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The Quality of Price Discovery Under Electronic Trading: The Case of Cotton Futures

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The Quality of Price Discovery Under Electronic Trading: The Case of Cotton Futures

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

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Abstract: We estimate the effect of electronic trade on the quality of price discovery in the Intercontinental Exchange cotton futures market. Between 2006 and 2009, this market transitioned from floor-only trade to parallel floor and electronic trade and then to electronic-only trade. We use a random-walk decomposition to separate intraday variation in cotton prices into two components: one related to information about market fundamentals and one a “pricing error” related to market frictions such as the cost of liquidity provision and the transient response of prices to trades. We find that on a typical day during the electronic-only period, the standard deviation of the pricing error is half what it was on a typical day during the floor-only period. This drop reflects a substantial improvement in average market quality, much of which is associated with an increase in the number of trades per day. We report three additional findings: (i) market quality was significantly more volatile during the electronic trading period than the prior periods meaning that there were more days with large deviations from average market quality, (ii) market quality was poor immediately following the closure of the floor and (iii) market quality was better on days when public information was released in the form of USDA crop reports but worse on days where prices change by the maximum imposed by the exchange.

Key words: commodity futures, price discovery, market quality, electronic trading, cotton.

JEL Classification Numbers: G13, G14, Q11.

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1 Introduction

In late February and early March 2008, Intercontinental Exchange (ICE) cotton futures prices were notably volatile. The nearby futures price rose from 70 cents per pound in mid-February to a high of almost 93 cents on March 5th, before falling back below 70 cents by mid-March. Nearby futures moved up or down by the daily limit set by the exchange on 12 of 18 consecutive trading days. One potential explanation for volatility in cotton futures markets was the transition from open-outcry to electronic trading. Notably, March 3rd, the day at the center of the price spike, was the first day without floor trading. In the words of market analyst Mike Stevens: “Everything changed in March 2008. That was when electronic trade came in. The price discovery mechanism began to get somewhat shaky” (Hall, 2011).

These perceptions echo claims often made regarding algorithmic trading in financial markets. Kirilenko and Lo (2013) report that the “mere presence” of algorithmic high frequency traders (HFTs) appears to have undermined the confidence of many traditional market participants in the price discovery process. During the so-called flash crash on May 6, 2010, the major U.S. stock indexes dropped by more than 5% in the space of a few minutes before bouncing back almost as quickly. Kirilenko et al. (2011) argue that HFTs exacerbated volatility during this episode and thereby reduced market quality. In contrast, studies that cover longer periods of time find that HFTs improve liquidity on average (e.g., Brogaard, Hendershott, and Riordan, 2013; Hasbrouck and Saar, 2012).

Market microstructure theory makes ambiguous predictions about the effect of electronic trading on price discovery. Under open-outcry, floor traders have access to information about order flow and the identity of potential counter parties not available on electronic trading systems. Eliminating these information flows may create information asymmetries that discourage liquidity provision by some traders and reduce pricing accuracy. Electronic trading makes the best bids and offers transparent and order matching precise, reducing human error. Previous studies sought to measure the net effect of these contrary forces on market liquidity. However, by opening the market to traders beyond the physical location of the pit, electronic trading systems enabled substantial growth in algorithmic and high-frequency trading (Hendershott, Jones, and Menkveld, 2011).

The ICE cotton futures market is an attractive laboratory in which to examine the impact of electronic trade on price discovery. In the relatively short period between February 2007 and March 2008, ICE introduced electronic trading and closed the trading pits. This creates three periods of floor trade, parallel floor and electronic trade, and electronic-only trade that should be closely related in terms of the fundamentals underlying the determination of the value of cotton. Over this period, production technology, tastes and preferences for consumption, and government policy with respect to the cotton market remained reasonably constant. We estimate the effect of electronic trading by comparing market quality before and after these changes. Our study has some parallels with Hendershott, Jones, and Menkveld (2011), who study market quality before and after the New York Stock Exchange automated quote dissemination in 2003.

To measure market quality, we decompose intraday variation in cotton prices into two components: one related to changes in the underlying fundamental value of cotton and one a pricing

error related to market frictions such as the cost of liquidity provision and the transient response of prices to trades. Large pricing errors represent periods of poor price discovery or low market quality. We perform this decomposition using the method developed by Hasbrouck (1993, 1996, 2002, 2007). Using a dataset of high frequency, transaction-by-transaction futures prices from the ICE cotton futures market for the period from 2006 to 2009, we estimate the standard deviation of the pricing errors on each trading day.

By estimating market quality on each day rather than averaging across time periods, we can test three hypotheses in addition to general tests of average market quality before and after the introduction of electronic trading and after the subsequent elimination of floor trading. First, is the market under electronic trade more vulnerable? That is regardless of average pricing errors, are large-pricing-error days more likely? Second, even if market quality was poor immediately after the elimination of floor trading, did it improve as traders adapted to the new system? Third, how does market quality vary with trading volume, price volatility, the imposition of daily price limits, and information events like the release of government crop reports?

We analyze summary statistics for our daily market quality measure across the three trading regimes and find that average market quality is better under the electronic trading system. Recognizing that other factors may confound such simple comparison of market quality measures in our natural experiment, we present a reduced-form regression of market quality on trading volume, volatility, and other variables. This regression is useful in characterizing the evolution of market across time. In addition, we test hypotheses related to the arrival of new information and the impact of price limits. We consider the effect of public information arrival and price limits by testing for significant relationships between daily market quality and indicators for USDA report releases and days where prices move up or down the maximum imposed by the exchange.

2 Cotton futures background

The transition from open-outcry to electronic trading in cotton futures was initiated through the takeover of the New York Board of Trade (NYBOT) by the Intercontinental Exchange (ICE). In September 2006, NYBOT, the parent company of the former New York Cotton Exchange, and ICE announced a potential merger. Upon the successful takeover of NYBOT in January 2007, ICE announced the introduction of cotton futures trading on its electronic platform beginning February 2, 2007. The availability of electronic trading expanded trading hours from 10:30am-2:15pm to 1:30am-3:15pm.

Prior to its introduction, electronic trading was viewed as both a technological innovation to replace open-outcry and an enhancement of the existing trading system. Some considered the two systems as complements. At the announcement of the ICE/NYBOT merger, NYBOT CEO C. Harry Falk stated that “the ICE electronic marketplace is an excellent complement to the vibrancy and liquidity of our trading floor” (Intercontinental Exchange, 2006). However, ICE had previously shown no devotion to open-outcry trading. ICE originated as an electronic energy marketplace and closed trading floors at futures exchanges it had acquired in Europe and Canada (Olson, 2010).

During 2007, cotton futures trading volume migrated to the electronic platform. Figure 1 shows the increasing proportion of both monthly trading volume and number of trades on the electronic platform in 2007. By July 2007, approximately 40% of trading volume and over 80% of trades occurred via electronic trading. As shown in figure 2, the absolute number of trades and trading volume both increased in 2007, with relatively larger increases in the number of trades. Trading volume fell after March 2008, but the number of trades remained high relative to historic levels. Volume per trade declined considerably following the introduction of electronic trading.

