Commodity Price Comovement: The Case of Cotton

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Abstract: During the commodity price boom and bust of 2007-2008, cotton futures prices rose and fell dramatically in spite of high levels of inventory. At the same time, correlation between cotton and other commodity prices was high. These two observations underlie concerns that cotton prices during this period were poor signals of cotton market fundamentals and that the cotton market was “taken along for a ride” with other commodities. The apparent coincidence of extreme price movement across a broad range of commodities requires an explanation. Were cotton prices driven by the same set of macroeconomic factors as the other commodities? Did cotton markets suffer from supply disruptions at the same time that the other commodities faced disruptions? How did expectations about future market conditions affect prices? What was the role of futures market speculators and the rise of commodity index trading? To answer these questions, we develop and estimate a structural vector autoregression model to test the relative contribution of global economic activity, current and expected supply and demand conditions, and financial speculation to observed cotton prices. To separately identify the impact of current and expected fundamental shocks, we employ a method-of-moments estimator that uses information about the variance of price innovations. We argue that the “kinked” demand curve for storable commodities (due to the zero lower bound on inventories) plausibly creates tranquil and volatile price regimes; the presence of multiple regimes generates additional moment conditions that identify the model. We find that supply and demand shocks specific to the cotton market are the major source of cotton price variation. There is scant evidence of comovement-type effects related to financial speculation. While most historical cotton price spikes are driven by shocks to current net supply, the 2007-2008 spike was caused by higher demand for inventories.

Key words: commodity prices, speculation, cotton, comovement.

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1 Introduction

Since 2006, the world has experienced two commodity price booms, where the prices of many, if not all, commodities rose dramatically. Figure 1 shows that between 2006 and 2008, the price of cotton doubled and the price of wheat tripled. Price increases were not limited to agricultural commodities. Energy prices rose sharply as the price of crude oil nearly tripled. Metals prices also rose over this period as the price of copper doubled and the price of silver increased by 50%. As they rose together, commodity prices fell together in 2008, before commencing a second boom and bust in 2010 and 2011.

If any commodity could have avoided the boom and bust of 2007 and 2008, it was cotton. The fundamental supply and demand situation was not bullish; unlike other crops, cotton levels in storage were high. Figure 2 shows the annual cotton stocks-to-use ratios since 2000. In 2007-2008, the stocks-to-use ratio was above 50%, levels higher than had prevailed since the early 1980’s when US government policy encouraged higher cotton stocks. In 2010-2011, cotton was scarce; lower than average planted acreage combined with negative weather shocks in the United States and Pakistan drastically reduced available supply. Unlike 2007-2008, there appears to be a strong cotton-specific explanation for the boom and bust of 2010-2011.

Cotton is the world’s most important textile fiber, representing 40% of fiber production, and 30-40% of cotton fiber crosses borders before processing (Meyer, MacDonald, and Foreman, 2007). The US, China, India, and Pakistan grow three-quarters of the world’s cotton. The US is the third largest producer after China and India, accounting for 14% of the global total over the period from 2007-2011 (USDA-Foreign Agricultural Service, 2011). Because cotton processing has largely moved from the US to low-cost areas such as China, the majority of US production is exported and the US is the world’s leading exporter. After initial local processing separates cotton fiber from cottonseed, the United States exports about 13 million bales of cotton fiber annually, or 36% of all global trade (USDA-Foreign Agricultural Service, 2011).

Common movements among commodity prices observed since 2006 could be caused simply by coincidental factors specific to each individual commodity or common shocks to macroeconomic factors such as the global level of economic activity. In 2007-2008 and 2010-2011, adverse weather affected agricultural production of many crops in many regions around the world (Trostle et al., 2011). Global economic growth prior to 2008, particularly in developing countries such as China and India, led to strong demand for all commodities. Similarly, aggregate demand for commodities collapsed during the economic downturn that followed the 2008 financial crisis (Carter, Rausser, and Smith, 2011).
Market observers such as Soros (2008) and Masters (2010) suggest that “financialization” of commodity markets, rather than supply-and-demand factors, is to blame for widespread commodity price spikes. This “increased acceptance of (commodity) derivatives as a financial asset” (Fattouh, Kilian, and Mahadeva, 2012) led to large amounts of speculative money entering commodity futures markets. According to critics, these speculative inflows caused the widespread boom and bust in commodity prices and broadened its effects across commodities such that some prices have been “taken for a ride” during this turbulent period.

We begin our study by reviewing the economic theory of commodity price formation derived from the canonical competitive rational expectations storage model that dates to Gustafson (1958). Critically, this model suggests that both current and expected future shocks to supply and demand impact current prices and that commodity price volatility is a function of available inventories. We incorporate these facts into a structural vector autoregression (SVAR) model of cotton prices. Similar to analyses of the crude oil market (Kilian and Murphy, 2012; Juvenal and Petrella, 2011; Lombardi and Van Robays, 2011), we use SVAR to identify structural shocks to cotton prices due to global commodity demand, financial speculation, precautionary demand based on expected future supply and demand conditions, and current cotton-specific supply-and-demand factors.

Previous SVAR studies have imposed sign restrictions on the responses of model variables to structural shocks to achieve identification. In some cases, the case for these sign restrictions based on economic theory is tenuous. To overcome this problem in our model, we propose an alternative identification scheme. We exploit the implication of the competitive storage model that prices will be more volatile when inventories are low than when inventories are high. The lower-bound on inventories implies a kinked demand curve that is less elastic when stocks are tight, so that prices are more volatile when above the kink point and less volatile below it. Essentially competitive storage model implies two price volatility regimes, one volatile and one tranquil. Using a technique developed by Rigobon (2003) known as “identification through heteroskedasticity,” we define additional moment conditions due to the presence of multiple volatility regimes to identify the structural shocks in our model.

