Commodity Price Comovement and Financial Speculation: The Case of Cotton

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Abstract: 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 not sufficient evidence 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 comovement 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, speculation, cotton, comovement, structural VAR.

JEL codes: Q11, G13, C32

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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 price of cotton, silver, and copper approximately doubled, while the price 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-1980’s 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 co-moved with other commodities in spite of contrary supply and demand fundamentals.

Pindyck and Rotemberg (1990) estimated that commodity prices, including cotton, tend to 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. Estimating comovement effects associated with financial speculation is difficult, however. 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, which may be disconnected from supply and demand for the underlying commodity, with rational speculation in physical or futures markets by storage firms that act to balance supply and demand over time. A study of comovement and
speculation requires both types of speculation be considered and separately identified.

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. 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, particularly those with significant weight in major commodity indices. We use the Standard & Poor’s Goldman Sachs Commodity Index (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 shocks into two components: (i) precautionary demand for inventories and (ii) 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. This method gives us exact identification of the model parameters. In contrast, previous studies of commodity pricing obtain only partial identification through sign restrictions and/or inequality constraints on short-run elasticities (Carter, Rausser, and Smith, 2016; Juvenal and Petrella, 2015; Kilian and Murphy, 2014; Lombardi and Van Robays, 2011).

We apply our model to the cotton market using data from 1970 through 2014. Contrary to Tang and Xiong (2012), we find that comovement related to 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. These price spikes were caused by two different cotton-specific factors; 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 supply-and-demand fundamentals rather than the machinations of financial speculators. The importance 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. The U.S., China, India, and Pakistan grow three-quarters of the world’s cotton, but there is substantial international trade. Between 30 and 40% of cotton fiber crosses borders before processing (Meyer, MacDonald, and Foreman, 2007). The U.S. is the third largest producer after China and India, accounting for 14% of global supply over the period from 2005-2014 (USDA-Foreign Agricultural Service, 2015). Because cotton processing has largely moved from the U.S. to low-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 all global trade (USDA-Foreign Agricultural Service, 2015).

Like many other agricultural commodities, cotton has a futures market that serves as an important vehicle for price discovery and a global price benchmark. Cotton futures are traded
at the Intercontinental Exchange (ICE), formerly the New York Board of Trade. The market has relatively small volume relative to other commodities, which makes it potentially susceptible to spillover effects from other markets due financial speculation. In 2014, approximately 5.7 million cotton futures contracts were traded at the ICE. This quantity represents approximately 131 million metric tons with a notional value of $220 billion. By comparison, 2014 trading volume in West Texas Intermediate crude oil futures, widely considered the largest and most liquid US futures market was 145 million contracts, representing a notional value of approximately $13.5 trillion, or 61 times ICE cotton trading volume (Acworth, 2015).

ICE cotton futures trading is mainly conducted among commercial traders and financial speculators. Commercial traders deal in both physical cotton and cotton futures. Financial speculators do not hold physical cotton and include large financial firms and commodity index traders, or CITs. Commodity indexes are a weighted average of futures prices across a set of commodities, and CITs construct portfolios designed to mimic these indexes. In 2014, CITs held 27% of long open interest in cotton futures contracts. Between 2006 and 2014, CITs held as much as 44% of long open interest (Commodity Futures Trading Commission, 2015). Although CITs are a large player 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). The combination of a large presence of CITs in cotton and negligible importance of cotton to CITs is another reason that cotton may be vulnerable to spillover impacts from unrelated commodities.

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 responded to the 2008 price spike with an inquiry into potential
market manipulation; they found no evidence suggesting any trader group, including CITs, had an outsized impact on prices (Commodity Futures Trading Commission, 2010). Price swings in 2011 (which in absolute terms were 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 Sources of 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. Early theories of commodity storage (Working, 1949; Telser, 1958) emphasized a no-arbitrage condition of the form:

$$P_t = (1 + c_{t,t+1})^{-1} F_{t,t+1}$$

where $P_t$ is the price for delivery at time $t$, $F_{t,t+1}$ is the futures price at $t$ for delivery in a future period $t + 1$, and $c_{t,t+1}$ represents all costs of carrying inventories between the two periods expressed as a percentage. Firms will hold inventories such that the futures price, adjusted for carrying costs, is equal to the current price.

