PRICE VOLATILITY AND LIQUIDITY COST IN GRAIN FUTURES MARKETS

BY

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DISSERTATION

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ABSTRACT

Significant changes have taken place in grain futures markets. This dissertation consists of three essays investigating issues in the price volatility and liquidity cost in grain futures markets influenced by these changes. The first essay examines the sources of long memory in three major grain futures contracts, and assesses its usefulness to forecast price volatility in periods of moderate and heightened uncertainty. Using data from corn, soybeans and wheat futures contracts in 1989-2011, statistical tests and estimation results indicate that much of the long memory patterns arise from seasonality and structural breaks. After accounting for these factors, a less pronounced but still significant long memory effect exists in corn and wheat, but it disappears in soybeans. Directly modeling structural breaks through a semi-parametric method generally fails to improve forecast accuracy due to likely estimation errors that can arise in over-parameterized models. During recent heightened structural breaks, a simple long memory model provides the best forecasts especially at distant horizons, but the forecast performance of all models in this period is poor. Our findings suggest that though long memory models can be used as a parsimonious specification for structural breaks in forecasting, the reduction in forecast errors is limited. While long memory forecasts have slightly fewer rejections of unbiasness, their improvement relative to short memory forecasts is marginal. Modeling seasonality is important for better forecasting performance in these markets.

The second essay is the first paper to analyze liquidity costs in agricultural futures markets based on the observed bid-ask spread (BAS) faced by market participants. Using the order book for electronically-traded corn futures contracts, this study reveals a highly liquid corn market, which with few exceptions offers order execution at minimum cost. BAS responds negatively to volume and positively to price volatility, but also affects volume traded and price

volatility. While statistically significant, these responses on a cents/bushel or a percentage basis are generally small. Liquidity costs are also virtually impervious to short-term changes in demand for spreading and trend-following trader activity, as well as differences from day-of-the-week changes in market activity. Much larger cents/bushel and percentage changes in BAS occur during commodity index roll periods and on USDA report release days. The roll period findings point to a sunshine trading effect, while announcement effects identify the importance of unexpected information and adverse selection on order execution costs. Overall, the research demonstrates that the move to an electronic corn market has led to low and stable liquidity costs even in a recent period of market turbulence.

The third essay pioneers research on the high frequency quoting noise in electronically traded agricultural futures markets. High frequency quoting – quickly canceling posted limit orders and replacing them with new ones – emerges as a strategy for liquidity-providing high frequency traders (HFTers) to cope with predatory trading algorithms. High frequency quoting can generate noise in price quotes which adds uncertainty to order execution and harms market quality. We measure high frequency quoting noise by the level of excess variance and discrepancies in bid/ask price co-movement at time scales as small as 250 milliseconds. Using the Best Bid Offer (BBO) dataset in 2008-2013, we simulate sub-second time stamps using a Bayesian framework. Excess variance and co-movement discrepancies are estimated using a wavelet-based short-term volatility model. We find excess high frequency quoting variance exists. It is highest at 250 milliseconds, which is 90% higher than normal. In terms of economic magnitude, net excess volatility – square root of variance – is negligibly small. At 250 milliseconds it ranges from 0.86% to 4.61% of one tick (0.025 cents/bushel), which is the minimum allowed price change. Bid/ask price co-movement shows a low degree of discrepancy with average correlation of 0.67 at 250 milliseconds. Both excess variance and bid/ask co-movement discrepancy indicate high frequency quoting noise has declined through the period.

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CHAPTER 1

INTRODUCTION

Significant structural changes have taken place in grain futures markets. Important events such like biofuel mandates, climate change, and transition from open outcry to electronic trading have transformed grain futures markets into a more volatile and faster trading environment. Biofuel mandates have strengthened the link of grains to the energy markets. The stronger linkage lead to volatility spillovers from energy to grain markets (Trujillo-Barrera et al. 2012). In recent years, tight stock levels and climate change, which increase production risk, also fueled the heightened volatility in grains. At the same time, futures trading have transitioned from open outcry to electronic markets. Since 2007, more than 90% of grain futures volume is generated in electronic markets (Irwin and Sanders 2012). Electronic trading improves the speed of information transmission. However, it also has caused concerns that added anonymity in trading, and new participants like high frequency traders (HFTs) and commodity index traders (CITs) can harm market quality, e.g., higher transaction cost and price risk in order execution. In this context, the dissertation provides three papers to improve our understanding of recent grain futures market behavior.

The first paper investigates the sources of observed long memory phenomena in three major grain futures contracts – corn, wheat and soybeans, and assesses the usefulness of long memory in forecasting price volatility in periods of moderate and heightened uncertainty. In the context of recent heightened volatility, evaluating the forecast ability of long memory models is a challenging yet potentially rewarding task. Using daily squared return volatility for 1989-2011, I capture long memory using a Fractional Integrated GARCH framework. Out-of-sample forecasts are generated for 2005-2011 and evaluated for forecast accuracy in comparison to short memory GARCH forecasts. Findings suggest much of the observed long memory patterns arise from seasonality and structural breaks. After controlling for these factors, a smaller yet still significant long memory effect exists in corn and wheat, but it disappears in soybeans. In forecasting, a long memory model with seasonality produces the best results, but the ability of the models to forecast volatility is quite limited.

Heightened volatility is likely to continue in the foreseeable future, which can influence the costs of immediate order execution—liquidity costs (Bryant and Haigh 2004; Frank and Garcia 2011). In addition, the recent transition from open outcry to electronic trading can cause changes to the structure of liquidity costs. Though several studies exist on open outcry markets (e.g., Thompson and Waller 1987), the behavior of liquidity costs in electronically-traded agricultural futures markets has not been studied comprehensively. In the second paper, I analyze the behavior of liquidity costs in the electronically-traded corn futures market. Liquidity cost is measured by the observed bid-ask spread (BAS) which is directly faced by traders in electronic trading. I document its structural patterns and examine a broad range of determinants for the BAS in 2008-2010. Regressions are estimated in a dynamic systems framework which accounts for the endogenous relationship with volume traded and volatility. BAS responds marginally to volatility and volume changes as well as other influencing factors. Rolling of CIT positions provides added liquidity and reduces the BAS in deferred contracts. A larger BAS occurs on USDA report release days, reflecting adverse selection. Changes in BAS also influence the volume traded and volatility in an interactive framework. Overall, the research demonstrates that despite turbulent market, the electronic market provides sufficient liquidity to maintain BAS at a low and relatively stable level.

Electronic trading has changed trader composition by attracting CITs, and HFTers who employ automated high speed trading programs. The emergence of HFTers changes the way that liquidity is provided in electronic markets. High frequency trading (HFT) can also introduce added volatility, which makes the futures market noisier and more costly for other traders to execute orders. There is very limited research on the impact of HFT in agricultural futures markets. In the third paper, I study the economic impact of high frequency quoting – a strategy used by liquidity-providing HFTers – in the corn futures market. I measure high frequency quoting noise by the level of excess variance and bid/ask price co-movement discrepancies at time scales as small as 250 milliseconds. Using the Best Bid Offer (BBO) dataset in 2008-2013, we simulate sub-second time stamps using a Bayesian framework. Excess variance and co-movement discrepancy are estimated from a wavelet-based short-term volatility model. We find high frequency quoting noise exists and is the highest at 250 milliseconds, where excess variance is 90% higher than normal, and bid/ask price co-move at a correlation of 67%. The magnitude of excess variance is small, ranging from 2.8% to 10.3% of the minimum allowed price change at 250 milliseconds.