The financial speculation component identified in our model represents a comovement effect among prices for fundamentally unrelated commodities that has been studied by economists at least since Pindyck and Rotemberg (1990) found “excessive comovement” among commodity prices. Recently, comovement effects in commodity markets have been attributed to financial speculators, such as commodity index traders, in work by Tang and Xiong (2010). We exploit this apparent empirical relationship between the prices...
of widely traded commodities such as crude oil and smaller, thinner markets such as cotton that are also components of major commodity indices to identify the impact of financial speculation. Doing so overcomes identification problems faced by studies that tried to measure financial speculation in the crude oil market using SVAR.

We find that comovement induced by financial speculation does not play a significant role in cotton price determination. To the contrary, our model suggests that fundamental factors specific to the cotton market underlie most observed price movement. Cotton price spikes in 2008 and 2011 were caused by two different types of shocks to fundamental factors; precautionary or inventory demand led to higher prices in 2008 as cotton plantings were reduced in light of higher prices for other commodities, whereas supply shortfalls drove prices to record highs in 2011. In general, we find that cotton futures prices, while extremely volatile, have reflected supply-and-demand fundamentals rather than the machinations of financial speculators.

2 Speculation and the Cotton Market

Cotton is a useful case study of commodity price spikes, the impact of speculation, and the potential influence of external markets on prices. Cotton prices are subject to global supply and demand shocks. The cotton futures market functions in part due to the presence of speculators. Cotton may be vulnerable to spillover impacts from unrelated commodities because it is a relatively small component of major commodity indices which attract speculators. Even merchant firms who deal in physical cotton, conceivably well-informed about supply-and-demand fundamentals, have incurred major losses in the cotton futures market in recent years suggesting that something other than supply-and-demand fundamentals may be driving cotton pricing. For these reasons we attempt to measure the contribution of various price drivers to the recent volatility in cotton prices.

Futures contracts traded on the Intercontinental Exchange (ICE), formerly the New York Board of Trade, serve as the central global price discovery mechanism for cotton. The physical cotton underlying these futures contracts is US cotton deliverable at points throughout the southern and southwestern United States, but the contract is traded by US and foreign cotton merchants, growers, and processors to manage price risk. The commercial futures traders who deal in physical cotton and cotton derivatives trade with a diverse group of speculators that includes large financial firms and commodity index traders.

ICE cotton futures are an established benchmark in part because of the importance of US cotton produc-
tion in the global market for textiles. The size of the cotton market relative to other commodities suggests that cotton may be more vulnerable to comovement-type influences on price compared to other commodities. Relative to other commodities, the cotton futures market is small and thinly traded. In 2011, approximately 5.3 million ICE cotton futures contracts were traded, representing 119 million metric tonnes of cotton with a notional value of $362 billion. The volume of trade for ICE cotton futures represents 35 times total US production and 4.5 times total world production. By comparison, the 2011 volume of trade in the West Texas Intermediate crude oil futures market represents a notional value of $16.6 trillion, 47 times US production and 5.5 times global production (Commodity Research Bureau, 2011). Another measure of the size of the cotton futures market is its weight in production-weighted commodity indices such as the Standard & Poor's - Goldman Sachs Commodity Index (S&P-GSCI). In 2011, 1.24% of this index was weighted to cotton, compared to 34.71% for WTI crude oil futures (and an additional 15.22% for the Brent crude oil market) (McGlone and Gunzberg, 2011).

Cotton futures prices fluctuated dramatically in 2008 and again in 2011. The impact of these price movements was severe. In 2008, margin calls on futures positions forced a number of 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 such manipulation was present (Commodity Futures Trading Commission, 2010). Price swings in 2011 (which in absolute terms were much larger than in 2008) caused further large losses for physical cotton traders, prompting market observers to label cotton futures as the “widow maker trade” of the commodities world (Meyer and Blas, 2011).

3 Fundamental sources of price variability

Understanding commodity price booms and busts implies recognition of the source of price shocks. A fundamental approach models price determination as an equilibrium between basic supply and demand factors. In the case of storable commodities, such as cotton, equilibrium prices consider not only contemporaneous production and demand factors but also the availability of inventories and the incentive to hold current supplies in storage. The canonical approach to understanding storable commodities pricing are competitive rational expectations storage models originating with the work of Williams (1936) and Gustafson (1958). Further refinements to these models were developed by Williams and Wright (1991), Deaton and Laroque
Following Williams and Wright (1991), the essential components of a competitive rational expectations storage model include a downward-sloping inverse demand function for use of the commodity at period $t$, 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 subject to uncertainty in the form of an i.i.d. production shock. Inventories, $I$, may be held between periods so that the quantity available at $t$, $(S_t + I_{t-1})$, equals consumption demand plus stocks carried into the next period $t+1$, $(D_t + I_t)$. Risk-neutral stockholding firms have rational expectations about future shocks and maximize expected profit from storing the commodity in a competitive market. The final key 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 competitive storage model implies a relationship between current and expected future prices. According to the model, stockholding firms will store the commodity according to the following no-arbitrage condition:

$$P_t = (1 + r_{t,t+1} + c_{t,t+1})^{-1} E_t(P_{t+1}) \quad \text{if} \quad I_t > 0$$

$$P_t \geq (1 + r_{t,t+1} + c_{t,t+1})^{-1} E_t(P_{t+1}) \quad \text{if} \quad I_t = 0,$$

(1)

where $r_{t,t+1}$ denotes the cost of capital and $c_{t,t+1}$ the cost of physical storage between period $t$ and a subsequent period $t+1$. This condition implies that inventories are positive when the discounted expected future price is greater than the current price. The nonlinearity introduced by the zero-lower-bound on inventories requires the use of numerical dynamic programming methods to solve for equilibrium prices and quantities. (Williams and Wright (1991) describe solution methods for this model.)