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. They added supply, demand, and market clearing conditions to the basic no-arbitrage relationship in equation (1) 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. Exogenous production in each period, $S_t$, is drawn from a distribution over which risk-neutral stockholding firms form rational expectations. These firms maximize expected profit from holding inventories, $I_t$ 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, i.e., $F_{t,t+1} = E_t(P_{t+1})$. The final important feature of the competitive storage 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 is 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). Later we assess empirically the correlation between the calendar spread and available measures of inventory.

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. Convenience yield is typically motivated as an option value generated by the transaction cost of obtaining the commodity (Telser, 1958) or by the possibility that future inventories could be driven to their lower bound (Williams and Wright, 1991; Routledge, Seppi, and Spatt, 2000).

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, p. 542). Seminal work by Mandelbrot (1963) on heteroskedasticity in commodity prices includes an empirical application to the cotton market. The competitive storage model explains such heteroskedasticity. Williams and Wright (1991, pp. 103-104) show how price volatility depends on the presence of inventories. Extensions of the competitive storage model including a convenience yield generate 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.

In sum, the competitive storage model equilibrium can be represented as the intersection of two forces, current net supply and precautionary demand for inventories. The correspondence between inventories and calendar spreads from the Working curve suggests that competitive storage model equilibria can be represented in price-spread space. Historical data on observed prices and calendar spreads form a scatterplot where each data point represents an equilibrium intersection of current net supply and precautionary demand functions. Prices and spreads for storable commodities are characterized by volatile and tranquil periods based on the abundance of inventories relative to current use. We use these fundamental features of commodity price determination to develop our empirical model.

Types of Speculation: Precautionary Demand vs Financial Speculation

The previous section described one type of speculative activity in commodity markets, namely precautionary demand for inventories. Firms that deal in the physical commodity have an incentive to store it for future sale if they expect future prices to be higher. This type
of speculation is an important component of a well functioning commodity market in which prices reflect not only current supply and demand conditions but also future expected supply and demand. A second type, financial speculation, generally describes trading in commodity derivatives markets by entities that do not deal in the physical commodity. It includes the recent growth in commodity trading by index funds to provide investor exposure to commodities as part of a portfolio diversification strategy, as well as trading by hedge funds and others that believe they have superior information about commodity price dynamics, but not a specific directional outlook about particular commodities.

The recent debate about financial speculation and its effects on commodity markets has focused on commodity index trading (Irwin and Sanders, 2011). Commodity indexes are a weighted average of futures prices across a set of commodities and are designed to measure broad commodity price movement. Two industry benchmarks are the GSCI, a production-weighted index, and the Dow Jones-UBS Commodity Index (DJ-UBSCI), a liquidity or volume weighted index. Cotton is a small component (∼1%) of both indices, reflecting the relative small value of world cotton fiber production and the relative small size of the cotton futures market. Financial firms have developed exchange-traded funds, swap contracts, and other vehicles to allow individual and institutional investors to track these and similar indexes in their investment portfolios and obtain potential diversification benefits unrelated to speculative returns for particular commodities (Gorton and Rouwenhorst, 2006; Bhardwaj, Gorton, and Rouwenhorst, 2015). Most traders following index-trading strategies tend to take only long positions (i.e., positions that make money if prices rise). Firms following index-tracking trading strategies are referred to as commodity index traders, or CITs.

Soros (2008), Masters (2010), and others claim that CITs have caused boom and bust cycles in commodity markets. Unlike inventory holders in competitive storage markets, CITs do not have directional views on the prices of a specific commodity. Rather, they wish to gain exposure to the broad movement of commodity prices because of perceived portfolio
diversification benefits. This lack of attention to fundamentals could cause prices to be determined by investor flows. 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 such financial speculation 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 prices is caused by the inclusion of commodities into major indexes such as the GSCI and the DJ-UBSCI.