In December 2007, ICE announced it would close the cotton trading floor, effective Monday, March 3, 2008. The weeks preceding and following March 3, 2008 were a period of considerable cotton futures price volatility culminating in a sharp spike in cotton futures prices peaking March 5. During this time, prices moved up or down the daily limit set by the exchange on 12 of 18 consecutive trading days. When daily price limits are hit, trading stops until the following trading day or until traders are willing to transact at prices inside the limit.

In the aftermath of the March 2008 price spike, some observers drew connection between extraordinary price changes and the elimination of floor trading. A *Wall Street Journal* report noted that in midst of limit moves on March 3rd and 4th, “frantic investors wondered where price pressure was coming from. But with no more floor traders to consult for scuttlebutt, they were in the dark” (Davis, 2008). These remarks corroborate the idea that floor traders may play an important role in incorporating fundamental information into commodity prices and transferring that information to other market observers.

However, given the small proportion of trading on floor just prior to March 2008 (see figure 1), it seems unlikely that many traders and market observers were wholly reliant on the trading floor. Nor did the elimination of floor trading coincide with declining numbers of traders. Each week the Commodity Futures Trading Commission reports the number of “reportable” traders who hold large positions in each futures market. The number of large traders in ICE cotton futures between June 2006 and October 2008 was consistently between 250 and 300 traders. The number of large traders declined during the financial crisis in late 2008 by approximately 30-35% but similar declines were seen in other agricultural futures markets (Commodity Futures Trading Commission, 2013).

In response to the events of March 2008 in the cotton futures market, the Commodity Futures Trading Commission issued a report that considered “...the trading patterns of market participants, the broad increase in commodity prices in general, the impact of the presence of certain market participants in the market, the possible tightening of credit conditions, the impact of price limits in general, and the potential that prices may have been manipulated” (Commodity Futures Trading Commission, 2010). They concluded that trading and price patterns in cotton were not consistent with any sort of market manipulation and that the elimination of floor trading was only coincidental to observed price volatility, not the cause.

2.1 Daily cotton futures trading summary statistics across trading periods

Based on the history of the adoption of electronic trading in cotton futures, we consider three periods: floor trade, parallel floor and electronic trade, and electronic-only trade. The parallel trade period contains 269 trading days between February 2, 2007 and February 29, 2008. We select a similar number of floor-only and electronic-only trading days to complete our dataset. The floor-only period is January 3, 2006 to February 1, 2007. The electronic-only period is March 3, 2008 to March 27, 2009.

We identify important dates in the daily time series related to the arrival of public information and exchange-imposed limits to price movement. We create indicator variables for days where USDA releases important information on cotton supply and demand conditions. The report day variable equals one on days when the USDA releases its monthly World Agricultural Supply and Demand Estimates and the annual Prospective Planting reports. During our study period, these reports were released at 8:30am so prices could react to report information on the day of release. We also create indicators for days where prices move up or down daily limits. According to ICE contract specifications during our study period, cotton futures could not trade more than three cents higher or lower than the previous day's closing price when that price is below 84 cents per pound. Above 84 cents, the daily limit was four cents.

Table 1 presents summary statistics for daily data on prices, price volatility, trading volume, and the number of trades for the entire sample and the three subperiods of floor-only, parallel floor and electronic, and electronic-only trade. In light of the extraordinary market conditions in the week March 3, 2008, we calculate separate summary statistics for the electronic-only period excluding this week. We also present counts for the number of USDA report days and limit price move days within each period.

The results in table 1 suggest that market conditions varied across the three periods in our sample. While mean price levels were generally similar, price volatility increased. The coefficients of variation for closing cotton futures prices during floor, parallel, and electronic periods were 0.04, 0.12, and 0.22, respectively. A fivefold increase in relative standard deviation is dramatic, but other agricultural commodity prices were also more volatile in 2008 than in 2006. Over the same March 2008 to March 2009 period, corn, soybean, and wheat futures closing prices had similar coefficients of variation (0.24, 0.21, and 0.25, respectively) though relative variability of closing prices only doubled or tripled compared to previous periods.

We consider intraday volatility using the standard deviation of log price changes over five minute intervals within the trading day. Table 1 shows intraday price volatility was greater and more variable in the electronic-only period, though intraday volatility was actually lower during the parallel period than in the floor trading period. Figure 3 plots daily intraday price volatility for the nearby cotton futures contract from January 2006 to March 2009. The pronounced spike in this graph occurs on March 4, 2008. Following this period of elevated volatility, intraday futures price volatility remained relatively high through the end of 2008 and early 2009.

Daily volume and trades statistics indicate that large market orders handled in a single trade

in the pit are now split into a series of smaller trades in order to be processed on the screen. Under electronic trade more transactions occurred, but the volume per transaction was lower. Daily trading volume in the floor-only and electronic-only periods was similar: approximately 11,000 contracts were traded daily in these periods. However, the number of trades grew dramatically from an average of 653 under floor-only trade to 3,712 under electronic-only trade.

3 Differences between open-outcry and electronic futures trading

Electronic and open-outcry futures markets have the same goals: to facilitate price discovery and risk management through hedging. Each system provides a venue for traders to buy and sell futures contracts. Electronic trade features an open limit order book. Whereas under open-outcry, traders shout out their bids and offers (the prices at which they are willing to buy or sell), in electronic markets, bids and asks are posted in the limit order book and viewable by all traders. They reside in the order book until filled or withdrawn. A computer algorithm matches incoming market orders to the standing limit orders in the book.

Traders evaluate the merit of open-outcry and electronic trading based on transactions costs associated with each system. Many market microstructure models decompose observed prices into parts due to the fundamental asset value and due to frictions in the trading process that may be influenced by market organization (Hasbrouck, 2007, p. 23). Transactions costs are a catch-all economic term describing these frictions. Biais, Glosten, and Spatt (2005) find two causes for such transactions costs: “order-handling costs” and “asymmetric information or strategic behavior.” Ates and Wang (2005) call these operational and informational costs and suggest that they differ between trading systems.

Operational differences between open-outcry and electronic trading are differences in order processing and matching. Electronic trading uses high-speed communications systems to rapidly deliver orders and match buyers and sellers. Orders are usually matched according to a “first in, first out” rule. Large market orders are quickly split into smaller transactions when the first-in limit order is smaller than the arriving market order. Splitting market orders results in multiple transactions, one reason why the number of trades is greater and the volume per trade lower in an electronic market relative to open-outcry, all else equal (Shah and Brorsen, 2011).

Out-trades, canceled trades on the floor where buyer and seller report incongruent information about the agreed price and size of the trade, are eliminated. Further, electronic trade does not require a physical presence in a capacity constrained trading pit, implying that the cost of participation is lower. In general, electronic trading should improve order processing and reduce transactions costs.

Informational differences relate to the role that prices and trades play in conveying information to market participants in each trading system. Electronic and open-outcry systems provide different types and amounts of information to traders, particularly information about the actions and intentions of other traders. Open-outcry markets allow traders to observe who is providing liquid-

ity by bidding or offering. It may also be possible to observe when orders are coming from off the floor and when floor brokers are trading to balance their positions. Traders in the open-outcry system can choose their counterparties. In addition, the massing of all traders in one physical location provides additional sensory cues to traders¹. In general, the open-outcry system provides traders in the pit with additional information not available on the electronic trading screen.