CHAPTER 2

DOES LONG MEMORY MATTER IN EXPLAINING AND FORECASTING GRAIN PRICE VOLATILITY?

2.1 Introduction

Recent changes in agricultural grain futures prices have raised questions about the sources of volatility and the extent to which volatility forecasts can be improved. Research based on data from an earlier period has identified persistent patterns of volatility in agricultural futures prices that can be described by long memory (Crato and Ray 2000; Jin and Frechette 2004; Baillie et al. 2007; Sephton 2009). Long memory is a form of nonlinear dynamics characterized by long-term dependence reflected in strong autocorrelations even at distant lags. The existence of these patterns implies that shocks in a market have significant effects over protracted horizons, and that accounting for long memory can lead to more accurate volatility forecasts.

To date, little attention has been given to identify the sources of long memory, and how it relates to our knowledge of grain market volatility. Considerable evidence exists that volatility in grain futures prices is time-varying and seasonal, reflecting crop development and inventory levels (Kendall 1953; Anderson 1985; Yang and Brorsen 1993; Egelkraut et al. 2007). Short-term changes in volatility can also be effectively characterized by conditional heteroscedastic models as changes in information and market responses often cluster near specific events (Goodwin and Schnepf 2000; Yang and Brorsen 1993; Szakmary et al. 2003). In terms of the sources of long memory, much less is known or posited. Jin and Frechette (2004) contend it might be an inherent component of market dynamics which arises from staggered supply and demand information flows, changes in inventories, and trader heterogeneity in futures and cash markets. An alternative explanation emerges from the observation that a few big shocks can create periods of clustered high volatility which are identified as long memory. In this context, Diebold and Inoue (2001) and Smith (2005) argue that long memory is an "illusion" caused by occasional level shifts in the baseline volatility. Empirical studies by Power and Turvey (2011), Baillie et al. (2007) and Smith (2005) provide mixed evidence on the source of long memory in agricultural markets, but point to seasonality and structural breaks as factors that can influence its measurement.

A closely related question is whether long memory can be used to improve volatility forecasts, particularly in recent years with strong volatility. The key point is that even if volatility is a short memory process containing level shifts, a parsimonious long memory model might still serve as an effective forecasting method. The limited research on agricultural price volatility forecasting has focused primarily on short-term forecasts using conditional heteroscedastic models in livestock markets (Manfredo et al. 2001; Brittain et al. 2011). In contrast, Egelkraut and Garcia (2006), using data through 2001 – a relatively stable period, generate reasonably effective intermediate interval forecasts using implied forward and historical volatilities for selected grains. Studies in financial, precious metals and crude oil markets reveal that long memory models may offer potential forecasting gains (Vilasuso 2002; Kang et al. 2009; Arouri et al. 2012a). However, how long memory models perform when the phenomenon is actually caused by level shifts is not clear (Morana and Beltratti 2004; Granger and Hyung 2004; Hyung et al. 2006; Lu and Perron 2010). Lu and Perron (2010) and Arouri et al. (2012b) identify that long memory models can forecast equally well and sometimes better than short memory models adjusted for structural breaks. In agricultural markets, the forecast accuracy of long memory models has not been studied. In the context of recent heightened volatility, evaluating the forecast ability of long memory models is a challenging yet potentially rewarding task.

Understanding the structure and developing accurate forecasts of price volatility can serve a useful role in risk management and option pricing, particularly in recent years as volatility has increased dramatically in agricultural markets. Through biofuel mandates, grains markets are increasingly linked to the energy complex (Thompson et al. 2009), leading to volatility spillover to the grain markets (Trujillo-Barrera et al. 2012). The transition to a global market with added information flows, tight stock levels and higher production risk also have contributed to dramatic changes in volatility. With these fundamental factors in place, heightened volatility will likely continue in the future (Irwin et al. 2008). Does long memory help provide more accurate volatility forecasts in this environment of dramatic change?

In this paper we investigate the sources of long memory and its forecasting ability in the volatility of three major grains futures. Daily settlement prices of nearby corn, wheat and soybean futures for 1989-2011 are used to generate daily volatilities. We first test the presence of long memory using the modified Geweke and Porter-Hudack test (Smith, 2005) which controls for level shifts. We then explicitly estimate volatility models that assess the effects of seasonality and recent structural breaks on long memory measurement. The basic procedure follows the General Autoregressive Conditional Heteroskedasticity (GARCH) model that has been shown to characterize well short-term volatility dynamics. Long memory is estimated using Fractional Integration of GARCH (FIGARCH) developed by Baillie et al. (1996) and applied recently by researchers to represent the long-term patterns in agricultural commodity volatilities (e.g., Jin and Frechette 2004). As a key component in grain markets, seasonality is included using a Fourier framework proposed by Goodwin and Schnepf (2000). Irregular structural breaks are addressed by an adaptive method developed by Baillie and Morana (2009) using flexible Fourier forms. Models are estimated using Quasi Maximum Likelihood and assessed with standard testing procedures on the full sample. Specifically, we use the Akaike Information Criterion (AIC) to specify the optimal number of parameters. Log-likelihood tests are used to identify the statistical significance of seasonality, structural breaks and long memory effects. Next, we recursively generate out-of-sample multi-step forecasts for 2005-2011, and investigate the forecast ability in periods of moderate (2005-2007) and heightened uncertainty (2008-2011). Forecast accuracy is evaluated by comparing loss functions among alternative models and by Mincer-Zarnowitz (MZ, Mincer and Zarnowitz 1969) regression. Two robust loss functions, the Mean Squared Error (MSE) and Quasi-likelihood (QL) are used (Patton 2011).

2.2 Literature Review

Two studies have examined the sources of long memory in agricultural markets with mixed results. Baillie et al. (2007) observe a confounding effect of seasonality on long memory in corn and soybean futures volatility in 1980-2001. After removing seasonality from the data by Fourier basis filter, they estimate a FIGARCH model on the volatility. They find the magnitude of the long memory parameter is still significant but smaller with 0.315 in corn and 0.345 in soybeans. They conclude that long memory is an inherent characteristic in daily price volatility. Power and Turvey (2011) use a robust wavelet-based estimator to account for the long memory effect. In contrast, after fractionally differencing volatility using the estimated long memory parameters, they discover that volatility in most grains is non-stationary, which leads them to conclude that long memory arises from stochastic breaks. While these two studies differ in their findings, they fail to account for both the presence of seasonality and structural breaks which could have affected the conclusions. Here, we estimate a more general framework that allows for both seasonality and structural breaks to assess the long memory measurement.[1]