The equilibrium solution to the stockholding firm’s dynamic programming problem is characterized by a downward-sloping inverse demand function for inventories, $P_t = g(I_t)$ (Carter, Rausser, and Smith, 2011). The current period equilibrium can then be represented graphically as originally expressed by Eastham (1939). The total demand function is the horizontal sum of the current-use demand function, $f(D_t)$, and the inventory demand function, $g(I_t)$. We present this graphical representation in figure 3. The zero lower bound on inventories implies that the total demand curve is kinked at the point where $I_t$ equals zero. Cafiero et al. (2011) confirmed the empirical validity of this kink point in their evaluation of the relevance of the competitive storage model.
Important for our analysis, the presence of the kink suggests that the price response to a supply shock will depend on the level of inventories. When inventories are low such that prices fall on the “steep” part of the demand curve, price response will be volatile. When inventories are plentiful, price response will be muted. This stylized fact underlies our econometric identification scheme discussed later.

The no-arbitrage condition in equation 1 suggests that the quantity stored, \( I_t \), is a function of the spread between the expected future price and the current price such that this spread measures the incentive to hold stocks. While we cannot measure the expected future price, we do observe forward or futures prices. Working (1949) documented a positive relationship between the futures term spread and the level of inventories. To explain the existence of positive stocks when futures term spreads are negative, he suggested that a convenience yield, a concept owing to Kaldor (1939) defined as the benefit accrued from having stocks on hand when inventories are tight. This leads to the following no-arbitrage condition:

\[
F_{t,t+1} = P_t(1 + r_{t,t+1} + c_{t,t+1} - y_{t,t+1}),
\]

where \( F_{t,t+1} \) represents the forward or futures price at \( t \) for delivery at \( t+1 \) and \( y_{t,t+1} \) is the convenience yield. Working’s model as expressed in equation 2 states that inventory demand shocks will manifest themselves both through changes in inventories, spot prices, and futures prices.

The presence of a convenience yield is difficult to measure empirically and remains controversial (e.g. Brennan, Williams, and Wright, 1997). However, a strictly nondecreasing relationship between the level of inventories and the price differential for delivery at different dates is widely acknowledged as a stylized fact in storable commodity markets (Carter and Revoredo-Giha, 2007). For this reason, Geman and Ohana (2009) and Alquist and Kilian (2010) suggest that the observed spread is a suitable proxy for inventory demand.

4 Financial speculation

The inventory demand component of the competitive storage model represents rational, economically-justified speculation that anticipates future supply and demand conditions. For this reason, inventory demand may also be referred to as speculative, precautionary, or anticipatory demand. Importantly, speculation of this nature is a fundamental characteristic of a well-functioning storable commodity market. In contrast, financial speculation is not precautionary or anticipatory. Financial speculation and the process of
financialization, whereby commodity derivatives are increasingly accepted as financial assets or investment vehicles (Fattouh, Kilian, and Mahadeva, 2012), refers to speculative trading unrelated to the competitive stockholding motive discussed above.

Criticism of the financialization of commodity futures markets, both from the general public and the financial sector\(^1\), is borne of a belief that financial speculators have alternative motives for trading commodity futures and that these motives drive prices away from fundamentally justified levels. Unlike inventory holders in the competitive storage model, many financial investors who participate in commodity markets 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.

**Commodity Index Trading**

Financial speculation is often conducted through indices designed to measure broad commodity price movement; many managed funds and exchange-traded funds track these popular indices. Two industry benchmarks are the Standard and Poor’s-Goldman Sachs Commodity Index (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI). Cotton is a component of both indices. Financial firms have developed exchange-traded funds, swap contracts, and other vehicles to allow individual and institutional investors to track these and similar indices to their investment portfolios (Stoll and Whaley, 2010). Most traders following index-trading strategies tend to take only long positions (i.e. positions that make money if prices rise); because they want exposure to commodity returns, they do not take short positions (i.e. positions that make money if prices drop.) Hereafter, we refer to firms following index-tracking trading strategies as commodity index traders, or CITs.

Some studies purport to find a time-series relationship between futures market positions held by CITs and commodity futures prices. Irwin and Sanders (2011) and Fattouh, Kilian, and Mahadeva (2012) provide extensive reviews of these studies, most of which assess whether increased CIT trading predicts the returns from holding commodity futures contracts. These reviews find methodological flaws in studies purporting to find a causal effect of CIT trading activity on commodity price movements (such as Singleton (2011)). A considerable body of evidence (e.g. Stoll and Whaley, 2010; Buyuksahin and Harris, 2011; Irwin and Sanders, 2011) suggests that CIT futures market positions are not associated with futures price levels or price changes.
Identifying financial speculation through comovement

Though financial speculation may not directly impact commodity prices in a time-series sense, Tang and Xiong (2010) show that financial speculation may have a cross-sectional influence. Correlation between many commodity prices and the price of crude oil, the most widely traded commodity futures market, has risen over the period in which CIT trading has become prevalent. Tang and Xiong (2010) tested the linkage between returns for many commodities and crude oil and concluded that this comovement among prices is caused by the inclusion of commodities into major indices such as the S&P-GSCI and the DJ-UBSCI. The “index inclusion” impact of CITs follows similar effects found in equity markets by Barberis, Shleifer, and Wurgler (2005). That study showed that inclusion in a widely-tracked index leads to comovement among the prices of the index components. This is an impact of financial speculation that is distinct from directional position taking by traditional inventory demand identified earlier.

Finding common movement in prices of fundamentally unrelated commodities is not unique to the study by Tang and Xiong (2010) or the presence of CITs. Economists have documented unexplained comovement in prices at least since Pindyck and Rotemberg (1990) presented findings of “excess co-movement” among seven commodities prices. Pindyck and Rotemberg posited that correlation among the prices for commodities whose fundamentals are unrelated that cannot be explained by microeconomic fundamentals and macroeconomic effects is excess co-movement. To control for these factors, they compared comovement among the prices of unrelated commodities in a seemingly unrelated regressions framework. They included macroeconomic variables such as aggregate output, interest rates, and exchange rates as controls. Cross-equation correlation of the residuals from these regressions constitutes evidence of excess comovement. Their test found evidence of persistent excess co-movement amongst monthly average prices for wheat, cotton, copper, gold, crude oil, lumber, and cocoa over the period 1960-1985.