Information provided through the floor trading mechanism may mitigate the adverse selection problem faced by any trader who provides liquidity by posting limit orders in the book. As noted by Copeland and Galai (1983) and Glosten (1994), when a trader shouts a bid or offer or when they submit a limit order they are exposed to counterparties with potentially better information about the fundamental value of the commodity. This is the source of the adverse selection problem. Informed counterparties will only hit this bid or offer if they expect to make positive profits, implying an expected loss for the market maker. In limit order book markets, quotes posted are valid until withdrawn. In open-outcry, quotes are valid only so long as “breath is warm”. Quote monitoring and quote revision may be more costly in the electronic trading environment. To compensate, market makers may widen bid-ask spreads and reduce the provision of liquidity resulting in poorer price discovery.

4 Empirical comparison of open-outcry and electronic trading

To resolve ambiguous predictions from theory about the effect of the trading mechanism on price discovery, empirical studies have estimated measures of market quality under open-outcry and electronic trading systems. Such measurement is difficult because neither observed transaction prices nor bid and ask quotes directly reveal whether their levels are due to information about the value of the underlying commodity or frictions in the trading system. In the literature on the impact of electronic trading, economists have employed two broad market quality measures: (i) bid-ask spreads and bid-ask spread estimators and (ii) price discovery measures based on permanent-transitory time-series decompositions.

In this section, we review previous studies in the context of a simple model of market microstructure where prices subsume unobservable components due to the fundamental value of the commodity and the cost of transacting. Define the efficient price, m_t , as the fundamental value of the underlying commodity at period t . The evolution of the efficient price over time is:

$$(1) \quad m_t = m_{t-1} + w_t,$$

where $E(w_t) = 0$, $E(w_t^2) = \sigma_w^2$, and $E(w_t w_s) = 0$ for $t \neq s$. That is, the efficient price follows a random-walk. The martingale property of the random-walk makes it an economically meaningful representation of the efficient price. The current efficient price m_t is an unbiased expectation of the future commodity value, past observations of m_t do not help predict future values, and the innovations, w_t , represent the arrival of new information about market fundamentals.

¹Coval and Shumway (2001) find that changing sound levels in the trading pit forecast changes in the cost of transacting.

Observed transaction prices, p_t , may not always fully reflect underlying fundamentals so that $p_t \neq m_t$. Deviations of the observed price from the fundamental value are represented as a “pricing error” term, denoted as s_t , so that observed prices are represented as:

$$(2) \quad p_t = m_t + s_t.$$

The pricing error, s_t impounds short-lived “microstructure effects” related to the transactions costs described in section 3. Unlike w_t , s_t has only a transient impact on observed prices; s_t is a zero-mean, covariance-stationary process, that is, $E(s_t) = 0$ and $E(s_t s_{t-k})$ depends only on k .

4.1 Bid-ask spreads and market quality

The bid-ask spread, the difference between standing offers to buy and sell at a given point in time, is one conception of the transactions costs represented by the pricing error, s_t . In the model of Roll (1984), orders to buy and sell arrive randomly, the efficient price is the midpoint between the bid and ask, and s_t equals $\pm(\text{spread})/2$, the half-spread a buyer or seller implicitly pays to have their transaction occur immediately. In the Roll (1984) model, the pricing error is caused by bid-ask bounce and s_t and w_t are uncorrelated.

Bid-ask spreads are an observable measure associated with market quality, but empirical analysis using bid-ask spreads has been hampered by the lack of reporting in open-outcry futures markets. Because quotes on the trading floor are only good so long as “breath is warm”, quotes are not recorded and only transactions prices are available. Using data from the electronic corn futures market, Wang, Garcia, and Irwin (2012) find that observed bid-ask spreads data are generally small (less than two ticks) and correlated with daily volume, volatility, time to contract maturity, and releases of public information. The lack of data from the open-outcry market in their analysis prevents comparison of bid-ask spreads across trading systems.

Two types of estimators have been developed to approximate bid-ask spreads when price data are available and quotes are unobserved or unavailable. Thompson and Waller (1988), Smith and Whaley (1994), and Wang, Yau, and Baptiste (1997) develop a set of estimators based on the magnitude of average absolute price changes; when price changes are large, bid-ask spreads are likely to be large. These estimators do not distinguish between price changes due to the incorporation of fundamental information into prices and changes due to transactions costs. As such, they are tenuous estimators of market quality.

The second type, due to Roll (1984), uses the serial covariance of successive price changes. The Roll measure relies on the assumptions in the simple microstructure model above, namely that pricing errors are uncorrelated with fundamental information and markets are informationally efficient. Hasbrouck (2002) notes that information asymmetries are likely, especially at high frequency. Prices are determined in part by informed trading, so that traders infer information about the efficient price from the direction and size of trades. Therefore, the assumptions underlying the Roll estimator are likely to be violated. Some analyses of electronic trading test the accuracy of various bid-ask spreads estimators against observed bid-ask spread data. For example, Bryant

and Haigh (2004) suggest that absolute average price change measures perform better than serial covariance estimators at estimating spreads for their data on coffee and cocoa futures.

Three recent studies of electronic trade in agricultural commodity futures use these bid-ask spread estimators, though they reach different conclusions. Bryant and Haigh (2004) consider the switch to electronic trade in London International Financial Futures and Options Exchange cocoa and coffee futures in 2000. They find that average spreads are significantly larger under electronic trade than under open-outcry. In contrast, estimated bid-ask spreads are smaller for electronic trading in studies of side-by-side open-outcry and electronic trading in Chicago Mercantile Exchange (CME) live cattle and live hog futures (Frank and Garcia, 2011), CME corn, wheat, and soybeans futures (Martinez et al., 2011), and Kansas City Board of Trade wheat futures (Shah and Brorsen, 2011). In each of these studies, reduced-form regressions measure the relationship between bid-ask spreads and trading volume, observed price volatility, and other variables.

4.2 *Random-walk decompositions and market quality*

Random-walk decompositions based on the simple microstructure model discussed above are an alternative to bid-ask spread estimation for the evaluation of market quality. These decompositions are structural econometric models that allow us to characterize two unobserved but economically meaningful variables: the innovations in the random-walk, w_t , representing information arrival and the pricing error, s_t representing deviations from the efficient price due to transactions costs. Large pricing errors represent periods of poor discovery where observed prices are far from fundamentals. The standard deviation, σ_s and variance, σ_s^2 , of s_t are intuitive measures of market quality representative of the magnitude of deviations from the efficient price or an “average” pricing error over some period of time.

Previous applications of random-walk decomposition methods to evaluate the transition from open-outcry to electronic trading divide their focus between w_t and s_t . Studies focused on w_t attribute some proportion of price discovery to the open-outcry or electronic market by considering prices in each market as cointegrated time series whose innovations can be related to w_t , the innovations in a single efficient price relevant to both markets. The information shares technique of Hasbrouck (1995) and the common long-memory factor weights method of Gonzalo and Granger (1995) are used to measure the proportion of price discovery occurring in each market by identifying the proportion of the random-walk innovations (representing new information) first revealed in the open-outcry or electronic market. Martinez et al. (2011) apply these methods to parallel open-outcry and electronic trading of Chicago Board of Trade agricultural futures contracts in 2006. Over this period, they find a growing proportion of price discovery occurred in electronic markets.