With regard to out-of-sample forecasting, studies using daily squared return volatility generally find long memory models perform better than short term models. Research mainly emerges from the oil, stock, and exchange rate markets. Kang et al. (2009) use daily squared return volatility to forecast on the 1 to 20 days horizons in 2006. Their sample is based on the highly volatile 1992-2005 crude oil market, with consistently rising price and volatility levels. They find FIGARCH performs significantly better than simple GARCH using both mean squared and absolute errors (MSE and MAE), by the Diebold and Mariano (DM, 1995) statistics. MSE reductions range from 6% in WTI to 30% in Dubai crude oil. Lu and Perron (2010) use a GARCH model with a randomly shifting intercept for structural breaks and a FIGARCH model. Using daily squared returns over thirty years, they forecast four stock index volatilities up to 200 days ahead and evaluate using MSE for forecast accuracy, and MZ-type regression for forecast unbiasness. Both models outperform the simple GARCH, with little difference between the two. Arouri et al. (2012b) compare forecasts in gasoline, heating and crude oil markets from 1 to 60 days ahead. They estimate for 1986-2009 which includes a dramatic 2008 financial crisis break, and forecast in 2010-2011 when volatility dampens. They observe the degree of long memory diminishes significantly after adjusting for structural breaks. Further, compared to GARCH, both FIGARCH and FIGARCH with structural breaks have lower MSE and MAEs. FIGARCH error reduction is from 0% (1 day) to 10% (60 days) with occasional worse MSEs, and structural break FIGARCH error reduction is from 10% (1 day) to 30% (60 days). These findings suggest that accounting for structural breaks can improve long memory forecasts in oil price volatility. But

[1] Several studies have found that a positive relationship between the strength of long memory and magnitude and number of structural breaks. For instance, in an analysis of stock index volatility, Lu and Perron (2010) find evidence that importance of long memory disappears after controlling for structural breaks.

their method requires pre-testing data for possible structural breaks, which is often infeasible when forecasting in real time.

Other forecast comparison studies use a variety of lower frequency data, absolute value of returns, or realized volatility measurement methods. These procedures are much less used in measuring agricultural futures price volatility, but their findings are informative. Baillie and Morana (2009) model structural breaks with a semi-parametric adaptive method. Applied on weekly S&P 500 squared return volatility in 1928-2007, they generate up to 12-step ahead recursive forecasts. Evaluated using the root of MSE and MZ regressions, FIGARCH, adaptive GARCH and adaptive FIGARCH all forecast better than GARCH. Among these models, the FIGARCH and adaptive GARCH provide almost identically attractive results, but the adaptive FIGARCH best of all. The forecast error reduction for the adaptive FIGARCH to compared to the GARCH is from 6% at 1 step to 11% at 12 steps. R^2s are relatively high due to lower data frequency. Adaptive FIGARCH forecasts explain up to 34% of volatility variations, which improves by about one-third compared to GARCH. In the presence of structural breaks, Granger and Hyung (2004) find that while a short memory model with occasional breaks can have better in-sample explanatory power, a fractionally integrated long memory model forecasts marginally better. The DM test shows that the MSE reduction in long memory model is insignificant. But their comparison is limited to only a 1-day forecast and they use absolute returns for the S&P 500 index as a measure of daily volatility, which do not exhibit as large spikes as squared returns. Moreover, the comparison does not include a simple short memory model. Hyung et al. (2006) forecast monthly absolute percentage change of inflation rates for 1 to 24 months and evaluate using the root of MSE. They find that data with structural breaks can be forecasted using long memory models. There is little difference between a simple long memory forecast and a short memory model with structural breaks. The root MSE reductions are 0% – 11% at 1 – 24-step ahead forecasts. Martens et al. (2009) use intraday prices to generate realized volatility and perform forecast comparisons. Realized volatility has smaller spikes than daily squared returns. They recursively forecast the S&P 500 index from 1998-2006 on 1-20 days horizons from a variety of specifications. Evaluated using MSE, MAE and MZ regression rankings, they find long memory forecasts better than simple short memory models. But the differences are small, with regression R^2s differing by less than 4%, and MSE differing by less than 10% in most cases. Informatively, they further find that explicitly capturing structural breaks in a long memory model by smooth polynomial functions does not improve forecast over simple long memory forecasts. Morana and Beltratti (2004) also use intraday returns to calculate daily realized volatility on exchange rates. They compare long and short memory models with structural breaks, and simple long memory forecasts. They find that long memory pattern is partially explained by a structural break process. Neglecting the break component does not affect forecast performance in the short run (1 day) when long memory is included. However, for longer horizons (5 and 10 days), both long memory and structural breaks are needed for better performance. In the MZ regression, R^2 differences are small among the models, from 1% at 1 day to as much as 7% at 10 days on average.

Overall, parsimonious long memory specification through fractional integration improves forecast performance. The direct evidence is that long memory forecast is better than simple short memory models. Compared to short memory models with structural breaks, the findings are more mixed, but often identify only limited improvements for using long memory models. In some cases, it appears that combining long memory and structural breaks may generate more precise forecasts particularly at distant horizons. Regardless, these findings support the positive relationship between structural breaks and observed long memory, and suggest that even if long memory is an illusion caused by structural breaks, a long memory model may still forecast well by accounting for changes in autocorrelation in a parsimonious manner.

2.3 Methods

2.3.1 Preliminary tests

We begin with tests for long memory. A commonly used procedure to test for long memory is the log-periodogram statistics developed by Geweke and Porter-Hudack (GPH, 1983). The sample periodogram $I(w_j) = \frac{1}{2\pi T} | \sum_{t=1}^{T} \varepsilon_t \, e^{-w_j t} |^2$ is the Fourier frequency at $J = \sqrt{T}$, where $w_j = 2\pi j/T$, *j*=1, 2,…, *J*. The long memory parameter *d* is estimated in the spectrum domain by log-periodogram regression

$$\ln[I(w_j)] = \beta_0 - d \ln\left[4\sin\left(\frac{w_j}{2}\right)\right] + e_j. \qquad (2.1)$$

where 0 < *d* < 1, and the higher its value, the stronger is the long memory effect. Smith (2005) points out that the GPH estimator does not consider the impact of level shifts in volatility. He proposes a feasible bias correction by adding an additional regressor

$$\ln[I(w_j)] = \beta_0 - d \ln\left[4\sin\left(\frac{w_j}{2}\right)\right] + \beta_z \ln\left[w_j^2 + \frac{(kJ)^2}{T^2}\right] + e_j, \qquad (2.2)$$

where *k* is a positive constant. The regressor controls for level shifts and yields a cleaner measure of *d*. Smith (2005) recommends using *k*=3, which minimizes the average absolute bias across different degrees of level shifts.

The modified GPH estimator is more robust to unspecified level shifts. However, it is not clear to what extent it can control for level shift impacts and neither GPH nor modified GPH gives information on the sources of long memory. To further test, we follow a strategy of estimating nested volatility models to account for seasonality, structural breaks, and long memory which allow more detailed inference (Lu and Perron 2010).

2.3.2 Models and procedures

We start with the basic GARCH, and gradually expand it to include features of long memory, seasonality and structural breaks. The price return series r_t has prediction error $\varepsilon_t = r_t - E_{t-1}[r_t]$. E_{t-1} is the expectation operator conditional on information at t-1. Define $\varepsilon_t = z_t\sigma_t$, where z_t is iid with zero mean and unit variance. The standard GARCH(1,1) (Bollerslev 1986) is

$$\sigma_t^2 = \omega + \alpha\sigma_{t-1}^2 + \beta\varepsilon_{t-1}^2, \omega, \alpha, \beta > 0, \alpha + \beta < 1. \quad (2.3)$$

To include long memory effect, we use the Fractional Integration of GARCH (FIGARCH(1,d,1)) model developed by Baillie *et al*. (1996) which takes the form

$$(1-\beta)\sigma_t^2 = \omega + [1 - \beta - \phi(1-L)^d]\varepsilon_t^2,$$

where $\phi = 1 - \alpha - \beta$, and 0<$d$<1. L is the backshift operator. Rearranging terms gives the conditional variance

$$\sigma_t^2 = \omega(1-\beta)^{-1} + \lambda(L)\varepsilon_t^2, \quad (2.4)$$

and $\lambda(L) = 1 - (1-\beta)^{-1}\phi(1-L)^d$.The term $(1-L)^d$ can be extrapolated as an infinite binomial expansion:

$$1 - dL - \frac{1}{2}d(1-d)L^2 - \frac{1}{6}d(1-d)(2-d)L^3 - \cdots.$$

The hyperbolic decay of $\lambda(L)$ models the long run decay of serial correlation.[2] Notice that GARCH(1,1) is nested in FIGARCH(1,d,1). When the fractional integration parameter d=0, FIGARCH(1,d,1) reduces to GARCH(1,1).