Pindyck and Rotemberg (1990) suggested that comovement arises because “traders are alternatively bullish or bearish on all commodities for no plausible reason.” Excess comovement as explained by Pindyck and Rotemberg is essentially identical to descriptions of commodity futures financialization: speculative positions taken by traders unrelated to expected future prices. For example, Masters (2010) argues that index trading creates massive, sustained buying pressure that causes prices to exceed fundamentally justified levels. Masters 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 has resulted in inflated food prices...”

Just as the claims of Masters (2010) and Singleton (2011) were countered by other researchers, the excessive comovement claims of Pindyck and Rotemberg (1990) were also contested. Deb, Trivedi, and Varangis (1996) questioned the validity of the test proposed by Pindyck and Rotemberg (1990). They suggested that findings of excess comovement were driven by the assumption of normal and homoskedastic errors in the seemingly unrelated regressions model. Deb, Trivedi, and Varangis (1996) proposed the use of a GARCH framework to account for the non-normality and heteroskedastic nature of commodity price changes. These models found minimal evidence of comovement for the commodities and time period used in Pindyck and Rotemberg (1990).

Ai, Chatrath, and Song (2006) revisited comovement among agricultural commodities. They pointed to the poor explanatory power of the macroeconomic variables used by Pindyck and Rotemberg (1990) and Deb, Trivedi, and Varangis (1996) and suggested that the process of considering “unrelated” commodities was inadequate. They develop a time-series model that incorporates quarterly data on net demand (that is, available supply less inventories) and show that this information explains the substantive portion of comovement among prices of the commodities in their dataset. Their data covered five commodities, wheat, barley, oats, corn, and soybeans, and 5 years, from 1997 to 2002. Ai, Chatrath, and Song (2006) note that their structural model explains much of the correlation among related commodities, but it does not explain why commodity prices for fundamentally unrelated commodities may have moved together.

5 Model

We propose a SVAR model of the global cotton market that jointly addresses financial speculation and commodity price formation as understood in the competitive storage model. That is, we consider an equilibrium determined by the interaction of current demand and supply, the precautionary demand for inventories based on expectations about future demand and supply conditions, and the impacts of financial speculation. Using SVAR allows us to measure the contemporaneous contribution of each factor, referred to as a structural shock, to observed cotton prices. Most importantly, the structural shocks identified by the model represent the outcome of a useful counterfactual, namely the cumulative contribution of that factor holding all others
fixed. This model requires a vector of endogenous variables, $y_t$, and a set of identifying assumptions that relate observed changes in these variables to the structural shocks attributable to financial speculation, current supply, current demand, and precautionary demand.

Before describing the specification and identification of the model, we outline some general notation. Denote the $K \times 1$ vector of included variables as $y_t$ and assume that $y_t$ can be approximated by an autoregressive process of some finite order, $p$, so that the SVAR model can be written as:

$$A(L) y_t \equiv (A_0 - A_1 L - A_2 L^2 - \ldots - A_p L^p) y_t = u_t$$

where $u_t$ are the structural shocks to be identified. An estimable reduced-form VAR is:

$$B(L) y_t \equiv (I - B_1 L - B_2 L^2 - \ldots - B_p L^p) y_t = \varepsilon_t$$

Pre-multiplying both sides of the SVAR model by the inverse of the first term in the autoregressive polynomial implies that the reduced-form innovations, $\varepsilon_t$, are equal to $A_0^{-1} u_t$. Essentially, the reduced-form shocks are a weighted sum of the structural shocks, where the matrix $A_0$ provides those weights. We can estimate a reduced-form VAR for any $y_t$ and extract reduced-form residuals, $\hat{\varepsilon}_t$. Identification assumptions are required to relate the reduced-form and structural residuals. Without these assumptions, we cannot relate $\varepsilon_t$ to $u_t$ because the condition relating them contains $K$ equations and $K \times K$ unknowns.

**Previous literature on SVAR and commodity speculation**

Previous empirical applications of SVAR have measured similar structural shocks in the crude oil market. Since the variables included in $y_t$ determine the interpretation given to each structural shock in $u_t$, we review this literature to determine which variables to include in our model. We want our model to address four structural shocks related to financial speculation, current supply, current demand, and the demand for inventories that influence the real price of cotton, so we need to include four variables in $y_t$.

Kilian and Murphy (2012) use monthly data on crude oil prices, production, and inventory levels as well as an index of economic activity to estimate an SVAR that considers competitive-storage-model-related shocks. They call these shocks “flow demand”, “flow supply”, and “speculative demand” shocks. These are similar to the components of the competitive storage model discussed above. In the Kilian and Murphy
(2012) model, the production variable accounts for variation related to current flow supply, the inventory variable addresses speculative (or precautionary) demand, and an economic activity index captures current or flow demand. The inclusion of inventory data and the speculative demand shock extended earlier work (Kilian, 2009) that only captured current or flow shocks to oil prices. The Kilian and Murphy (2012) 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.

There are three complications in applying the Kilian and Murphy (2012) SV AR model to cotton. First, their approach assumes that the flow demand shock is mainly related to broad-based commodity demand driven by the state of the macroeconomy; demand idiosyncratic to the crude oil market does not run counter to global economic forces. In the case of cotton, demand-side forces such as tastes and preferences for cotton and substitute fibers in apparel may not coincide with changes in general economic activity. We circumvent this problem by capturing a broad “real economic activity” shock and bundling current shocks idiosyncratic to the cotton market into a single factor that we call a “net supply” shock.

Second, data issues limit the ability of the Kilian and Murphy (2012) model to capture competitive-storage-model-type shocks for other commodities. Pirrong (2008) notes that the competitive storage model is difficult to apply to seasonally produced agricultural commodities where production levels are observed only annually. An SVAR model using annual price and production information disregards information contained in daily, weekly, or monthly prices. Since we seek to understand rapid boom and bust price cycles such as the 2007-2008 cotton price spike, we do not directly estimate the functions contained in the competitive storage model, but use our understanding of the competitive storage model to inform our econometric identification. As in Kilian and Murphy (2012), we account for rational-expectations-based speculation, but we must use different variables to capture the incentive to hold precautionary inventories in expectation of future supply and demand shocks. We call this a “precautionary demand” shock.

