplementary appendix.

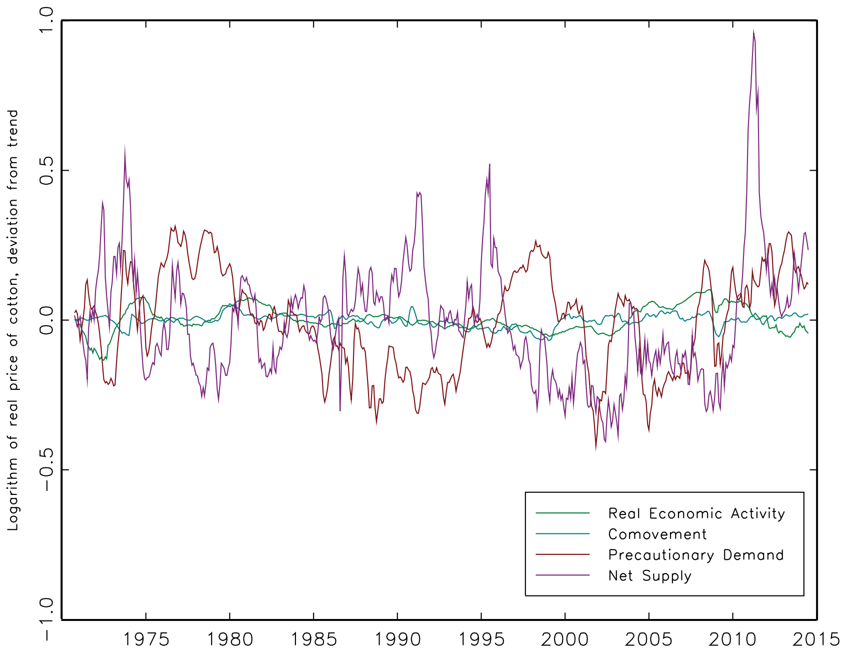

Figure 8. Historical decomposition of structural shocks with crude oil as external market

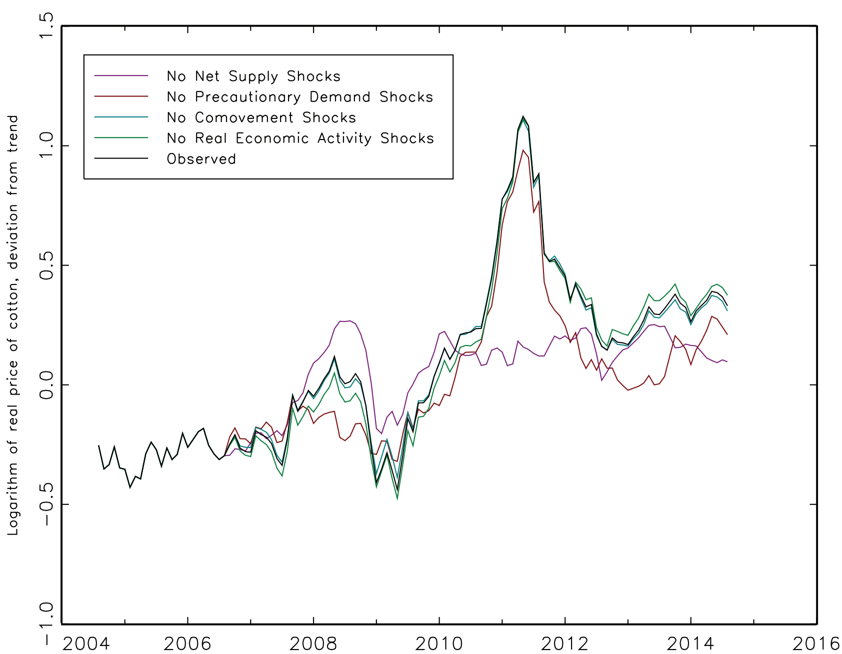

Figure 9. Counterfactual analysis of cotton prices, 2006–2014, for SVAR with crude oil as external market

that cotton-market-specific precautionary demand and net supply shocks dominate the determination of cotton prices. The effect of the comovement shock is larger than in the crude oil model but smaller than in the GSCI model. Our central finding of significant but modest effects of financial speculation is robust to the consideration of alternative measures of commodity price comovement. However, this measure or any similarly-derived index of commodity prices has the disadvantage of not being directly related to commodity index investing or other types of cross-commodity financial speculation.

Conclusions

We use a SVAR model to attribute observed cotton futures price changes to four factors: real economic activity, cross-commodity comovement, precautionary demand for inventories, and current net supply. The comovement-driven portion of cotton prices reveals the effects of trader sentiment about commodities (Pindyck and Rotemberg 1990) or financial speculation through commodity index trading (Tang and Xiong 2012). We find limited evidence that financial speculators are the cause of cotton price spikes. The portion of observed price changes due to comovement across commodity markets suggested as being characteristic of the impact of financial speculators is estimated to be small, and prices would have spiked in the absence of comovement shocks. Unlike studies of other commodity markets such as Kilian and Murphy (2014) for crude oil and Carter, Rausser, and Smith (2017) for corn, we find that global commodity demand has only small effects on cotton prices.

Our results imply that factors specific to the cotton market drive prices. To decompose these factors, we use changes in volatility across time to identify shocks to current supply and demand separately from shocks to precautionary demand for inventory. We find that most cotton price spikes stem from shocks to current net supply. The 2008 price spike was an exception, however. We find that precautionary demand, likely induced by projections of lower acreage and steady demand, drove prices higher in 2008. Thus, although we find limited evidence of financial speculation effects through the comovement channel, we do find evidence of fundamental speculation through precautionary demand, which is an important feature of a well-functioning market.

Turbulent commodity prices have significant economic and political implications. High and volatile commodity prices hurt consumers, especially in countries where food or energy commodities constitute a major share of household budgets. When many commodity prices move simultaneously, opportunities for substitution are limited and many households are pushed into poverty. Price shocks have also been linked to subsequent political unrest (Bellemare 2015). Policy proposals to address commodity price variability such as price stabilization schemes (e.g., Von Braun and Torero 2009) or regulatory controls on commodity futures trading (e.g., Masters 2010) are based on particular assumptions about the cause of commodity price booms and busts. Such policies may be ineffective or even counterproductive if they incorrectly attribute the cause of observed price shocks.

Our results suggest that comovement-related financial speculation by CITs, hedge funds, pension funds, and others have had limited impact on cotton prices. This finding is consistent with previous studies using different empirical approaches (e.g., Stoll and Whaley 2010; Buyuksahin and Harris 2011; Irwin and Sanders 2011; Fattouh, Kilian, and Mahadeva 2013). Accordingly, legislative and regulatory efforts to restrict the trading activities of these traders will not prevent future price spikes. As the literature on rational storage shows, even though storage firms can mitigate the effects of shocks, price spikes are an inherent characteristic of storable commodity markets.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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