[2] For estimation, the number of lags is truncated at 1000. Baillie *et al*. (1996) have shown that bias resulting from truncation is negligible.

We also model the well-established seasonality patterns in grains futures volatility. Seasonality reflects regular fixed cycles that are largely repeating each year. Goodwin and Schnepf (2000) and Sorensen (2002) demonstrate that seasonal level shift s_t can be successfully modeled by adding Fourier pairs $s_t = \sum_{i=1}^{m}(a_i \cdot \cos\frac{2\pi it}{252} + b_i \cdot \sin\frac{2\pi it}{252})$ to the conditional mean ω in equation (2.3). The period for seasonality is 252, the number of business days in a year. Combining seasonality with long memory leads to seasonal GARCH (S-GARCH) and FIGARCH (S-FIGARCH) specified as

$$\sigma_t^2 = \omega + s_t + \alpha\sigma_{t-1}^2 + \beta\varepsilon_{t-1}^2 , \tag{2.5}$$

$$(1-\beta)\sigma_t^2 = \omega + s_t + [1-\beta-\phi(1-L)^d]\varepsilon_t^2 . \tag{2.6}$$

To model structural breaks in the conditional volatility, we employ an adaptive method proposed by Baillie and Morona (2009). The conditional mean ω is further augmented by smooth flexible Fourier forms (Gallant, 1984). Define $\omega_t = \omega_0 + \sum_{j=1}^{k}(\gamma_j \cos\frac{2\pi jt}{T} + \delta_j \sin\frac{2\pi jt}{T})$ for each observation *t*, where *T* is usually set as the total number of observations. Combining seasonality and adaptive structural models leads to seasonal-adaptive GARCH (SA-GARCH) and seasonal-adaptive FIGARCH (SA-FIGARCH) models,

$$\sigma_t^2 = s_t + \omega_t + \alpha\sigma_{t-1}^2 + \beta\varepsilon_{t-1}^2, \tag{2.7}$$

$$(1-\beta)\sigma_t^2 = s_t + \omega_t + [1-\beta-\phi(1-L)^d]\varepsilon_t^2 . \tag{2.8}$$

The adaptive method of measuring structural breaks can reflect either abrupt or slowly-progressing breaks at any time. It is not confined to finite volatility regimes (Granger and Hyung 2004; Lu and Perron 2010), nor does it require pre-testing to determine the number of break points since they are simultaneously estimated (Arouri et al. 2012b). It is especially useful in real time forecasting as it does not require any *ex ante* data knowledge. Simulation and empirical analyses suggest the method works well in the presence of embedded breaks, cycles and other changes in conditional volatility (Baillie and Morona 2009). Compared to other methods for non-linear structural movements, e.g., non-parametric spline functions (Engle and Rangel 2008; Martens et al. 2009), flexible Fourier forms are more parsimonious and reduce the over-parameterization risk.

To specify model structure, selection procedures like Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) can be used to choose the optimal number of parameters. In model selection, a tradeoff exists between consistency and efficiency. Diebold (2012) concludes that BIC is more consistent, which means when one of the models reflects the true data generating process (DGP), BIC points to the right specification almost surely. However, AIC is more efficient, which means under an unknown DGP, it chooses the model that asymptotically converges to the true DGP. He suggests that when the true DGP is unknown, efficiency is more desired. In grains volatility, since the true DGP is unknown due to the presence of structural breaks and seasonality, we use AIC for model selection.

2.3.3 Forecasting and evaluation procedures

We recursively generate out-of-sample forecasts. Brownlees et al. (2011) suggest using the longest estimation window to give better results. In the presence of structural breaks, it is necessary to re-estimate the model at each step. Additionally, long memory requires a long history of observations to accommodate its effect. For these reasons the daily out-of-sample forecasts are generated recursively. Quasi Maximum Likelihood Estimation (QMLE) proposed by Bollerslev and Wooldridge (1992) is used because it has the advantage of consistency when the assumption of error normality is violated. The limiting distribution is still normal given a large sample size.

To evaluate forecast errors we first compare loss functions. Patton (2011) demonstrates two loss functions that are robust to noise in volatility measures are Mean Squared Errors (MSE), $MSE = \frac{1}{n}\sum_{i=1}^{n}(\sigma_{f,t}^2 - \sigma_{a,t}^2)^2$ and Quasi-Likelihood (QL) loss $QL = \frac{1}{n}\sum_{i=1}^{n}[\frac{\sigma_{a,t}^2}{\sigma_{f,t}^2} - \log\left(\frac{\sigma_{a,t}^2}{\sigma_{f,t}^2}\right) - 1]$. $\sigma_{f,t}^2$, $\sigma_{a,t}^2$ are the forecast and actual volatility for day *t*, and *n* is the number of forecasts. The QL function is a standardized MSE loss function. Since QL uses a ratio as input, it is not affected by changes in volatility level and difference in QLs purely represents changes in forecast accuracy (Brownlees et al. 2011). For a perfect forecast, QL is zero.

Forecast errors are commonly compared using Diebold and Moriano (DM, 1995) statistics to conduct pair-wise tests for the significance of forecast improvement. For two sets of forecast errors $e_{1,t}$ and $e_{2,t}$ corresponding to forecasts σ_{f1}^2 and σ_{f2}^2, $t = 1,2\ldots n$, let $g(e_{1,t})$ be the loss function. Then the hypothesis of equal forecast accuracy is $E(d_t) = 0$, where $d_t = g(e_{1,t}) - g(e_{2,t})$. The asymptotic variance of the difference $\bar{d} = n^{-1}\sum_{t=1}^{T} d_t$ is $V(\bar{d}) \approx n^{-1}(\rho_0 + 2\sum_{k=1}^{h-1}\rho_k)$, where *h* is the step of forecast, ρ_k is the *k*-th autocovariance of d_t, and is estimated as $\hat{\rho} = n^{-1}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d})$. The DM statistics formula is

$$DM = \eta[\widehat{V(\bar{d})}]^{-1/2}\bar{d}\ , \tag{2.9}$$

$\eta = [\frac{n+1-2h+n^{-1}h(h-1)}{n}]^{1/2}$ is the adjustment for forecast step *h*. The DM follows a *t*-distribution with *n*-1 degrees of freedom under the null hypothesis of same forecast accuracy.