Finally, the Kilian and Murphy (2012) model does not address financial speculation as a differentiated effect separate from the incentive to hold precautionary inventories driven by (expected) intertemporal price differences. Two subsequent papers (Lombardi and Van Robays, 2011; Juvenal and Petrella, 2011) try to adapt the Kilian and Murphy (2012) model to capture the effect of financial speculation on crude oil prices. Using similar variables but alternative sign restrictions to identify the structural shocks, they attribute a significant portion of crude oil price volatility to financial speculation. However, the sign restrictions required for identification in these papers are not theoretically credible (Fattouh, Kilian, and Mahadeva,
To extract a structural shock due to financial speculation, we use different variables and identification methods from those used by Kilian and Murphy (2012), Juvenal and Petrella (2011), and Lombardi and Van Robays (2011). Our method relies on the fact that cotton is a small market relative to other commodities and the assumption that financial speculation effects can be approximated using the prices of commodities that are more widely held by financial speculators and more heavily weighted in major commodity indices. If the implications of the financialization hypothesis are correct, then we should find that comovement with non-agricultural commodity prices has driven cotton price changes. According to Tang and Xiong (2010), cotton prices should have become increasingly related to crude oil prices since 2004, so we include the price of West Texas Intermediate crude oil in our model. Since our identification of this shock relies on the presence of common movements between commodity prices, we label this a “comovement” shock.

Since our model uses the price of crude oil to represent the comovement effect, our methodology cannot be applied to measure financial speculation in the crude oil market itself. Additionally, comovement due to financial speculation will not only manifest itself in energy prices, though Tang and Xiong (2010) suggests that financialization implies that the effect runs from crude oil to other commodities. For robustness, we repeat our analysis using the value of the silver and copper as representative measures of external market price movement for other commodity classes.

We include four variables in $y_t$: real economic activity, $rea$, the real price in the external market, for example the price of crude oil, $ext$, the spread between distant and nearby futures prices for cotton, $spr$, and the real price of nearby cotton futures, $pct$. The four variables are related to four structural shocks in $u_t$. The first three variables, $rea$, $ext$, and $spr$, are associated with the real economic activity, comovement, and precautionary demand shocks, respectively. The fourth shock is residual variation which we attribute to the net supply shock.

To measure $rea$, we use an index of economic activity developed in Kilian (2009). This index employs 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 growth in emerging economies to stimulate cotton consumption, our aggregate commodity demand measure must be a global measure.

We do not have monthly measures of cotton inventories that might measure the activities of precaution-
ary, speculative storage, but economic theory provides an alternative measure. As noted above, the calendar spread, \( spr \), between distant and nearby prices provides a measure of the returns to storage. When stocks are tight, spreads will be low or negative, inducing storers to release inventories to accommodate current demand. Conversely when stocks are plentiful, \( spr \) will approach the full cost of holding physical stocks between the two periods.

**Econometric Identification**

Extracting the structural shocks requires identification of the parameters in the \( A_0 \) matrix that relates the reduced-form and structural residuals. Two standard assumptions to identify structural shocks in a SVAR are normalization and recursion. Normalization refers to setting the diagonal elements of \( A_0 \) to equal one, implying that the magnitude of the identified structural shocks are interpreted relative to each other. The recursion assumption uses a Cholesky decomposition to identify a unique matrix \( A_0 \) where the above-diagonal elements in \( A_0 \) equal zero. Relying entirely on recursion to identify the \( A_0 \) matrix implies a strict ordering to the structural shocks. The shock in the \( j \)th row of vector \( u_t \) cannot have a contemporaneous effect on the variables in the data vector \( y_t \) placed in higher rows \((1, ..., j - 1)\).

Using the recursion assumption in empirical SVAR work requires the modeler have ready evidence that feedback effects between some shocks and other variables cannot occur. Such evidence is not available in our case. Kilian (2011) outlines a series of alternatives, the most popular being the use of sign restrictions on the elements of \( A_0 \). In reviewing Juvenal and Petrella (2011) and Lombardi and Van Robays (2011) above, we note that the data and sign restrictions employed in these studies do not identify the financial speculation effect.

We use an alternative identification method suited to the context of storable commodity markets: the Identification through Heteroskedasticity (ItH) estimator of Rigobon (2003). This estimator relies on differences in the variance of the structural shocks across time to identify the parameters of the \( A_0 \) matrix. No assumptions about the direction or magnitude of the impulse response of the variables in \( y_t \) are required. Employing ItH to identify the contemporaneous impact of all structural shocks on all model variables requires the presence of (at least) two volatility periods or regimes, where the 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.

ItH is a method-of-moments estimator that considers the second moments of the condition relating the
reduced-form and structural shocks. The moment conditions are given by the following identities:

\[ A_0 \Omega^{tr} A_0' = \Sigma_u^{tr}, \]
\[ A_0 \Omega^{vl} A_0' = \Sigma_u^{vl}, \]

where \( A_0 \) is the translation matrix, \( \Omega \) is the variance-covariance matrix of the reduced-form residuals, \( \varepsilon_t \), and \( \Sigma_u \) is the variance-covariance matrix of the structural residuals, \( u_t \). The superscripts \( tr \) and \( vl \) denote the tranquil and volatile regimes, respectively.

The competitive storage model suggests that inventory levels (relative to the size of the market) will dictate which regime applies to a given crop year. Since the total demand curve is kinked due to the zero lower bound on inventories, structural shocks will have different consequences depending on the level of available stocks. For example, a weather-induced crop failure will have a relatively small price impact when inventories are plentiful and a relatively large price impact when inventories are scarce.