Multi-price decomposition methods are not suited to the comparison of market quality across periods where trading occurs on some venues but not others. These methods necessarily compare price discovery in related markets at a single point in time. However, trading tends to consolidate in a single venue (Silber, 1981) and open-outcry trading has been eliminated for some markets, so measuring a “share” of price discovery is not possible. We turn our focus to measuring the magnitude of the pricing error, s_t .

The pricing error captures deviations from the efficient price in both open-outcry and electronic markets. The structural model underlying the random-walk decomposition is agnostic with respect to specific mechanisms that generate observed sequences of trades. For example, we note above that the procedure for matching large incoming market orders differs between open-outcry and electronic trades. To the extent that either trading system encourages a transient price response to the incoming market order, our model will capture that transient response in the pricing error.

5 Identifying the pricing error variance through random-walk decomposition

In section 4, we characterized the dynamics of observed and efficient prices and made the case for the pricing error standard deviation and variance as summary measures of market quality and the accuracy of price discovery. To compare price discovery across the three periods of open-outcry, side-by-side, and electronic trading, we treat prices as a single time series whether transactions occur on the trading floor or the electronic platform and compare the pricing error standard deviation across periods. When open-outcry and electronic trading operated in parallel, contracts were fungible across the two platforms, traders in the pit had access to the electronic system, and settlement prices were determined by both open-outcry and electronic transactions.

Given the basic representation of the fundamental value and observed prices in equations 1 and 2, Hasbrouck (1993, 2002, 2007) develops a statistical representation of the underlying microstructure model that identifies the pricing error variance. The statistical model uses data on transaction prices, p_t and trade direction, x_t , a variable signed to be positive if the trader who initiated the trade at time t is a buyer and negative if a seller. The data vector $y_t = [\Delta p_t \quad x_t]'$ is presumed covariance stationary. By the Wold theorem, the data vector y_t has a vector moving average representation:

$$(3) \quad y_t = \begin{pmatrix} \Delta p_t \\ x_t \end{pmatrix} = \Theta(L)\varepsilon_t$$

where

$$\Theta(L)\varepsilon_t = \begin{pmatrix} \Theta_{11}(L) & \Theta_{12}(L) \\ \Theta_{21}(L) & \Theta_{22}(L) \end{pmatrix}, \quad \Theta(0) = \mathbb{I}, \quad E[\varepsilon_t \varepsilon_t'] = \Omega = \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{pmatrix}.$$

This statistical model simply states that price changes are a linear combination of current and past shocks to price changes and trade direction. The covariance matrix, Ω , is unrestricted, so the two shocks may be correlated.

The Beveridge and Nelson (1981) decomposition employed by Hasbrouck allows for identification of permanent and transitory components in the VMA process. This method uses the autocorrelation structure of price changes and trade direction to identify the pricing error. By this decomposition, we can represent y_t as:

$$(4) \quad \begin{aligned} y_t &= \Theta(1)\varepsilon_t + \Theta^*(L)\Delta\varepsilon_t. \\ &= \text{permanent} + \text{transitory} \end{aligned}$$

By taking the first difference of equation 2, price changes in the structural model can be expressed as $\Delta p_t = w_t + \Delta s_t$, where s_t is a mean zero, covariance stationary process. The correspondence between this representation and the first row of equation 4 implies:

$$(5) \quad \begin{aligned} w_t &= \Theta_{11}(1)\varepsilon_{1t} + \Theta_{12}(1)\varepsilon_{2t} \\ s_t &= \sum_{i=1}^m (\Theta_{11}^*(L)\Delta\varepsilon_{1i} + \Theta_{12}^*(L)\Delta\varepsilon_{2i}) = \Theta_{11}^*(L)\varepsilon_{1i} + \Theta_{12}^*(L)\varepsilon_{2i} \end{aligned}$$

Here w_t is a linear combination of the two shocks and is white noise. The coefficients in $\Theta_{11}(1)$ and $\Theta_{12}(1)$ accumulate the current and future impacts of the present shocks and therefore represent the permanent effect of shocks on prices.

Hasbrouck (1993, 2007) follows standard time series practice in approximating the VMA(∞) in equation 4 with a finite VAR amenable to estimation:

$$(6) \quad \begin{pmatrix} \Delta p_t \\ x_t \end{pmatrix} = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t$$

where p is some lag length beyond which serial dependencies are assumed to be negligible. Using the VMA representation of the model, Hasbrouck (2007, Ch.9) derives the formula for the pricing error variance:

$$(7) \quad \begin{aligned} \sigma_s^2 &= \sum_{k=0}^{\infty} C_k \Omega C_k' \\ \text{where } C_k &= - \sum_{j=k+1}^{\infty} \Theta_1(j) \end{aligned}$$

where $\Theta_1(j)$ denotes the first row of $\Theta(j)$. The pricing error variance represents the magnitude of the deviations of the pricing error time series from its zero mean.

Including x_t in the data vector y_t strengthens the estimate of the pricing error variance. Since the permanent component is based on the forecast of the current and future impact of current shocks, conditioning information will increase the precision of this forecast. According to Hasbrouck (2007, pp. 87-88), x_t is ideally a vector of public information used by traders to draw inference about m_t over the relevant (very short run) time interval. For example, larger trades may contain more information than small ones (Holthausen, Leftwich, and Mayers, 1990). Omitting such information may bias coefficient estimates from the VAR model. Later we assess the robustness of our results to the inclusion of additional trade size information in x_t .

As a measure of market quality, σ_s^2 faces several complications. Lower values represent better price discovery, so σ_s^2 actually measures inverse market quality. σ_s^2 is a unitless measure, so it cannot be compared in terms similar to prices and spreads. To address these concerns and improve the interpretation of our results, we refer to “market quality” as the negative standard deviation of

the pricing error:

$$(8) \quad MQ = -\sqrt{\sigma_s^2}.$$

Where we consider a logarithmic transformation of market quality, we express this as: $\ln MQ = -\ln(\sqrt{\sigma_s^2})$.

Tse and Zobotina (2001) apply the Hasbrouck (1993) methodology to assess market quality in the transition to electronic trading. They study the transition of FTSE 100 stock index futures from open-outcry to electronic trade in 1999. They calculate average standard deviation of the pricing error (σ_s) over two three-month trading periods before and after the switch and find that the floor-trade period is associated with higher market quality; the pricing error variance is lower in this period. Our application of the Hasbrouck (1993) method considers more than average market quality. We expand on previous studies by considering the evolution of market quality across time.

6 Estimation and results

Estimation of the Hasbrouck (1993) model requires data on two variables, returns and trade direction. We generate these variables using intraday tick-by-tick transaction data for ICE cotton futures acquired from TickData Inc. This dataset records the time and price of each futures market transaction. Transactions are time-stamped to the second. Electronic trades include the number of contracts exchanged; open-outcry trades do not report trade quantity. We supplement transaction-level data with daily price and volume information from the Commodity Research Bureau.