However, the DM test is not applicable for the nested structure of GARCH-type models we use to forecast. Clark and McCracken (2001) show in nested models, the forecasts are correlated and forecast errors asymptotically converge. Test statistics can produce degenerate distributions as larger models introduce noise into forecasts. In finite samples, larger models' MSEs are inflated compared to the parsimonious model. Clark and West (2007) propose a modification to the MSE to adjust for the noise in larger models. The difference of two MSEs is adjusted by $d_t' = g(e_{1,t}) - g\left(e_{2,t}\right) + (\sigma_{f1}^2 - \sigma_{f2}^2)^2$, where $e_{1,t}$ and $e_{2,t}$ are from GARCH and alternative models. DM statistics using the modified MSE differences asymptotically follow a normal distribution. An inconsistency can occur with the adjusted MSE when the forecasts of GARCH σ_{f1}^2 and the alternative model σ_{f2}^2 differ greatly. When the $(\sigma_{f1}^2 - \sigma_{f2}^2)^2$ term is large enough, d_t' can still be positive though the observed MSE from alternative model ($g\left(e_{2,t}\right)$) is larger. But these occasions are rare. There is no adjustment procedure to compare nested forecasts for the QL.

Next we compare forecast unbiasness through the MZ regressions (Mincer and Zarnowitz 1969). The actual volatility of a given horizon *h* is regressed on the forecast from model *i* for the same horizon,

$$\sigma_{a,t,h}^2 = \theta_0 + \theta_1 \sigma_{f,t,h}^2 + \epsilon_{i,t} \,. \tag{2.10}$$

An unbiased forecast should have $\theta_0 = 0$ and $\theta_1 = 1$, and R^2 is an indicator of how closely the forecast tracks volatility. Because of the serial dependence that can emerge when generating forecasts, the Newey-West (1994) correction procedure is used to obtain asymptotically consistent standard errors.

2.4 Data Description

The data are the Chicago Board of Trade (CBOT) corn, wheat and soybean nearby futures contract daily settlement prices. The price series span from January 1989 through December 2011. The daily percentage returns, $r_t \equiv 100(\ln(f_t/f_{t-1}))$, are derived from futures prices f_t. Since contracts only last for a limited period, the deferred contract is combined into the series in a way to avoid jumps that can emerge at expiration. Specifically, on the expiration day of the month (day *t*), the return is calculated using the old contract's settlement prices for days *t* and *t*-1. On next day (*t*+1), we switch to the nearby contract and the return is calculated using the settlement prices for the new contract for day *t*+1 and *t*. The process continues with subsequent contract prices to generate a continuous returns series. The daily volatility (variance) is calculated as the squared returns r_t^2, a simplification consistent with market efficiency. This is the standard procedure that studies have used to document the existence of long memory in agricultural futures (Jin and Frechette 2004; Baillie et al. 2007; Sephton 2009).[3] With approximately 252 observations a year, the total observations are 5795.[4]

Table 2.1 summarizes descriptive statistics for daily return and volatility, and the volatility is plotted in figure 2.1. The average daily returns are very close to zero (-0.02% to 0.02%) with little skewness, which is consistent with market efficiency. The return volatility is substantial with standard deviations ranging from 1.48% (soybeans) to 1.78% (wheat), and displays strong kurtosis (2.60 to 3.16), suggesting distribution with fat tails. Since strong kurtosis and skewness are observed in the volatility, the QMLE method is appropriate for estimation. Examination of figure 2.1 reveals in recent years there are extremely high spikes and persistence in volatility. The most dramatic changes in volatility consistently occur in 2008 when grain prices increased sharply to record highs and then dropped precipitously in response to the decline in the economy due to the financial crisis. Comparing across the three commodities reveals that corn and wheat have higher levels of volatility compared to soybeans as shown in the mean, standard deviation and kurtosis statistics. While more difficult to observe directly in figure 2.1,

[3] Volatility measured by the squared return is known to be noisier and harder to forecast than realized and absolute ones, but we use them in the analysis for consistency with the other volatility studies in agricultural markets.
[4] The 1996/3/20 observation for wheat futures and 2008/9/12 for soybeans futures are deleted because on those date the maturing contracts suffer from market manipulation at delivery, which results in artificial price spikes.

recurring seasonal volatility peaks in the summer for corn and soybeans are strong, but are less pronounced in wheat.

Figure 2.2 provides the volatility autocorrelation functions (ACF) for 800 daily lags to illustrate the long memory pattern. Several informative points emerge. It is clear that corn provides the strongest evidence of both long memory and seasonality. The autocorrelations differ from zero (the horizontal dash lines identify the confidence boundaries) at very distant daily lags which is a sign of long memory. Local peaks occur repeatedly at a frequency of 252 days, which coincides with the number of trading days in a business year, and is consistent with pronounced seasonality. Wheat also shows strong evidence of long memory, but with limited seasonality. The monotonic declining ACFs suggest weak seasonality compared to corn. The evidence of long memory in soybeans is weaker as its ACFs fall within the confidence bands faster than corn and wheat. But seasonality appears to be strong in the soybean volatility as evidenced by the recurring spikes at 252 days.

2.5 Test and Estimation Results

The GPH and modified GPH test statistics are reported in table 2.1. Both tests identify the presence of significant long memory in all markets. While all fractional difference estimates *d* differ significantly from zero, the magnitudes differ. After controlling for level shifts, the long memory parameter *d* is strongest in corn (0.524), lower in wheat (0.452) and the weakest in soybeans (0.385), consistent with the ACF patterns. The large decline in long memory after adjusting for level shifts in soybeans is consistent with Smith's (2005) results, but with his data the effect becomes insignificant. We next examine the importance of long memory allowing specifically for seasonal and structural breaks in a nested GARCH framework.

We start with a simple GARCH(1,1) model, then include seasonality (S-GARCH) and structural breaks (SA-GARCH), using the AIC to determine the number of seasonal and structural triangular pairs. The corresponding BIC values are also generated for comparison purposes. The seasonal level shifts s_t are estimated for up to 4 pairs in the seasonal GARCH (S-GARCH). We then fix the seasonal pairs and choose the long term structural adaptive pairs up to k = 8 in the SA-GARCH, which is the maximum pairs used by Baillie and Morana (2009) in their empirical application. Next we model the long memory FIGARCH and its seasonal and structural variants following the same procedures. The six models are estimated for each commodity for the entire sample period, but a reduced sample will be used to recursively generate out-of-sample forecasts and evaluate their performance.

Tables 2.2-2.4 report the estimation results. The models generally provide an adequate fit to the data, with much lower kurtosis in the residuals than in the corresponding descriptive statistics. There is no serial correlation in the squared residuals up to the 10^{th} and 20^{th} lags. The AIC and BIC both point to the same number of seasonal parameters in corn and soybeans (eight) and wheat (two). AIC values continue to decline in all three grains when the adaptive structural break terms are included. For corn and soybeans, and nearly for wheat, AIC is the lowest in SA-GARCH where the seasonal and adaptive break components are modeled directly, rather than indirectly through fractional integration. Also, adding the adaptive terms in FIGARCH increases the AIC. While the same seasonal structure is identified by both the AIC and BIC, the more stringent BIC never includes structural adaptive terms for any commodity. Minimum BIC values are obtained with the S-FIGARCH in corn and wheat, and GARCH in soybeans, suggesting the adaptive terms for structural breaks are redundant. This result arises from the large number of insignificant parameters among the adaptive terms, as observed in the SA-GARCH and SA-FIGARCH estimates.