Identification of parameters in \( A_0 \), \( \Sigma^{tr} \), and \( \Sigma^{vl} \) through ItH requires \( \Omega^{tr} \neq \Omega^{vl} \). The variance of the reduced-form residuals must differ between the tranquil and volatile regimes, so that equations 5 and 6 each define a unique set of moment conditions. In the case of two regimes, the model is just-identified. There are \( K(K+1) \) parameters to be identified, the off-diagonal terms in the \( A_0 \) matrix plus the two sets of structural shock variances. Equations 5 and 6 each define \( K(K+1)/2 \) moment conditions for each regime. (Recall that only half of the off-diagonal terms in equations 5 and 6 define unique moment conditions due to the symmetry of the variance-covariance matrices.)

Equation 7 expands the moment conditions for our estimation procedure provided in equations 5 and 6, where the superscript \( r \) denotes parameters that vary across regimes. In practice, we use a combination of normalization, recursion, and ItH to identify our SVAR model. We find that the real economic activity and comovement shocks are weakly identified across regimes, because the reduced-form variances and covariances in the first two rows and columns of \( \Omega^r \) do not vary greatly between regimes. Therefore, we restrict these terms to be constant across regimes, essentially adopting the recursion assumption for the first two structural shocks. This implies that only the lower right hand corner of the \( \Omega^r \) matrix varies across regimes.
\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
A_{21} & 1 & 0 & 0 \\
A_{31} & A_{32} & 1 & A_{34} \\
A_{41} & A_{42} & A_{43} & 1
\end{bmatrix}
\begin{bmatrix}
\Omega_{11} \\
\Omega_{21} & \Omega_{22} \\
\Omega_{31} & \Omega_{32} & \Omega_{33}^r \\
\Omega_{41} & \Omega_{42} & \Omega_{43}^r & \Omega_{44}^r
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 & 0 \\
A_{21} & 1 & 0 & 0 \\
A_{31} & A_{32} & 1 & A_{34} \\
A_{41} & A_{42} & A_{43} & 1
\end{bmatrix}
\] = 
\begin{bmatrix}
\sigma_{rea} & 0 & 0 & 0 \\
0 & \sigma_{ext} & 0 & 0 \\
0 & 0 & \sigma_{spr}^r & 0 \\
0 & 0 & 0 & \sigma_{pet}^r
\end{bmatrix}
\]

Some previous studies of commodity price dynamics (e.g. Kilian, 2009) have made similar assumptions about the precedence of real economic activity shocks, assuming there is no contemporaneous feedback from the other variables to the level of real economic activity. This assumption restricts the terms in \(A_{1k}\) equal to zero, for \(k = 2, 3, 4\). We also make a similar assumption for the external market price variable, the second variable in \(y_t\). This assumption implies that any contemporaneous comovement effects run from other markets into the cotton market. This assumption restricts the terms in \(A_{2k}\) equal to zero, for \(k = 3, 4\). In some sense this is restrictive. However it bolsters the validity of our conclusions if we find no evidence of comovement effects because this model gives comovement effects precedence over cotton-specific structural shocks.

We cannot assume that precautionary demand shocks take precedence over net supply shocks, or vice-versa. Contemporaneous observed changes in prices and spreads could be the result of precautionary demand shocks or net supply shocks. We expect a positive precautionary demand shock to have a positive impact on price and a positive impact on the term spread. A net supply shock should also have a positive price impact but a negative impact on spreads. Importantly, net supply and precautionary demand shocks may affect prices and spreads simultaneously, so assigning priority to one or the other is not realistic.

Restricting \(\sigma_{rea}^r\) and \(\sigma_{pet}^r\) to be constant across regimes gives us thirteen parameters to be identified, seven in the \(A_0\) matrix and six structural shock variances. In this setup, the model remains just-identified; there are thirteen moment conditions. Multiplying out produces a symmetric matrix, where again only the bottom right hand corner contains terms that vary across regimes. Since the matrix is symmetric, only
three terms in the product of $A\Omega A'$ vary across regimes. Therefore, the thirteen unique moment conditions implied by this setup are accounted for as follows: there are seven unique conditions in the first two columns and six unique conditions represented by the three bottom right hand corner terms from each regime. This setup implies that if the variance of the reduced-form and structural shocks does not vary across regimes, then the parameters remain unidentified.

6 Data

We use monthly data spanning the period from January 1968 to December 2011. Why do we construct such a long time series when our period of ultimate interest is only the last four years? As in all econometric work, more data allows for more precise estimation of model parameters. More importantly, we are concerned about periods of dramatic price volatility. Our time series contains arguably four periods of general boom and bust in commodity prices centered around 1973, 1996, 2008, and 2011. Using a shorter time series removes these periods, limiting our ability to observe price response during volatile periods and to identify our econometric model using l'H.

As stated above, the four variables in our model are economic activity, external commodity market prices, the intertemporal price spread in the cotton market, and the price of cotton. All variables are expressed in real terms, using the US Consumer Price Index (CPI) as a deflator. To measure real economic activity, we use the real economic activity index developed by Kilian (2009). The index is derived from dry cargo shipping rates measured in deviations from long term trend. Data on cotton and other commodity market prices are collected from Commodity Research Bureau (2011). The cotton price series is the logarithm of the monthly average nearby futures price, deflated by CPI. The crude oil price series is the cash price for West Texas Intermediate crude oil. Again this series is the logarithm of the real monthly average price. The cash price series is used because crude oil futures only began trading in 1983. Nearby copper and silver futures prices to represent external markets for industrial and precious metals, just as crude oil is representative of the price of energy commodities.

The cotton calendar price spread, our proxy measure of precautionary demand, is the log-difference of futures price for delivery in one year less the futures price for nearby delivery. The difference between the time to expiration between the sixth most distant and nearby futures contract is constant, so the resulting spread represents the term structure of cotton prices over a constant period of time. This measure always an
old-crop/new-crop spread, representing expectations about the scarcity of cotton now compared to a future period when production can respond.