The “index inclusion” impact of CITs follows similar effects found in equity markets. According to Barberis, Shleifer, and Wurgler (2005), upon inclusion in the widely-followed S&P 500 index a stock’s price becomes more correlated with the index and less correlated with non-S&P 500 stocks. Barberis, Shleifer, and Wurgler (2005) use this result to argue that trader sentiment removed from fundamental factors specific to individual stocks is an important determinant of prices. This speculative sentiment effect related to index inclusion is distinct from the incorporation of information about future supply and demand conditions associated with precautionary demand for inventories.
We focus on a specific type cross-market spillover effect, common movement among commodity prices. Other recent work on cross-market linkages related to financial speculation in agricultural markets considers comovement across asset classes. Bruno, Büyükşahin, and Robe (2017) consider correlations between agricultural commodities and equities prices. They find that market fundamentals remain the pre-eminent driver of agricultural commodity price dynamics but do not explicitly test for cross-commodity comovement as in Tang and Xiong (2012).

Finding common movement in commodity prices is not unique to the study by Tang and Xiong (2012) or the presence of CITs. Economists have documented unexplained comovement in prices at least since Pindyck and Rotemberg (1990) presented findings of “excess comovement” among seven commodity prices. Pindyck and Rotemberg posited that correlation among fundamentally unrelated commodity prices that cannot be explained by macroeconomic factors is excess comovement. Their test for excess comovement relied upon the selection of commodities that were unrelated as substitutes or complements in production or consumption, not co-produced, and not used as major inputs in the production of others. To control for macroeconomic factors, they employed a seemingly unrelated regressions framework in which prices for cotton, wheat, copper, gold, crude oil, lumber, and cocoa were dependent variables. They used macroeconomic variables such as aggregate output, interest rates, and exchange rates as 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 price comovement across commodity classes. Each noted the importance of controlling for general economic activity that generates common shocks to all commodity prices.

Pindyck and Rotemberg (1990, p. 1173) suggested that excess comovement arises because “traders are alternatively bullish or bearish on all commodities for no plausible reason.” Excess comovement as described by Pindyck and Rotemberg is essentially identical to de-
criptions of the effects of financial speculation in commodity futures markets: price changes due to trader sentiment rather than information about current and futures supply and demand conditions. For example, Masters (2010, 2011) argues that index trading creates massive, sustained buying pressure that causes prices to exceed fundamentally justified levels. Masters (2010) states: “Since the GSCI is an index of 24 commodities, it includes many commodities, such as most agriculture commodities, where there is no large concentrated group of commodity-producers exerting selling pressure. Nonetheless, because Goldman created the GSCI, index speculators are exerting enormous buying pressure for these commodities in the absence of concentrated selling pressure... This dramatic increase in buying pressure has led to increased prices.”

Just as other researchers countered the claims of Masters (2010, 2011) 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) suggested 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). They proposed a GARCH framework to account for the heteroskedastic nature of commodity price changes and found minimal evidence of comovement for the commodities and time period used in 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, they
could not test for comovement effects resulting from the increased presence of CITs, which 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 analysis addresses these shortcomings.

Data

We include four variables in the data vector, $y_t$, used 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 expressed in real terms, using the U.S. Consumer Price Index (CPI) as a deflator. 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. Kilian notes an empirically documented correlation between freight rates and economic activity. 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. Given the importance of demand in emerging economies as a driver of cotton usage, our aggregate commodity demand measure must be a global measure.

We collect data on cotton and other commodity market prices from Commodity Research Bureau (2014). The cotton price series is the logarithm of the monthly average nearby futures price, deflated by CPI. 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. We also collect monthly data on non-agricultural commodity prices for heating oil, natural gas, lead, zinc, copper, gold and silver. These are nearby futures prices where available and cash prices otherwise.

To measure the incentive to hold cotton inventory, we use the cotton futures price calendar spread over a one-year time span. 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 in March, May, July, October, and December, so we use the spread between the sixth most distant and the nearby futures contract. The time difference between these contracts is always a year, so the resulting spread represents the term structure of cotton prices over a constant period of time. We use the logarithm of the sixth most distant price minus the logarithm of the nearby contract price. By taking logs, we measure the spread as a percentage of the price rather than in cents per pound.