We consider transactions for one nearby contract each trading day rolling to the next contract on the twentieth day of the month prior to the delivery month. For cotton futures, the most-active nearby contract is usually the nearest to delivery, except for the October contract which is more lightly traded than the December contract. Therefore, we ignore the October contract and roll from the July to the December contract during the June roll period. We ignore natural time and treat the data as an untimed sequence of observations. Returns are calculated as the log price change, $\ln(p_t/p_{t-1})$, between the current and previous transaction so that t indexes transactions rather than clock time. Calculating returns in event time mitigates against heteroskedasticity in returns caused by periods of frequent transactions. The covariance stationarity assumption underlying the statistical model is more likely valid in event time (Hasbrouck, 2007).

Trade direction cannot be classified relative to quoted bids and offers because quote data is unavailable for the open-outcry period, so we cannot use the widely-used trade classification algorithm of Lee and Ready (1991). Instead, we employ a simple tick rule whereby the trade direction is classified as buyer-initiated if the previous price was lower than the transaction price and seller-initiated if the previous price was higher than the transaction price. When the previous price is the same as the transaction price, the trade is classified the same as the previous trade classification. The trade direction variable, x_t , is an indicator variable that takes on the value negative one when a trade is seller-initiated and one when a trade is buyer-initiated, following the tick rule outlined above. Though the tick rule considers less information than quote-based trade classification rules,

validation studies such as Ellis, Michaely, and O'Hara (2000) suggest that the difference in trades misclassified may not be large.

For each day in our sample, we estimate the VAR model for log returns, Δp_t , and trade direction, x_t presented in equation 6. Lag selection is based on Akaike (AIC) and Schwarz-Bayesian (SBIC) information criteria. We calculate optimal AIC and SBIC for each day. The average optimal AIC is slightly greater than four, so we use five lags². Using the VAR results, we calculate the intraday pricing error variance using equation 7.

Market quality improved, but became more variable over the period of our analysis. Figure 4 plots our market quality measure over the January 2006 to March 2009 period on a logarithmic scale. Vertical bars indicate the dates where electronic trading was introduced and floor trading was eliminated. Summary statistics for this series appear in table 2 for the full sample and the three trading system regimes. Mean market quality improved from the floor-only to the electronic-only period. A simple t-test of the difference in means between the floor-only and electronic-only periods finds that average market quality was significantly better under electronic-only trading. This improvement occurred gradually, beginning some time in the second quarter of 2007 after electronic trading gained a substantial share of trading volume.

Relative to the floor trading and parallel trading periods, market quality was more volatile during the electronic trading period. The absolute value of the coefficient of variation for market quality in the electronic-only period (excluding the week of March 3) was 0.697, nearly three times higher than during the floor period and nearly 50% higher than during the parallel period. We know that price volatility was also higher during these latter periods, however steadily growing dispersion of market quality about its trend in 2007 and into 2008 is not accompanied by similar steady increases in intraday price volatility.

We find that market quality adapted quickly to the elimination of floor trading in March 2008. The period of the 2008 price spike was an outlier in terms of market quality as demonstrated by the final two columns of table 2. The minimum market quality statistic of -0.339 was calculated for the March 4, 2008 trading day. On this day, the nearby May 2008 cotton futures contract traded up the limit most of the day. Excluding the period immediately surrounding the 2008 price spike shows the impact of these outlier observations: without them the standard deviation of market quality under electronic trading was 0.008, the same as under floor-only trading.

Improved market quality over our period of analysis is *prima facie* evidence that the operational efficiencies from electronic trading lead to improved price discovery. However, if some traders are particularly sensitive to periods of poor price discovery, rising variability in market quality may undermine confidence in the price discovery mechanism. Substantial variation in market quality within each trading period argues for more detailed analysis using additional data on variables related to the permanent and transitory components of observed prices identified in the Hasbrouck model.

²We also estimate the pricing error variance using the AIC-selected optimal lag length for each day. This does not significantly affect our results.

6.1 Incorporating trade size information

Hasbrouck (2007) suggested that including trade size in the data vector y_t may convey additional information about the fundamental value because large orders have greater information content. Our data do not contain trade size information for floor trades, but we incorporate the trade volume information we do have to assess the robustness of our results to the exclusion of trade size data. We calculate an average daily trade size for floor trades by dividing daily floor trading volume by the number of floor trades on that day. We replace the missing trade size values for each floor trade with the average daily trade size for that day. Using this information, we can generate additional trade classification variables to incorporate what trade size data is available and incorporate them into the VAR model.

Call the binary trade direction variable x_{1t} . We generate x_{2t} , the volume-weighted trade direction by multiplying trade size (or average daily size for floor trades) by x_{1t} . To capture non-linearities in the response of price to trade size, Hasbrouck (2007) suggests also using the square root of x_{2t} , or x_{3t} . We estimate daily MQ using the four-variable VAR where $y_t = [\Delta p_t \ x_{1t} \ x_{2t} \ x_{3t}]'$. For the floor-only trading period, the variables x_{it} are perfectly collinear, so the second and third variables are dropped from estimation and the MQ results are the same as our initial estimation procedure.

Additional trade size information does not substantially alter our results. Table 3 presents the same summary statistics for market quality as in table 2. Summary statistics for the floor trading period remain the same since we have no additional trade size information for this period. We find that including additional information lowers average market quality and reduces relative variability. The magnitude of the change in means ($\tilde{0}.02$) is small relative to the differences in means across periods.

6.2 Reduced-form regression results

Comparisons of market quality across trading systems in our sample may be confounded by changes in other jointly determined variables. We employ a reduced-form regression analysis to consider how market quality changed holding these other variables constant. The regressions do not estimate causal impacts but simply describe associations present in the data. We present five simple linear regression specifications in table 4 where the dependent variable is the logarithm of the daily market quality, $\ln MQ$. We also transform continuous control variables using logarithms. These transformations dampen the effects of outliers such as the March 2008 period and allow regression coefficients to be interpreted as approximate percentage changes.

The regression results confirm our univariate analysis of market quality. We find that market quality was significantly better under electronic trading. The first specification in table 4 controls for changes in number of trades, volume, intraday price volatility, and days to contract maturity. We find that market quality is 18% better under electronic trading relative to other periods. This estimate is statistically significant at the 95% confidence level. Volatility and the number of trades

are significantly related to market quality; high volatility implies poorer price discovery. Specification (2) shows that our estimate of the impact of electronic trading on market quality is robust to the inclusion of controls for report days and limit move days. In specifications (2), (4), and (5), the magnitude of the electronic trading effect on market quality is between 20 and 22%.

We find that inclusion of the number of trades variable in the regression equation greatly affects the results. Comparing specifications (2) and (3) in 4, the coefficient on the electronic trade indicator increases dramatically in (3). The coefficient for trading volume also becomes statistically significant. Much of the benefit of electronic trading for improved market quality appears to be associated with the increased number of trades. As we noted in section 3, the limit order book electronic market is more likely to break large orders into smaller transactions. At first appearances, the ability to quickly match large orders with the best available bids and offers may be part of the operational benefits associated with the electronic market. However, electronic trading is associated with improved market quality even controlling for the number of trades.

Understanding how our structural model reacts to market order splitting under electronic trade may provide some additional explanation for the effect of the number of trades. Suppose the efficient price remains constant; a single buy order in an electronic market leads to some number of small transactions at prices progressively further from the efficient price as the order is “walked up the book”. In a floor market, the market order is more likely to result in a single transaction that may take longer to be matched but all else equal, the price impact of the trade is the same. Since the market price reverts to the constant efficient value in this example, our model assigns both price changes to the transitory component with similar implications for the pricing error variance. However, since our model cannot conclusively establish causal inference with respect to decreased volume per trade, we leave this for future work.