The estimated seasonal and structural patterns are plotted in figure 2.3 using the most general specification (SA-FIGARCH).[5] We perform likelihood ratio tests for the significance of seasonal and structural break parameters using these general specifications. Comparing the SA-FIGARCH to A-FIGARCH (unreported) likelihoods, seasonal pairs as a group are significant at the 1% level, following χ_8^2 (corn and soybeans) and χ_2^2 (wheat) distributions, and the adaptive terms as a group are significant at the 1% level following a χ_{16}^2 distribution for all commodities. The plots reveal the seasonal effect in wheat is less pronounced, while in corn and soybeans the seasonal patterns are more complex and highlighted by the peak in July which is consistent with the stages of crop growth and the importance of favorable growing conditions in this month. The structural patterns over time are similar for corn and wheat, with slightly higher levels for wheat. They all have a sharp increase in the latter part of the sample that peaked in 2008 followed by a decline. The increase reflects low ending stocks at that time, and the rapid decline reflects the reduction in demand from the financial crisis. In contrast, the soybean structural adjustment seems less pronounced and even moves in a different direction. For instance, when corn and wheat volatility begin to increase sharply in 2006, soybean volatility declines. Nevertheless, following the peak in 2008, soybean volatility quickly dampens to normal levels.

With the estimated models, we investigate whether long memory is present after controlling for seasonality and structural breaks. The overall effect of long memory when combined with seasonality and structural breaks can be identified by the fractional integration parameter *d* in the FIGARCH specifications. In the initial FIGARCH models for corn and

[5] The patterns from SA-GARCH models are similar.

soybeans, *d* is close to one-half. It is lower in wheat at 0.354. The magnitudes are close to those found by Jin and Frechette (2004) using the same grains for 1979-2000. When we add the seasonality and adaptive structural breaks, *d* declines in all three markets. It drops by almost one third from FIGARCH to S-FIGARCH in corn and soybeans. These values are close to what Baillie et al. (2007) found, 0.32 for corn and 0.35 for soybeans, after filtering the seasonal component. The long memory estimate remains almost the same in wheat which is consistent with its less pronounced seasonal pattern observed in figure 2.2. As we include the adaptive structural breaks (moving from S-FIGARCH to the SA-FIGARCH), *d* estimates decline further. For soybeans, the *d* estimate in SA-FIGARCH does not differ from zero, suggesting fractional integration is unnecessary. This result in soybeans is in line with earlier findings by Smith (2005) in soybeans, and Lu and Perron (2010) who find that once structural breaks are accounted for, long memory disappears. Long memory in corn and wheat is still significant, but at a much lower level, only 34% and 44% of the magnitude found in their respective FIGARCH models. The decline of *d* in value and significance suggests that a large part of long memory in these commodity volatilities emerges from unaccounted seasonality and structural breaks.

In sum, the GPH and modified GPH tests reveal the presence of long memory in all three commodities, but the evidence is least compelling in soybeans. Estimation of GARCH-type models allowing for seasonality, long memory and structural breaks indicates that long memory is heavily influenced by seasonality and structural breaks. For corn and wheat, evidence shows that long memory continues to persist, but is much reduced after accounting for these factors. For soybeans, after accounting for these factors, long memory disappears. In effect, in soybeans the structural break and seasonality components are quite strong.

2.6 Forecast Results

Out-of-sample daily forecasts are recursively generated for 2005/1/3 - 2011/12/30. Forecasts are made for 1 day, 10 days, 25 days and 40 days ahead. Each day we add the next observation, re-estimate the model, and generate the forecasts. At each step, the optimal number of parameters for seasonality and structural changes are reselected by AIC. The forecasts cover a highly volatile period. In both figures 2.1 and 2.3, structural breaks can be identified starting in 2008 with much higher levels of volatility. We follow Brownlees et al. (2011) and split the forecasts into two periods: 2005-2007 and 2008-2011. The first period reflects moderate volatility, while the second period is much larger, reflecting low stocks and tighter linkages to the energy and financial markets. In the presence of a structural break in second period, a parsimonious long memory model may produce effective forecasts if it accounts for added autocorrelation which can emerge with level shifts. Not as apparent as the dramatic increase in volatility in the second period is the change in the normal seasonal pattern in corn and soybeans. Due to the financial crisis which sharply reduced demand and increased volatility in late 2008, the normal pattern of high summer volatility followed by lower volatility approaching harvest in the fall was disrupted.

Tables 2.5 and 2.6 provide MSE and QL results for all commodities in the two forecast periods.[6] MSE losses for each model and horizon are compared to the simple GARCH. The Clark-West (2007) test assesses the significance of the differences. For purposes of presentation, for each model, horizon, and loss function, percentage reductions relative to the GARCH model are calculated and reported in the tables. Tables 2.7 and 2.8 report the Mincer-Zarnowitz (1969) regression R^2s and F-statistics for the joint test of unbiasness, $\theta_0 = 0$ and $\theta_1 = 1$. Models with the lowest MSE, QL, and the highest R^2 for each horizon are in bold font in all these tables.

[6] The adaptive structural change models can generate occasional negative volatility forecasts. This occurred only using the corn SA-FIGARCH model at the end of 2006 when a limited number of negative values were generated. When calculating the loss functions, these were not included.

Prior to considering the forecasting effectiveness of long memory models, several points emerge from the tables. In Tables 2.5 and 2.6 notice the large differences between the MSEs in the two periods. For instance, for all commodities at the 1-day horizon, the MSE increases more than three-fold in the second period. Even after standardizing the loss function to account for changes in volatility, the forecast errors are much larger in the second period with QL functions reaching values of 1.49 at the 1-day horizon. These changes are a sign of structural break in the markets and rising volatility in the second period. Second, while statistical differences do exist among the MSEs, the large errors in a highly volatile period make it difficult to find specific models that are uniformly superior. Finally, in Tables 2.7 and 2.8 the large errors are reflected in the limited degree of statistical coherence observed in R^2s in the MZ regressions for both periods. This tendency is more evident in the second period in which R^2s for the best forecasts barely reach 1% at more distant horizons.

In terms of the effectiveness of long memory in forecasting, evidence from the loss functions suggests that while benefits to the use of long memory models may exist, they are not large. In the moderately uncertain 2005-2007 period, S-FIGARCH and FIGARCH provided the smallest forecast errors in terms of MSE and QL, with the largest forecast error reductions relative to GARCH often emerging at more distant horizons. In both corn and soybeans in which seasonality is particularly important, the seasonal models differ statistically from the simple GARCH. Despite the relatively better performance of S-FIGARCH and FIGARCH, their loss functions are only slightly smaller than corresponding non-long memory models (e.g., for corn compare SA-GARCH to S-FIGARCH, for soybeans compare S-GARCH to S-FIGARCH). Nevertheless, the performance of S-FIGARCH in soybeans is somewhat unexpected given the limited evidence that emerges in the statistical testing in support of long memory, but could reflect the relatively stable pattern observed in figure 2.3 in this period. In the 2008-2011 period of heightened uncertainty, FIGARCH consistently generates the smallest loss functions in terms of MSE and QL. But the percentage reductions compared to the simple GARCH are small except at distant horizons. In soybeans, FIGARCH has the smallest loss functions, but it struggles to improve on a simple GARCH. In corn, FIGARCH and S-FIGARCH have the smallest loss functions which differ statistically from GARCH despite only modest reductions in the forecast errors. In wheat, while FIGARCH shows the largest reductions in forecast errors relative to the GARCH, it is SA-FIGARCH that generates consistent reductions in the QL and significant differences in the MSEs at all horizons.