Data on physical inventories would be an alternative to the calendar spread variable in our model. Ideally this would be a measure of global cotton inventories at monthly frequency over our entire sample period. No such measure is available. To verify the suitability of the calendar spread, we collected data on actual US monthly stocks from the US Census Bureau Current Industrial Reports and projected US ending stocks from the USDA World Agricultural Outlook Board for portions of our sample period where available. Actual stocks display strong seasonal patterns. Simple regressions of actual stocks and projected ending stocks on the cotton calendar spread and a set of monthly indicator variables show strong correlation between stocks and spreads.

Figure 3 plots these variables for the period July 1970 to 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. We use a simple 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. As seen in figure 1, US cotton ending-stocks-to-use for 1985-86 was 112%, or more than four standard

\begin{footnote}
\textsuperscript{1}The standard 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.
\end{footnote}
deviations above mean ending-stocks-to-use for the period 1970-2014. In early 1986, the U.S. Department of Agriculture announced details of the cotton-specific provisions of the 1985 Farm Bill creating incentives to store cotton in the 1985-86 marketing year and sell it during the 1986-87 marketing year (Anderson and Paggi, 1987; Hudson and Coble, 1999). This planned release of inventories meant that, through the first six months of 1986, old-crop cotton futures contracts traded at a substantial premium over new-crop contracts. In June 1986, the average price on the July contract was 67 cents per pound, whereas the October contract averaged 33 cents per pound. This government intervention generated a highly unusual market situation in which a large negative spread coincided with high inventory. In terms of our model, precautionary demand for inventory was high in the first six months of 1986, even though market prices were such that holders of inventory would make a huge loss. We include four control variables to account for this period: an indicator variable for the first six months of 1986, an indicator variable for the last six months of 1986, and interactions between each of these variables and a linear trend.

**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) extends 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 (2016), who estimate a SVAR model of corn prices. They 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 (2016) avoid this problem by using annual data in their corn model. Annual data avoids the need to observe the effective inventory level at high frequencies, but necessitates a small sample 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 as a differentiated effect separate from speculative precautionary demand related to future supply
and demand conditions. 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 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, particularly the crude oil price as suggested by Tang and Xiong (2012). Finding such comovement is not sufficient to prove this financial speculation effect, but it is necessary.

**Identification**

We include four variables in a vector $y_t$: (i) real economic activity, $rea$, (ii) the real price in an external market, $ext$, (iii) the spread between distant and nearby futures prices for cotton, $spr$, and (iv) the real price of nearby cotton futures, $pct$. A SVAR model for $y_t$ is:

$$A_0 y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + C x_t + u_t,$$

where $x_t$ denotes a vector of deterministic components that includes a constant, a linear trend, and seasonal dummy variables and the structural shocks $u_t$ are white noise and uncorrelated with each other. We label the four structural shocks (i) real economic activity, (ii) comovement, (iii) precautionary demand, and (iv) current net supply.

Multiplying through by $A_0^{-1}$ produces an estimable reduced-form VAR:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + D x_t + \varepsilon_t.$$
The reduced-form shocks, $\varepsilon_t$, are prediction errors and are a weighted sum of the structural shocks, where the matrix $A_0$ provides those weights, i.e., $\varepsilon_t = A_0^{-1}u_t$. Identifying the structural shocks requires making sufficient assumptions to enable consistent estimation of the unknown 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 price as exogenous to the cotton market within a month. With these assumptions, the elements of the equation $A_0\varepsilon_t = u_t$ are:

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

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 co-movement effect rather than an effect of events in the cotton market on the external market. 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, this identification scheme estimates an upper bound on the influence of financial speculation. Giving primacy to comovement shocks also mitigates misattribution of speculation impacts in cotton through other agricultural markets,
for example through speculative impacts on the corn or wheat markets that lead to substitution in production with cotton. So long as all agricultural markets were affected by financial speculation-driven comovement in a similar way as suggested by Tang and Xiong (2012), our model attributes financial speculation impacts that flow from non-agricultural markets to other agricultural markets to cotton to the comovement shock.

The parameters $A_{34}$ and $A_{43}$ in equation 4 represent short-run elasticities implied by the slopes of the precautionary demand and net supply curves in figure 2. Further use of the recursion assumption by setting $A_{34} = 0$ would imply that the spread cannot respond contemporaneously to the net supply shock, i.e., that 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.