Figure 4 plots each variable in $y_t$, applying controls for trend and seasonality. The trend is a simple linear trend. Seasonal controls are monthly indicator variables. For the cotton price and spread variables, we adjust for the impact of the 1985 Farm Bill. In early 1986, the US Department of Agriculture announced details of the cotton-specific provisions of the 1985 Farm Bill. These provisions created incentives to store cotton in the 1985-86 crop year and sell it during the 1986-87 crop year, affecting cotton term spreads and prices (Anderson and Paggi, 1987). Calendar spreads rose in early 1986 as inventories reached record levels; when the Farm Bill programs took effect in summer of 1986, spreads and prices plummeted as old-crop cotton flooded the market. We include four control variables to account for the effects of the 1985 Farm Bill: 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.

7 Estimation and results

We estimate a reduced-form VAR for the four variables constructed above using ordinary least squares with two lags. Lag lengths are selected using Akaike and Schwarz-Bayesian information criteria. We include a linear trend, monthly indicator variables, and 1985 Farm Bill controls as exogenous variables in this VAR specification. 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 sets corresponding to the tranquil and volatile regimes. We select dates for each regime using an ad hoc rule based on predictions from price-of-storage-type theoretical models, namely that prices will be more volatile when stocks are low relative to use. We declare as volatile any crop year where projected cotton ending-stocks-to-use ratios (as defined by USDA World Agricultural Outlook Board forecasts) were below 0.25 for at least three months. This creates seven volatile windows in our sample, including the 1973-74, 1974-75, 1979-80, 1990-91, 1994-95, 1995-96, 1998-99, 2003-04, and 2010-2011 crop years.

From the reduced-form residuals for each regime, we calculate the variance-covariance matrices, $\Omega_{tr}$ and $\Omega_{vl}$. Because we do not use ItH to identify parameters in the first two rows or columns of $A_0$, we replace terms in the first two rows of $\Omega_{tr}$ and $\Omega_{vl}$ with the terms from the variance-covariance matrix calculated using all reduced-form residuals. We define a set of constraints on the $A_0$ matrix, namely the zero terms in
Using a constrained optimization routine subject to these constraints, we solve for the parameters in $A_0$, $\Sigma^{tr}$, and $\Sigma^{vl}$ by minimizing a distance function equal to the sum of the squared differences $A_0 \Omega' A_0' - \Sigma^r$ from each regime $r$.

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 the time path for the response of each variable in our model to the economic activity, external market, speculative 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 1000 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 shock from the assumed zero mean. Note that the normalization used to identify the model implies that each of the shocks causes an increase in the price of cotton. In particular, positive 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 observed structural shocks 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 the validity of the identification scheme used to identify the endogenous net supply and precautionary demand shocks in the cotton market. Price responds positively to precautionary demand shocks and net supply shocks. If an precautionary demand shock occurs, the spread should also increase to encourage stockholding by providing higher returns to
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 in storage to the market. The precautionary demand shock displays some evidence of overshooting: prices increase quickly in the months following the shock and then drop towards zero. In contrast, net supply shocks have a long-lasting impact on prices.

Figure 5 shows that external forces have a small impact on cotton prices, relative to the precautionary demand and net supply shocks specific to the cotton market. Real economic activity and external market shocks are small but long lived. However, neither of these effects are statistically significant on average. Even though our model allows these forces to take precedence over cotton-specific factors, we find no evidence in the impulse response functions to corroborate the hypothesis that external markets are driving cotton prices. The insignificance of crude oil market shocks suggests that broad-based commodity market speculation has not impacted cotton prices.

**Historical decomposition of cotton price shocks**

The impulse response analysis is incomplete in the sense that it only allows us to assess the average response of cotton prices to the structural shocks. Historical decompositions in figure 6 allow us to assess the structural origins of variation in any of the variables in our model. In our case, we are most interested in the effect of structural shocks on observed cotton prices. The series in figure 6 are constructed so that the sum of the four series equals the realized price net of trend in any period.

Most of the variation in cotton prices is due to the two cotton-market-specific shocks. Longer, smaller swings in price are attributed to the real economic activity and external market shocks. This suggests that these factors can contribute to periods of high and volatile prices, but they are likely to be a small component. 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 minute relative to the precautionary demand and net supply disruptions that occur over the same period. Crude oil price shocks have negligible effect across the entire time period, suggesting that external market comovement-type impacts driven by commodity market financialization are minimal and have not changed significantly since 2004.

The results of our decomposition analysis differ from analyses of crude oil prices by Kilian (2009) and Kilian and Murphy (2012) 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 (2012) find that between its 2003 low and 2008 high, the contribution of real economic activity to corn prices increased by approximately 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 5-10%. This is not trivial, but it is small relative to the net-supply generated portion of the price spike.

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 US and world cotton production. The 2007-08 price spike is not associated with major changes in the net supply shock, a point we return to in the next section.

Counterfactual analysis of the 2008 and 2011 price spikes

Because of the orthogonality of the shocks, we can eliminate individual 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 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 shocks did not affect cotton prices? We use such counterfactual analysis to consider the two most recent price spikes in cotton that occurred in 2007-08 and 2010-11. The counterfactuals are plotted in figure 7. The four series shown are the observed cotton price and the cotton price in the absence of external market, precautionary demand, and net supply shocks.

During the 2006-2011 period, comovement shocks are nearly imperceptible. We find that comovement shocks related to crude oil prices raised cotton prices only 2% at the peak of their impact. In absolute terms, the maximum cotton price impact of comovement shocks at any point in our analysis is less than $0.02 per pound. Relative to the price volatility observed over this period such an effect is miniscule; cotton futures prices rose nearly $0.50 per pound in 2007-08 and by more than $1.20 per pound in 2010-11.

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. In March 2008 at the peak of the initial spike, we estimate that prices would have been 26% lower without precautionary demand shocks and 11%
higher without net supply shocks. In contrast, absent the shock to net supply in 2010-2011 prices would have remained close to historic levels in real terms, rather than setting records. At the March 2011 peak, cotton prices would have been just 12% lower without precautionary demand shocks. In contrast, the log-difference between observed prices and prices absent the net supply shock was 1.07, corresponding to an approximately 70% difference.