In terms of the MZ regressions, the results in general demonstrate a high degree of bias and a low degree of statistical coherence, with R^2s never reaching double digits and often not reaching 5% even at the 1-day forecast horizon. Fewest rejections of forecast unbiasness emerge at the 1-day horizon for all commodities, after which the quality of forecasts appears to decay quickly. In 2005-2007, long memory models generate slightly fewer rejections of unbiasness, led by S-FIGARCH in soybeans which also registers the highest R^2s. In corn and wheat, the SA-FIGARCH also registers the highest R^2s, but exhibits some of the strongest rejections of unbiasness. In 2008-2011, again the long memory models (S-FIGARCH and FIGARCH) generate slightly fewer rejections of unbiasness led by soybeans. Here for all three commodities, the long memory models do not overwhelm their corresponding non-long memory model. In soybeans, the results are quite similar for the GARCH/S-GARCH compared to the FIGARCH/S-FIGARCH. Similarly, in corn there appears to be little difference between the S-FIGARCH and the S-GARCH models. In wheat, the results of the FIGARCH and the GARCH are nearly identical.

Overall, several points can be drawn from the forecast results. First, the results support the use of long memory models, though the evidence is far from overwhelming. In most cases, the long memory models perform marginally better than their corresponding non-long memory models or the simple GARCH particularly at more distant horizons. Also, the long memory models tend to produce slightly fewer rejections of the forecast unbiasness hypothesis. The general consistency of these findings in the three commodities lends added support to the value of long memory. Importantly the relative success of FIGARCH in 2008-2011 suggests that long memory through fractional integration may provide a parsimonious forecasting specification in the presence of significant structural breaks. Second, directly modeling structural breaks using the adaptive semi-parametric method either in the SA-FIGARCH or SA-GARCH overall fails to produce smaller loss functions, leads to negative forecast variances in certain cases, and generates extremely large errors at distant horizons. There are modest but significant error reductions only in wheat in 2008-2011 with the SA-FIGARCH, and in corn in 2005-2007 with the SA-GARCH. However, in both cases the reductions are not appreciably larger than those generated by other long memory models. In 2005-2007 slightly higher R^2s with SA-FIGARCH in corn and wheat appear but they are accompanied by strong rejections of unbiasness. The limited success of adaptive method in a forecasting context may reflect estimation errors that can emerge in over-parameterized models, or speak to the sharp and spiky nature of structural change.[7] Finally, the results show the importance of seasonality in forecasting the volatility in grain markets. In 2005-2007, S-FIGARCH and S-GARCH generate the smallest QL and MSE loss functions for all three commodities. However, in 2008-2011 when the seasonal pattern is weakened by the financial crisis, FIGARCH becomes more prominent as it appears to account

[7] Recall the adaptive component never enters the models specifications using the BIC.

for the structural change. Nonetheless, the seasonal models often are less likely to reject forecast unbiasness (e.g. SA-FIGARCH and S-GARCH for corn in 2008-2011, and S-FIGARCH for soybeans in 2005-2007). In sum, the combined the findings highlight the importance of a forecasting framework that integrates the seasonal dimension of these agricultural markets and is able to capture structural breaks in a parsimonious manner. In this context, the S-FIGARCH model performs best in the moderately volatile period, and is still able to perform relatively well in the heightened volatility period which included disruptions to seasonal patterns.

2.7 Conclusions

We investigate the sources of long memory in three major grains futures volatility, and assess the usefulness of long memory models to forecast volatility in periods of moderate and heightened uncertainty. Using data from corn, soybeans, and wheat futures contracts for 1989-2011, statistical tests and estimation results support the notion that much of the observed long memory patterns in grain price volatility arises from seasonality and structural breaks. After accounting for both factors, a smaller but still significant long memory effect exists in corn and wheat volatility, but it disappears in soybeans. In forecasting, our findings offer marginal support for the benefits of using long memory models. The loss functions are only slightly smaller than their corresponding non-long memory models in both moderate and heightened volatility. Long memory models also generate the fewest rejections of unbiasness in both situations, but all forecasts demonstrate a large degree of bias and a low degree of statistical coherence. Direct modeling of structural breaks through the adaptive semi-parametric method overall failed to produce smaller loss functions, and in certain cases led to extremely large errors. The limited success of the adaptive method in a forecasting context may reflect added error that can emerge in over-parameterized models, or from the sharp and spiky nature of structural breaks.

Nevertheless, we observe the importance of modeling seasonality in forecasting grain markets volatility, which is consistent with a rather extensive literature explaining seasonal patterns in agricultural markets (e.g. Goodwin and Schnepf 2000; Sorensen 2002) as well as the more limited volatility forecasting research (Egelkraut and Garcia 2006). On balance, S-FIGARCH which models both long memory and seasonality generates the best forecasts.

Our results contrast with previous findings that long memory in agricultural commodity volatility is strong and highly significant (Crato and Ray 2000; Jin and Frechette 2004; Baillie et al. 2007; Sephton 2009), or completely driven by a stochastic process (Power and Turvey 2011). Occasional level shifts can contribute to the long memory phenomenon (Smith 2005), and in these grain markets it is the combination of seasonality and structural breaks that have resulted in persistent and highly significant long memory patterns.

In forecasting, our results confirm previous findings that long memory generally improves accuracy over simple short memory models, particularly at more distant horizons (Morana and Beltratti 2004; Hyung et al. 2006; Baillie and Morana 2009; Martens et al. 2009; Kang et al. 2009; Lu and Perron 2010; Arouri et al. 2012b). However, here improvements in terms of MSE and QL error reduction sizes are much smaller (5% at best). For instance, among the studies using similar volatility measures (Kang et al. 2009; Lu and Perron 2010; Arouri et al. 2012b), only Kang et al's smallest improvement (6% in WTI, 2009) is close to our largest error reduction. In part this is due to the daily squared return volatility measure we use. While it is a volatility measure common to the study of agricultural markets, it leads to spiky and less predictable volatility patterns in our sample. Limited forecasting success may also reflect our focus in assessing predictive accuracy in a highly volatile period in these markets.

Our results suggest that combining long memory and structural breaks does not improve forecasting compared to a simply long memory model. It is similar to Martens et al. (2009) who found that capturing the smoothed structural changes does not improve daily volatility forecast compared to a simple long memory model. However, it contrasts with findings in Arouri et al. (2012b), Morana and Beltratti (2004), and Baille and Morana (2009) which were estimated in ways which may have allowed this relationship to more clearly emerge. For instance, Baillie and Morana's (2009) use lower frequency and smoother volatility data over a long span of years. Morana and Beltratti (2004) use realized volatility based on intraday returns data, and Arouri et al. (2012b) include the largest structural breaks in energy prices during the ex post identification and estimation period while the ex ante forecasting period reflects much dampened volatility.

Does long memory help provide more accurate volatility forecasts in an environment of dramatic change? Modeling long memory in various models marginally improves volatility forecasts particularly at more distant horizons. During periods of dramatic change, our findings also point to the use of parsimonious specifications. However, none of the models perform well during this volatile period, a finding consistent with Brownlees et al. (2011) who demonstrate that volatility forecast power deteriorates in the financial crisis.