Market quality on USDA report days and limit move days

Specifications (2) and (4) allow us to consider the impact of public information arrival as represented by USDA report days on market quality. According to our simplest specification, (2), we find market quality is 11% better on USDA report days. In the context of our structural model, price changes on report days are more likely to reflect the permanent component associated with information arrival about the efficient price. USDA reports contain supply and demand data shown to have market impacts at lower frequency (e.g., McKenzie, 2008; Adjemian, 2012).

These results are consistent with the finance literature on public information disclosure and liquidity beginning with Diamond and Verrecchia (1991) and Kim and Verrecchia (1994). This literature suggests that disclosure reduces information asymmetry between informed and uninformed traders and reduced asymmetry leads to improved price discovery. USDA report days represent periods where commodities traders evaluate similar information, so information asymmetries, a potential source of transactions costs, are reduced on these days. Specification (4) also considers market quality on the day immediately prior to release days, finding poorer market quality on these days. Information asymmetries may be particularly acute on pre-report days where traders with heterogeneous expectations attempt to position themselves in advance of the report release.

We also estimate the impact of limit move days on market quality using specifications (2) and (4). We find limit move days are associated with a statistically significant 34% reduction in market quality. When prices move up or down the limit and the efficient price change exceeds price limits, informed traders cannot incorporate their information into observed prices and market quality suffers. Any trading that does occur is likely due to inventory control and margin call concerns³ not associated with permanent shocks to observed prices.

Kyle (1988) suggests that price limits, when applied, may actually create greater uncertainty about the fundamental value. Later studies consider whether price limits reduce price volatility and assess the potential for price volatility on limit move days to spill over to subsequent trading days (e.g., Kim and Rhee, 1997). In specification (4), we find that days following limit move days are not associated with statistically significant differences in market quality relative to other non-limit move days.

We test whether market reaction to public information arrival changes after electronic trading was introduced by including an interaction between the USDA report day and electronic trading indicators in specification (5). We find improved market quality, though our coefficient estimates are not statistically significant. We conduct a similar test of the effect of price limits in the presence of electronic trading by including a limit move-electronic trading interaction term. This specification shows that the impact of price limits on market quality is greater under electronic trading, but the coefficient on the limit move days indicator is no longer statistically significant. Generally, information arrival and price limit impacts appear to be magnified under electronic trading though these estimates are not statistically significant. Given the length of our sample period, there may simply not be enough report days or limit move days in our sample to precisely estimate the magnitude of these effects.

7 Discussion and conclusions

We find that the introduction of electronic trade has improved the quality of price discovery in the ICE cotton futures market. Using random-walk decomposition methods, we define market quality using the variance of deviations from an unobserved efficient price. Lower variance of this pricing error represents better market quality and more accurate price discovery. We find market quality is lower during the electronic-only trading period than during the periods of floor-only and parallel floor and electronic trade.

The elimination of floor trading for cotton futures coincided with a period of volatile prices and high trading volume. Measured market quality at the height of the volatile price period was poor, but our results do not find any relationship between lower market quality and electronic trade. Market quality improved significantly in the months that followed the introduction of electronic trading. It appears that traders adapted to the new system and did so quickly. Given the volume of trade that had moved to the electronic platform before the elimination of open-outcry trading, this

³Carter and Janzen (2009) review the events surrounding the 2008 cotton price spike and discuss the extraordinary margin call risk faced by cotton futures traders at a time when limit price moves were frequent.

result is not surprising.

Improved market quality under electronic trading is robust to changes across time in the level of trading volume, price volatility, and the number of trades. Regression analysis estimates an 18-22% increase in market quality during the first 13 months of electronic trading in cotton futures, relative to the 25 preceding months. Our results also show that the relative variance of market quality increased upon the elimination of floor trading. This result suggests that criticism of cotton futures price discovery post-March 2008 may be driven by variability of price discovery rather than changes in the level of market quality. Traders sensitive to variability in the price discovery process may be skeptical of purported benefits of electronic trading. Similar skepticism of algorithmic and high frequency trading may have the same cause.

Our analysis of market quality in the cotton futures market does not establish a specific, causal link between the electronic trading mechanism and market quality or the variability of market quality. We do observe more transactions during the electronic-only period, consistent with the splitting of large orders into smaller transactions than were previously matched on the trading floor. Our regression results point to a significant relationship between the number of trades and market quality. Whether dealing in smaller volume per trade helps traders tighten bid-ask spreads or reduces costs related to adverse selection is an open empirical question. Further analysis of price discovery dynamics under electronic, algorithmic, and high frequency trading should explore the relationship between volume per trade and market quality.

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Figures

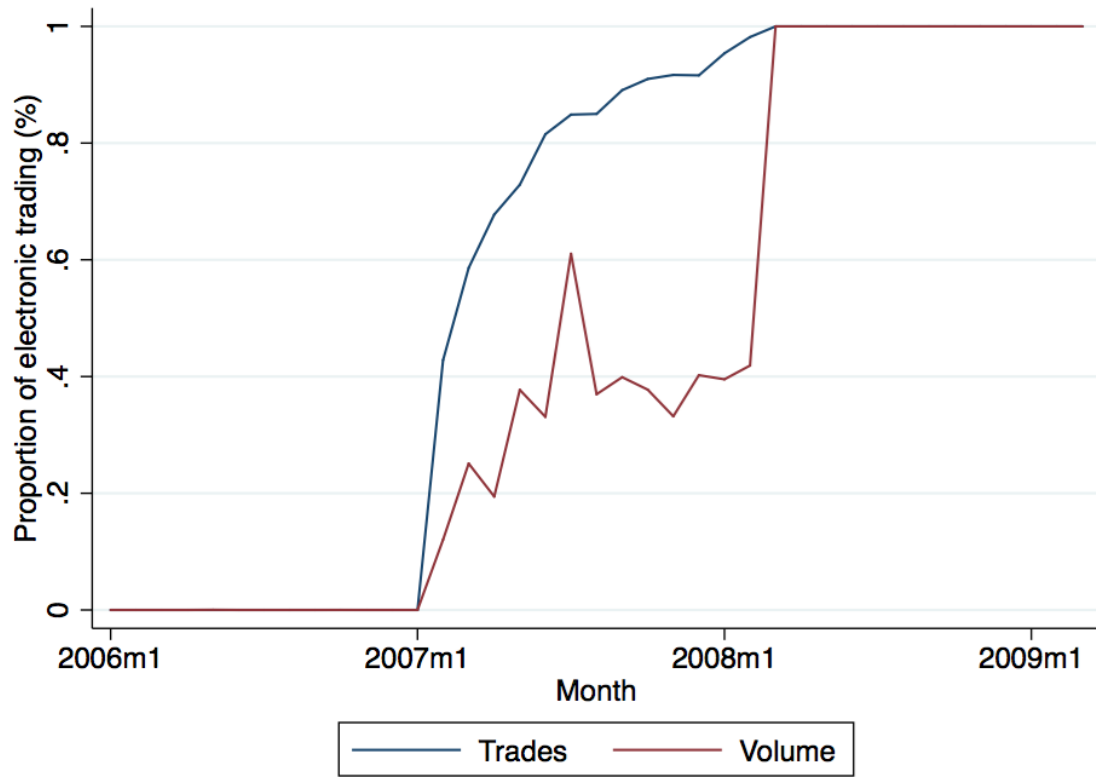


Figure 1: Proportion of trades and trading volume on ICE electronic trading platform for the nearby cotton futures contract by month, January 2006 to March 2009