Market intelligence produced in early 2008 corroborates the precautionary demand explanation for the 2007-2008 spike. Early US Department of Agricultural projections for the 2008-2009 cotton crop year called for “sharply lower production and ending stocks” in the US. As projected plantings of other field crops were expected to increase, cotton planted acres were to decline by 25%. Projections also called for “strong but decelerating growth in consumption” and increased imports in China in the coming crop year (USDA-World Agricultural Outlook Board, 2008). These expectations are consistent with price increases in early 2008 due to precautionary demand. Later US 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. Floods in Pakistan and periodic export bans in India limited available supplies (Meyer and Blas, 2011). The market suddenly became aware of “shortages in (current) mill inventories” in late 2010 (USDA-World Agricultural Outlook Board, 2010) that continued to bolster prices.

Assessing Robustness

We consider two robustness checks of our findings with respect to the influence of financial speculation on cotton prices. First, we replace the crude oil price variable in our SVAR model with prices representative of other commodity classes such as industrial and precious metals and consider the magnitude of the structural shocks due to financial speculation. Second, we test 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 crude oil and cotton prices.

Figures 8-9 show similar counterfactual analyses as shown earlier for crude oil, but with silver and copper used as the external market. The pattern of cotton price movement from 2006 to 2011 in the absence of external market shocks is largely the same when silver and copper represent external market movements. Price spikes still occur in March 2008 and March 2011, but at lower levels.
Counterfactual analysis using silver and copper suggests that speculation-driven comovement effects raised prices at most by 10-25% during the 2006-2011 period. While this effect may seem large, it is much smaller than the effect of cotton-specific shocks. One potential explanation for this result is the common influence of Chinese demand on cotton and copper prices. Variation that we have labelled an external market shock may be picking up the influence of economic growth in China, rather than speculative comovement. Given that index trading concentrates speculative capital most heavily in energy rather than precious and industrial metals, it seems unlikely that financialization-driven comovement accounts for all of the external market effect observed in figures 8-9.

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 prices for 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 January 2004 as our break point. Irwin and Sanders (2011, p. 6) document, beginning in 2004, a steady increase in the value assets invested in commodity index products. Using publicly unavailable data on open interest held by CITs prior to 2006, they also document a significant increase between 2004 and 2006 in the number of agricultural futures contracts and percentage on long open interest held by CITs. Tang and Xiong (2010) showed a change in the relationship between crude oil and other commodity prices post-2004.

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 cannot only test stability of the coefficients on lagged \( ext \) in our reduced-form VAR model; we must also test the stability of the parameters \( A_{32} \) and \( A_{42} \) that determine the current response of cotton price and spread to the external market shocks. (Recall that only the parameters \( A_{j2} \) affect the contemporaneous response due to recursion assumption for the first two variables.)

We reestimate the equations in the reduced-form VAR where cotton price and spread are the dependent variables, including contemporaneous values of real economic activity and crude oil price as regressors. We include interactions between each of the crude oil price variables and an indicator variable equal to one in the period post-January 2004. We then test the joint significance of the coefficients for these interaction terms and the post-January 2004 indicator variable. We fail to reject the hypothesis that any of the external market coefficients vary across periods at the five percent significance level.
8 Conclusions

We use a structural vector autoregression model to attribute observed price changes in cotton to four factors: real economic activity, the precautionary demand for inventories, shocks to current net supply, and comovement induced by speculative trading. The comovement-driven portion of cotton prices represents the impact of speculation that is unrelated to expected future prices and attributable to financial speculators and commodity index traders who some blame for recent periods of elevated prices in agricultural markets.

Unlike some past studies, we find that financial speculators are generally not the cause of cotton price spikes. The portion of observed price changes due to comovement has been small. Factors specific to the cotton market are the major determinants of cotton prices. Our model even allows comovement shocks to take precedence over cotton-specific shocks and we still find minimal comovement effects.

Unlike studies of other commodity markets such as Kilian and Murphy (2012), we find that broad trends in global commodity demand related to real economic activity matter less than cotton-specific supply-and-demand. Most cotton price spikes are fundamentally driven and strongly associated with shocks to current supply. The 2008 price spike was an exception. 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.

Our results suggest that complaints about the accuracy of cotton futures price discovery based on the belief that index traders and other financial speculators are manipulating prices are unfounded. Accordingly, legislative and regulatory efforts to restrict the trading activities of these traders will not prevent future price spikes. Price spikes are characteristic of storable commodity markets when inventories are unavailable to mitigate the effect of shocks.
Notes

1 See Soros (2008); Masters (2010) for non-academic criticisms of the impact of commodity futures financialization.
2 In a different empirical context, Rigobon and Rodrik (2005) used a combination of recursion and ItH to identify an SVAR model.
3 We also tested similar ad hoc rules for setting the regime windows and found that our results were robust to other specifications.
4 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 percent to refer to these log differences.
References


Figure 1: Prices for selected agricultural, energy, and metals commodities, monthly average nearby US futures prices, 2005-2011, January 2005 = 100.

Source: Commodity Research Bureau
Figure 2: US crop-year ending stocks-to-use, 1968-69 to 2011-12
Source: USDA PS&D Online
Figure 3: Equilibrium in a commodity market with storage
Figure 4: Data plot for variables in $y_t$, January 1968 to December 2011
Figure 5: Impulse response functions with crude oil as external market
Figure 6: Historical decomposition of structural shocks with crude oil as external market
Figure 7: Counterfactual analysis for SVAR with crude oil as external market
Figure 8: Counterfactual analysis for SVAR with silver as external market
Figure 9: Counterfactual analysis for SVAR with copper as external market
Table 1: Reduced-form VAR Regression Results

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<tr>
<th>Equation</th>
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<th>$ext_{t-1}$</th>
<th>$spr_{t-1}$</th>
<th>$pct_{t-1}$</th>
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Note: Heteroskedasticity-robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels. Coefficient estimates for seasonal indicators and time trend are not reported.