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. ItH relies on differences in the volatility or 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 periods or 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, one volatile $vl$ and one tranquil $tr$, to satisfy the following properties:

$$
\text{var}(u_t | t \in \text{tr}) = \Sigma^{tr} \quad \text{and} \quad \text{var}(u_t | t \in \text{vl}) = \Sigma^{vl},
$$

(5)

---

2Some SVAR applications to agricultural commodity price dynamics such as Bruno, Büyüksahin, 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.
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 must also be heteroskedastic.

Defining $\Omega^{tr}$ and $\Omega^{vl}$ 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:

$$A_0 \Omega^{tr} A_0' = \Sigma^{tr} \quad \text{and} \quad A_0 \Omega^{vl} A_0' = \Sigma^{vl}. \quad (6)$$

For each regime $r$, these conditions are:

$$\begin{bmatrix}
1 & 0 & 0 & 0 \\
A_{21} & 1 & 0 & 0 \\
A_{31} & A_{32} & 1 & A_{34} \\
A_{41} & A_{42} & A_{43} & 1
\end{bmatrix}
\begin{bmatrix}
\omega_{11} & \omega_{21} & \omega_{31} & \omega_{41} \\
\omega_{21} & \omega_{22} & \omega_{32} & \omega_{42} \\
\omega_{31} & \omega_{32} & \omega_{33}^r & \omega_{34}^r \\
\omega_{41} & \omega_{42} & \omega_{43}^r & \omega_{44}^r
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 & 0 \\
A_{21} & 1 & 0 & 0 \\
A_{31} & A_{32} & 1 & A_{34} \\
A_{41} & A_{42} & A_{43} & 1
\end{bmatrix}'
\begin{bmatrix}
\sigma_{REA} & 0 & 0 & 0 \\
0 & \sigma_{CM} & 0 & 0 \\
0 & 0 & \sigma_{PD}^r & 0 \\
0 & 0 & 0 & \sigma_{NS}^r
\end{bmatrix}
= \begin{bmatrix}
\sigma_{REA} & 0 & 0 & 0 \\
0 & \sigma_{CM} & 0 & 0 \\
0 & 0 & \sigma_{PD}^r & 0 \\
0 & 0 & 0 & \sigma_{NS}^r
\end{bmatrix} \quad (7)$$

There are 13 free parameters in $\Omega^{tr}$ and $\Omega^{vl}$. We have 13 parameters to be identified, seven in the $A_0$ matrix and six structural shock variances, so the model satisfies the order condition. To obtain identification, we also require that the relative variance of the structural shocks ($\sigma_{PD}^r / \sigma_{NS}^r$) differs across regimes (Rigobon, 2003, p. 780).

The condition that ($\sigma_{PD}^r / \sigma_{NS}^r$) 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 precautionary demand or a current net supply curves as shown in the panel B of figure 2. However if, say, 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. Rigobon (2003) likens ItH to a “probabilistic instrument” in the sense that we cannot be certain that we are identifying shifts in a particular curve for any particular observation, but under one regime we are more likely to observe shifts in one curve.

**Empirical Suitability of Model, Data, and Identification Assumptions**

We use monthly data from July 1970 to June 2014. Why do we construct such a long time series when our ultimate interest is in recent price spikes? As in most econometric work, more data allows for more precise estimation of model parameters. More importantly, we aim to use periods of dramatic 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, limiting our ability to observe the cotton price response to general commodity price cycles. A shorter time series also reduces the number of volatile periods necessary to identify our econometric model using ItH. In a later section, we test whether the model parameters are stable over time and find no evidence of a change in the parameters after 2004.

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 forecasts) were 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 “normal” inventory levels over our sample period. Selecting regimes in this manner creates ten volatile windows in our sample,

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 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 levels data are unsuitable for analysis using a linear VAR. Taking logarithms as described above addresses this non-linearity. The cloud of data points in the right panel of figure 4 remains downward sloping. This suggests that net supply shocks more prominently trace out the precautionary demand curve, though some variation in precautionary demand leads to variation in prices and spreads along the net supply curve.