Source: TickData, Commodity Research Bureau

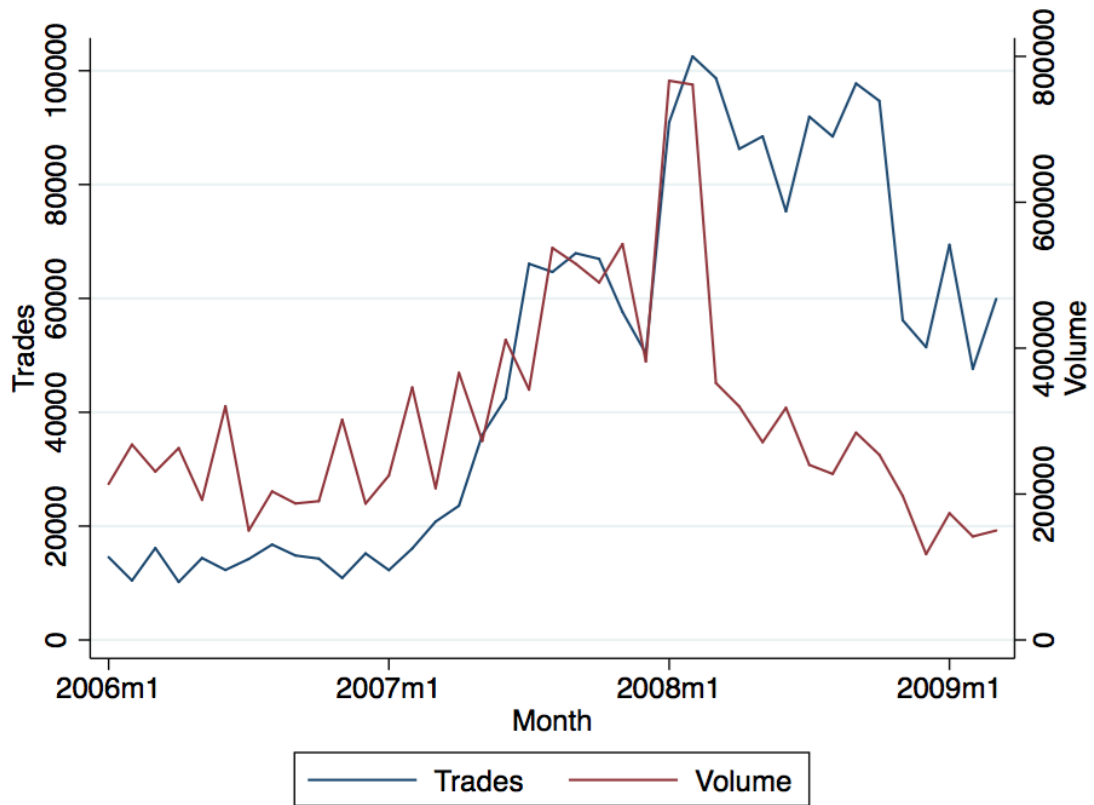


Figure 2: Number of trades and trading volume for the nearby cotton futures contract by month, January 2006 to March 2009

Source: TickData, Commodity Research Bureau

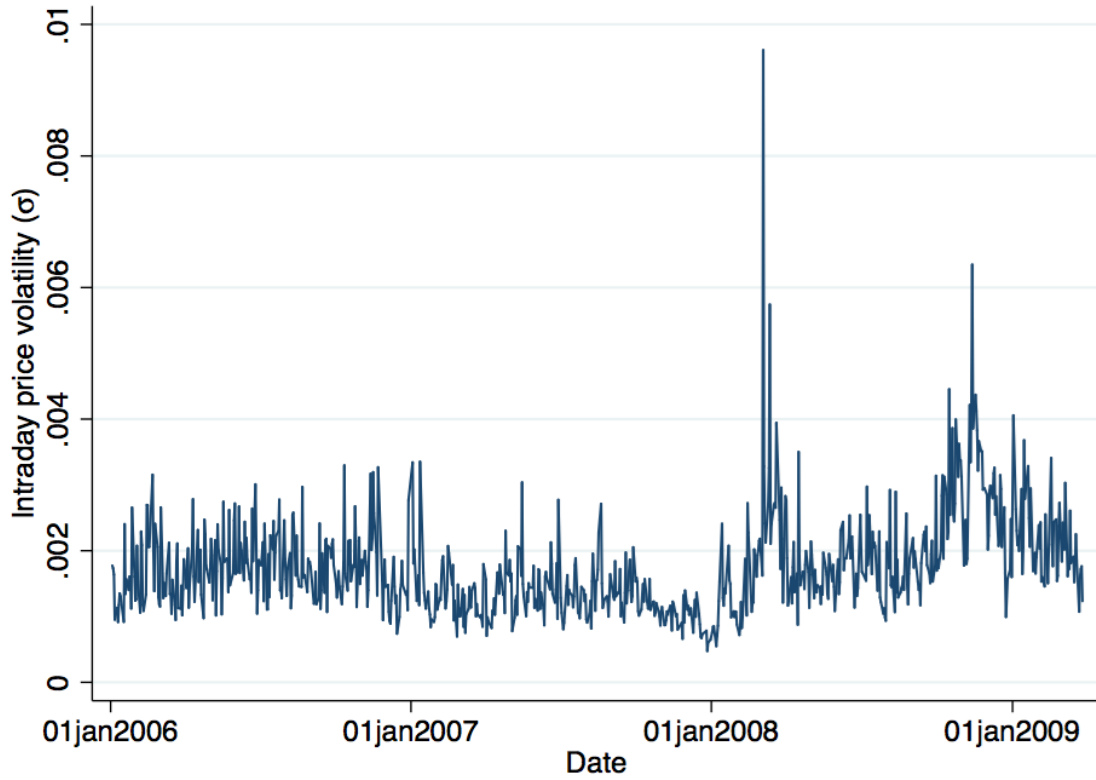


Figure 3: Daily cotton futures price volatility (Standard deviation of intraday log returns over five minute intervals), January 2006 to March 2009