Figure 4 also suggests that the relative variance of the structural shocks ($\sigma_{PD}^2/\sigma_{NS}^2$) varies across regimes. The figure labels each data point as belonging to the volatile or tranquil regime. 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

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3We 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.
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 ($\sigma_{PD}^r$ and $\sigma_{NS}^r$) across regimes.

**Estimation and Results**

We estimate the reduced-form VAR of equation 3 using ordinary least squares with two lags. We select lag length using the Akaike and Schwarz-Bayesian information criteria. Both criteria select a lag length of $p = 2$. We consider prices measured in log-levels and include a linear trend, monthly indicator variables, and 1985 Farm Bill controls as exogenous variables in this VAR specification. Stationarity testing using 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 the VAR estimated in levels produces an asymptotically consistent estimate of the true impulse responses even in the presence of some unit roots. The parameter estimates and their standard errors are presented in table 1. From the VAR estimates, we extract the reduced-form residuals, $\hat{\varepsilon}_t$. We divide these residuals into two groups corresponding to observations from 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 set the terms in the first two rows of $\hat{\Omega}_{tr}$ and $\hat{\Omega}_{vl}$ equal to the corresponding terms from the variance-covariance matrix calculated using the full sample. We define a set of constraints on the $A_0$ matrix, namely the zero terms in the first two rows. Parameters in $A_0$ and $\Sigma^r$ are computed by minimizing a distance function equal to the sum of the squares of each element of $A_0 \hat{\Omega}^r A_0' \hat{\Sigma}^r - \hat{\Sigma}^r$ 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 percent larger than in the tranquil regime (these are the parameters inside the boxes in table 2). The associated structural shock variances, \( \sigma_{PD}^r \) and \( \sigma_{NS}^r \) also vary across regimes. The net supply shock has a variance 45 percent 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 regime holds.

To formally test the heteroskedasticity assumption, we perform standard F-tests of equality across regimes for the variances \( \sigma_{PD}^r \) and \( \sigma_{NS}^r \). 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.

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). Since the innovation in any of the variables in the model in each period can be represented as a weighted sum of the structural shocks from that period, we can create time-series representations 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 crude oil represents the external market and then for alternative external markets.
Impulse Response Functions

Figure 5 plots 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 pointwise 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.

Focusing on the bottom-right corner of figure 5, we can check whether the results are consistent with the identification scheme. If a precautionary demand shock occurs, the price and the spread should increase to encourage stockholding by providing higher returns to storage. Our results show 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 are small and not statistically significant on average. Comovement effects associated with the GSCI have a small impact on cotton prices,
relative to the precautionary demand and net supply shocks specific to the cotton market, but these shocks are statistically significant and long-lived. Recall that our identification assumptions imply that we interpret any correlation (net of the effect of real economic activity) as a causal effect of the external market on cotton. Even so we find that cotton-specific supply and demand shocks have greater influence on observed cotton prices.

**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 show the accumulated effect of each shock on the observed price at each point in time. Thus we can assess the structural origins of observed variation in cotton prices. The series in figure 6 are 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 such as China, 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 period of rising prices that ended in 2008. Similarly, Carter, Rausser, and Smith (2016) 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 period, real economic activity raised cotton prices by up to 6%. 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, an 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, a point we return to in the next section.

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. When we use crude oil prices as the external market variable, the maximum positive impact of comovement shocks is 6% in 1979 and the maximum negative impact is 10% in 1998. In the next section, we generate counterfactual price series to estimate what prices would have been in 2008 and 2011 without each of the shocks.

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4We 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 percent to refer to these log differences.
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 demand, and net supply shocks set to zero for the period 2006 to 2014.

During the 2006-2014 period, we find modest effects of comovement shocks. However 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, we find that 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 U.S. Department of Agriculture projections for the 2008-2009 cotton marketing year called for “sharply lower production and ending stocks” in the U.S. 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. Subsequently, U.S. Department of Agriculture forecasts were considerably less bullish, consistent with falling prices later in 2008.