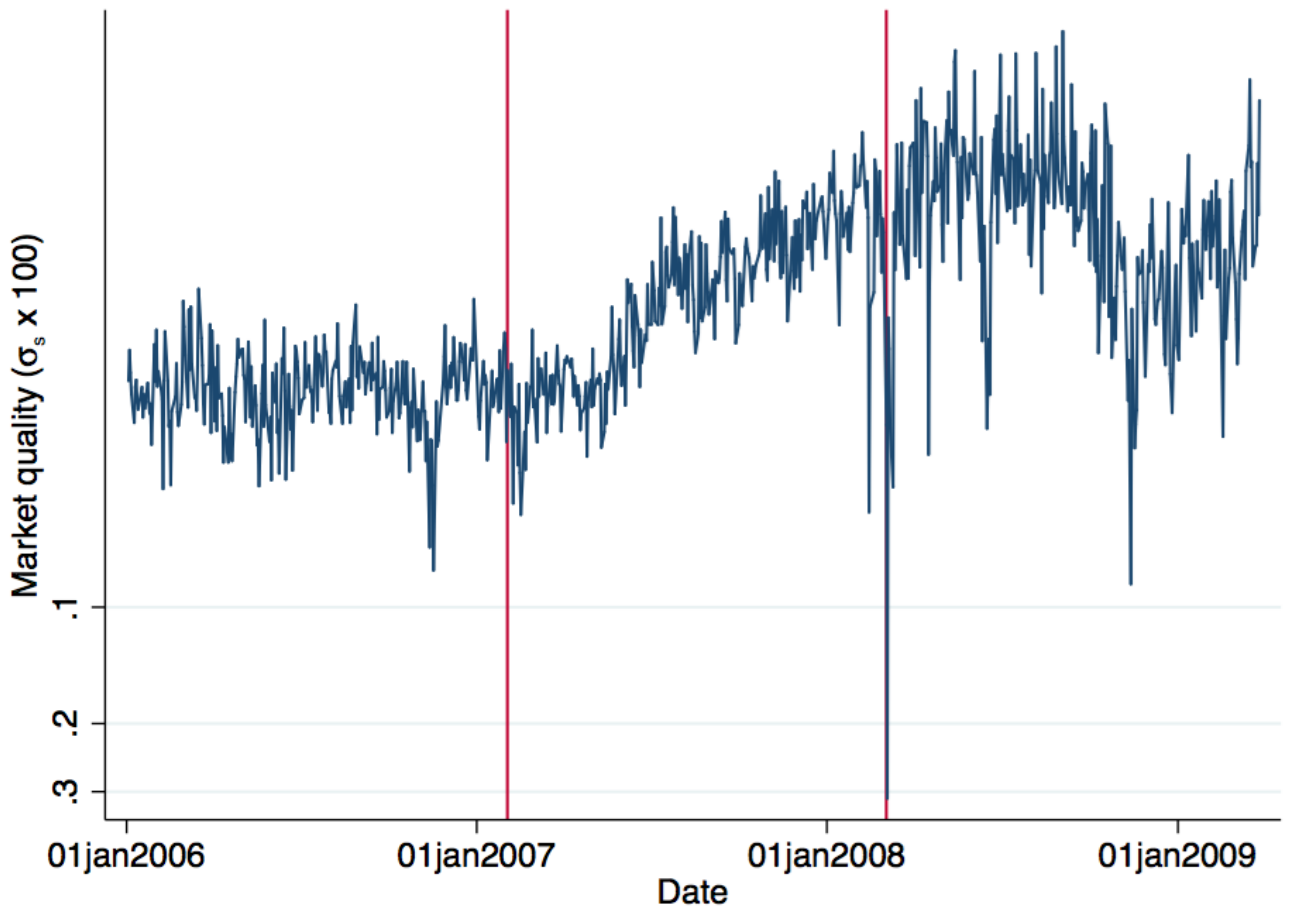


Figure 4: Market quality as measured by standard deviation of the pricing error, January 2006 to March 2009

Tables

Table 1: Summary Statistics of Cotton Futures Market Variables, January 2006 to March 2009

		Trading system subperiods				
		All	Floor	Parallel	Electronic	post-3/8/08
Trading days		811	271	269	271	266
Closing Price (cents/lb)	Mean	57.87	53.28	60.49	59.87	59.38
	St. Dev.	9.51	2.35	7.30	13.45	13.09
	Min	39.14	47.40	46.92	39.14	39.14
	Max	89.28	57.34	81.86	89.28	82.06
Intraday Volatility ($\sigma_{\Delta p} \times 100$)	Mean	0.173	0.171	0.130	0.218	0.215
	St. Dev.	0.075	0.054	0.041	0.093	0.081
	Min	0.048	0.074	0.048	0.088	0.088
	Max	0.961	0.335	0.304	0.961	0.635
Volume	Mean	14703	10874	22043	11247	11124
	St. Dev.	9640	5449	11550	6025	5839
	Min	915	3263	3505	915	915
	Max	64880	29275	64880	40495	40495
Trades	Mean	2328	653	2622	3712	3714
	St. Dev.	1820	199	1612	1579	1551
	Min	168	168	337	493	493
	Max	11438	1301	9968	11438	11438
Report days	Count	42	14	14	14	14
Limit move days	Count	36	0	7	29	25

Table 2: Summary Statistics for Market Quality, January 2006 to March 2009

		Trading system subperiods				
		All	Floor	Parallel	Electronic	post-3/08/08
Trading days		811	271	269	271	266
Market Quality	Mean	-0.020	-0.028	-0.018	-0.013	-0.012
$(-\sigma_s \times 100)$	St. Dev.	0.015	0.008	0.009	0.020	0.008
	CV	0.750	0.266	0.508	1.531	0.709
	Min	-0.312	-0.080	-0.058	-0.312	-0.087
	Max	-0.003	-0.015	-0.006	-0.003	-0.003

Table 3: Alternative Summary Statistics for Market Quality Generated Using Trade Volume Information, January 2006 to March 2009

		Trading system subperiods				
		All	Floor	Parallel	Electronic	post-3/08/08
Trading days		811	271	269	271	266
Market Quality ($-\sigma_s \times 100$)	Mean	-0.021	-0.028	-0.020	-0.015	-0.014
	St. Dev.	0.015	0.008	0.009	0.021	0.010
	CV	0.705	0.266	0.472	1.359	0.710
	Min	-0.318	-0.080	-0.059	-0.318	-0.087
	Max	-0.004	-0.015	-0.007	-0.004	-0.004

Table 4: Reduced-form regression estimation of relationships between market quality and covariates

	Specification				
	(1)	(2)	(3)	(4)	(5)
ln(Trades)	.545*** (.045)	.549*** (.045)		.545*** (.045)	.539*** (.042)
ln(Volume)	-.046 (.038)	-.033 (.036)	.307*** (.035)	-.027 (.036)	-.029 (.035)
ln(Intraday Volatility)	-.668*** (.060)	-.630*** (.050)	-.611*** (.061)	-.634*** (.051)	-.631*** (.050)
Days to maturity	-.0005 (.0006)	-.0004 (.0006)	.003*** (.0007)	-.0003 (.0006)	-.0003 (.0006)
Parallel trading	-.403*** (.052)	-.398*** (.051)	.063 (.047)	-.399*** (.051)	-.396*** (.050)
Electronic trading	.181** (.081)	.201** (.079)	1.129*** (.036)	.206*** (.079)	.220*** (.074)
Report day		.107** (.047)	.090 (.059)	.104** (.047)	.066 (.049)
Report day ($t + 1$)				-.104** (.041)	
Report \times Electronic					.127 (.104)
Limit move day		-.342*** (.098)	-.325*** (.118)	-.344*** (.098)	-.070 (.158)
Limit move ($t - 1$)				.014 (.070)	
Limit \times Electronic					-.348* (.205)

Note: The dependent variable is the logarithm of the daily market quality measure. Newey-West HAC standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for day-of-week and contract month fixed effects are not reported.