In contrast, precautionary demand shocks had very little to do with rising prices in 2010-2011. Evidence from this period suggests a series of shocks to current net supply were behind the large price increase. 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 available supplies during the 2010-2011 marketing year that encompassed most of the price spike (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

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. This factor augmented VAR approach is a relatively new approach to assessing commodity price comovement (e.g. Byrne, Fazio, and Fiess, 2013). Second, we test the stability of the VAR parameters over time to account for the possibility that the rise in financial speculation and commodity index trading caused a break in the relationship between external market prices and cotton prices.

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 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 before, approximately 5-10% during the most recent period.

As an alternative measure of comovement driven spillovers from non-agricultural commodity prices to the cotton market, we construct an alternative index using principal components analysis. We consider only non-agricultural commodities included in major commodity indices to avoid intra-agricultural price relationships driven by substitution in production or other fundamental factors. These represent prices for energy, precious metals and industrial metals. Principal components analysis finds two significant components (whose eigenvalues are greater than one) responsible for 82% of the 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, shown in figures 8-9. This approach again shows 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.
Parameter instability may affect our model’s capacity to capture financial speculation impacts. Increasing activity of financial speculators may have caused a break in the relationship between cotton prices and the prices of other commodities. To address the issue of model stability, we test for a structural break in the coefficients that determine the impact of external commodity prices on the cotton market using as a break point July 2004, the beginning of the 2004-2005 marketing year. Irwin and Sanders (2011, p. 6) document, beginning in 2004, a steady increase in investment in commodity index products. Using publicly unavailable data on open interest held by CITs prior to 2006, they document a significant increase between 2004 and 2006 in the number and proportion of agricultural futures contracts held by CITs. Tang and Xiong (2012) select 2004 as a break point and found a change in the relationship between crude oil and other commodity prices after 2004. Similarly, Wright (2014) observes a biofuels-induced regime change for agricultural commodity prices between 2004 and 2005.

Our model stability test must address the potential for structural breaks in parameters that determine the impact of lagged and current values of external market prices, $ext$, that represent the effect of financial speculation. We test not only whether the coefficients on lagged $ext$ are constant across time, but also the stability of the parameters $A_{32}$ and $A_{42}$ that determine the current response of cotton spread and price to the external market shocks.

To conduct this test, we re-estimate the equations in the reduced-form VAR model for the cotton price and the calendar spread, including contemporaneous values of real economic activity and crude oil price as regressors. This specification is implied by the exclusion restrictions in the first two rows of the $A_0$ matrix. We include interactions between each of the crude oil price variables and an indicator variable equal to one in the period post-June 2004, $D_{\geq 2004}$. Table 3 presents the coefficient estimates for the external market variables and the post-June 2004 interaction terms for each equation in the two-variable VAR. None of interaction terms are individually significantly different from zero according to simple $t$-tests. We conduct a Wald test of the joint significance of the interaction term coefficients and
the post-June 2004 indicator variable from both equations. We fail to reject the joint null hypothesis that none of the external market coefficients vary across periods.

**Conclusions**

We use a structural vector autoregression model to attribute observed cotton futures price changes to four factors: real economic activity, cross-commodity comovement, the 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 such as CITs are the cause of cotton price spikes. While financial speculation may have played a role in raising the level of cotton prices during recent booms and busts, the portion of observed price changes due to speculative comovement 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 (2016) for corn, we find that broad trends in global commodity demand have only small effects on cotton prices.

Our results imply that factors specific to the cotton market drive prices. To model 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. Market intelligence from 2008 corroborates this explanation. Thus, although we find limited evidence of financial speculation effects through the comovement channel, we do find evidence of fundamental speculation, i.e., speculation through storage of physical cotton based on expectations about future supply and demand. Such speculation is an important feature of a well-functioning
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 for observed price shocks.

Our results suggest that index traders and other financial speculators 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.
References


Figure 1: U.S. and world crop-year ending stocks-to-use, 1970-71 to 2013-14
Source: USDA PS&D Online
Figure 2: Price, spread, and inventory determination in a stylized single-period representation of the competitive storage model
Figure 3: Data plot for variables in $y_t$, controlling for linear trend and seasonality, July 1970 to June 2014
Figure 4: Scatter plots of $spr$ and $pct$ variables in levels (left) and detrended logarithms (right) by volatility regime
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Figure 7: Counterfactual analysis of cotton prices, 2006-2014, for SVAR with GSCI as external market
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
Figure 10: Historical decomposition of cotton prices, 1970-2014, generated using Structural Factor Augmented VAR
Figure 11: Counterfactual analysis of cotton prices, 2006-2014, generated using Structural Factor Augmented VAR.
### Table 1: Reduced-form VAR Regression Results

<table>
<thead>
<tr>
<th>Equation</th>
<th>( r_{ea,t-1} )</th>
<th>( ext_{t-1} )</th>
<th>( spr_{t-1} )</th>
<th>( pct_{t-1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.022</td>
<td>0.116**</td>
<td>0.062</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.046)</td>
<td>(0.049)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>( r_{ea,t-2} )</td>
<td>-0.161**</td>
<td>-0.019</td>
<td>-0.026</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>( ext_{t-2} )</td>
<td>-0.179*</td>
<td>-0.228**</td>
<td>0.041</td>
<td>-0.110</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.053)</td>
<td>(0.042)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>( spr_{t-2} )</td>
<td>-0.250*</td>
<td>-0.264**</td>
<td>0.279*</td>
<td>-0.502**</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.067)</td>
<td>(0.143)</td>
<td>(0.188)</td>
</tr>
<tr>
<td>( pct_{t-2} )</td>
<td>-0.223**</td>
<td>-0.215**</td>
<td>0.212**</td>
<td>-0.456**</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.055)</td>
<td>(0.066)</td>
<td>(0.097)</td>
</tr>
</tbody>
</table>

Note: Heteroskedasticity-robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels. Coefficient estimates for seasonal indicators and linear time trend are not reported.
Table 2: Structural vector autoregression model parameter estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Tranquil</th>
<th>Volatile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_0$</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>-0.084</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>-0.032</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>-0.126</td>
<td>-0.107</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Tranquil</th>
<th>Volatile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega^r$</td>
<td>0.491 0.043 -0.009 0.034</td>
<td>0.491 0.043 -0.009 0.034</td>
</tr>
<tr>
<td></td>
<td>0.043 0.183 0.003 0.040</td>
<td>0.043 0.183 0.003 0.040</td>
</tr>
<tr>
<td></td>
<td>-0.009 0.003 0.156 -0.186</td>
<td>-0.009 0.003 0.221 -0.284</td>
</tr>
<tr>
<td></td>
<td>0.034 0.040 -0.186 0.369</td>
<td>0.034 0.040 -0.284 0.479</td>
</tr>
</tbody>
</table>

| $\sigma^{REA}$ | 0.491 | 0.491 |
| $\sigma^{CM}$   | 0.179 | 0.179 |
| $\sigma^{PD}$   | 0.073 | 0.054 |
| $\sigma^{NS}$   | 3.025 | 4.369 |

Note: For ease of presentation, we report the estimated variance and co-variance parameters multiplied by 100 and we include a box around the reduced-form parameters that vary by regime.
Table 3: Coefficient estimates for external market variables in parameter stability regressions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Equation</th>
<th>spr</th>
<th>pct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>0.046</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.076)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>$ext_t$</td>
<td></td>
<td>0.028</td>
<td>0.205</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.045)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>$ext_{t-1}$</td>
<td></td>
<td>-0.064</td>
<td>-0.153</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.070)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>$ext_{t-2}$</td>
<td></td>
<td>0.043</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.046)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>$D_{\geq 2004}$</td>
<td></td>
<td>0.019</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.145)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>$D_{\geq 2004} \times ext_t$</td>
<td></td>
<td>-0.008</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.030)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>$D_{\geq 2004} \times ext_{t-1}$</td>
<td></td>
<td>-0.003</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.012)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>$D_{\geq 2004} \times ext_{t-2}$</td>
<td></td>
<td>0.005</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.013)</td>
</tr>
</tbody>
</table>

Wald test statistic $\chi^2(8) = 8.87$
P-value = 0.354

Note: Standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels. Coefficient estimates for variables unrelated to parameter stability tests are not reported.