In the presence of continued changing volatility in agricultural markets, emphasis may need to be placed on developing a more in depth understanding of when shocks occur in these markets and under what conditions shocks are likely to have the largest effect. Important announcements containing crop progress and stock and consumption ratios often cause big price moves. Including these release dates may allow us to anticipate large price spikes. Periods of low stock-use ratio also may signals potential breaks are forthcoming. Ultimately, this may lead to more short-term real-time volatility models which are conditioned on market fundamentals.

Martens et al. (2009) and Morana and Beltratti (2004) also find that long memory improves forecasts on the less noisy realized volatility. In agricultural futures markets, further tests are needed on whether long memory models can yield more forecast improvement in intraday realized volatility measures.

2.8 References

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2.9 Tables and Figures

Table 2.1. Summary and Test Statistics of Return and Volatility, 1989/1/3 – 2011/12/30

	Return			Volatility		
	Corn	Wheat	Soybeans	Corn	Wheat	Soybeans
Mean	-0.02	-0.02	0.02	2.49	3.17	2.19
Median	0.00	0.00	0.04	0.70	1.07	0.62
Std Dev	1.58	1.78	1.48	5.47	6.79	4.96
Kurtosis	2.81	2.60	3.16	59.87	50.36	45.91
Skewness	-0.04	-0.02	-0.29	6.06	6.03	5.72
Minimum	-10.41	-9.97	-8.39	0.00	0.00	0.00
Maximum	8.66	8.79	7.63	108.34	99.46	70.40
N	5795	5794	5794	5795	5794	5794
GPH				0.554*	0.400*	0.448*
Modified GPH				0.524*	0.452*	0.385*

Note: GPH and Modified GPH are the Geweke and Porter-Hudack (1983) and Smith (2005) modified estimators for long memory parameter. The Smith (2005) estimator is performed at k=3. The * indicates passing the 5% significance level.

Table 2.2. Results for the Corn Volatility Models, 1989/1/3 – 2011/12/30

	GARCH		S-GARCH		SA-GARCH		FIGARCH		S-FIGARCH		SA-FIGARCH	
ω	0.017	(0.005)	0.017	(0.006)	0.228	(0.073)	0.139	(0.034)	0.287	(0.053)	0.842	(0.178)
β	0.925	(0.009)	0.949	(0.010)	0.853	(0.034)	0.634	(0.068)	0.533	(0.076)	0.369	(0.178)
d							0.478	(0.061)	0.323	(0.032)	0.163	(0.039)
ϕ	0.071	(0.009)	0.044	(0.008)	0.062	(0.012)	0.237	(0.045)	0.272	(0.070)	0.266	(0.175)
seasonals												
a_1			0.017	(0.003)	0.003	(0.008)			0.057	(0.059)	-0.006	(0.050)
b_1			-0.016	(0.005)	-0.078	(0.024)			-0.460	(0.075)	-0.558	(0.084)
a_2			-0.016	(0.004)	-0.018	(0.008)			-0.076	(0.055)	-0.051	(0.068)
b_2			0.008	(0.005)	0.030	(0.012)			0.203	(0.066)	0.238	(0.064)
a_3			0.011	(0.006)	0.014	(0.009)			0.022	(0.015)	0.010	(0.008)
b_3			-0.007	(0.005)	-0.023	(0.010)			-0.147	(0.059)	-0.172	(0.059)
a_4			-0.019	(0.006)	-0.011	(0.009)			-0.008	(0.012)	0.015	(0.021)
b_4			0.005	(0.006)	0.020	(0.008)			0.162	(0.046)	0.134	(0.055)
structurals												
δ_1					-0.144	(0.049)					-0.471	(0.103)
γ_1					0.042	(0.037)					0.210	(0.104)
δ_2					-0.078	(0.038)					-0.422	(0.121)
γ_2					-0.042	(0.026)					-0.097	(0.177)
δ_3					0.000	(0.030)					-0.068	(0.090)
γ_3					-0.005	(0.015)					-0.150	(0.132)
δ_4					-0.013	(0.030)					0.055	(0.100)
γ_4					0.009	(0.014)					-0.125	(0.118)
δ_5					-0.041	(0.027)					0.047	(0.061)
γ_5					-0.007	(0.019)					0.046	(0.158)
δ_6					-0.016	(0.018)					-0.099	(0.134)
γ_6					-0.025	(0.023)					0.200	(0.067)
δ_7					0.002	(0.012)					-0.143	(0.057)
γ_7					0.002	(0.016)					-0.093	(0.064)

Table 2.2. (cont.)

δ_8			-0.014 (0.011)			-0.124 (0.055)
γ_8			-0.022 (0.013)			-0.029 (0.067)
AIC	1.756	1.749	1.742	1.755	1.747	1.743
BIC	1.758	1.756	1.758	1.758	1.754	1.759
LL	-10171.6	-10125.2	-10068.0	-10167.9	-10109.7	-10073.7
Q(10)	0.679	0.262	0.520	0.551	0.597	0.424
Q(20)	0.398	0.141	0.218	0.317	0.309	0.240
Kurtosis	4.449	4.326	4.029	4.391	4.258	4.066
T	5795	5795	5795	5795	5795	5795

Note: β is the parameter for conditional variance and ϕ is for the unconditional variance. Asymptotic standard errors are reported in parenthesis. AIC and SIC are the Akaike and Schwarz information criteria. Seasonal and structural terms are included based on the lowest AIC value up to four and eight pairs respectively. LL is the value of the log-likelihood function. Q(k) is the Ljung-Box test p-value for k lags on the squared standard residuals. Kurtosis is for the standardized residuals.

Table 2.3. Results for the Wheat Volatility Models, 1989/1/3 – 2011/12/30

	GARCH		S-GARCH		SA-GARCH		FIGARCH		S-FIGARCH		SA-FIGARCH	
ω	0.014	(0.006)	0.011	(0.006)	0.239	(0.064)	0.313	(0.055)	0.343	(0.057)	1.171	(0.167)
β	0.950	(0.009)	0.959	(0.011)	0.877	(0.025)	0.590	(0.059)	0.591	(0.061)	0.367	(0.136)
d							0.354	(0.035)	0.341	(0.033)	0.155	(0.026)
ϕ	0.046	(0.009)	0.039	(0.009)	0.046	(0.009)	0.287	(0.052)	0.296	(0.053)	0.248	(0.136)
seasonals												
a_1			0.012	(0.003)	0.013	(0.007)			0.146	(0.079)	0.117	(0.057)
b_1			-0.002	(0.003)	-0.025	(0.010)			-0.221	(0.063)	-0.234	(0.060)
structurals												
δ_1					-0.127	(0.036)					-0.653	(0.136)
γ_1					0.061	(0.022)					0.271	(0.110)
δ_2					-0.095	(0.030)					-0.413	(0.157)
γ_2					-0.011	(0.011)					-0.118	(0.101)
δ_3					-0.056	(0.020)					-0.239	(0.107)
γ_3					-0.028	(0.015)					-0.194	(0.140)
δ_4					-0.001	(0.013)					0.108	(0.106)
γ_4					-0.054	(0.018)					-0.289	(0.134)
δ_5					0.013	(0.012)					0.133	(0.106)
γ_5					0.002	(0.012)					0.079	(0.097)
δ_6					-0.047	(0.017)					-0.321	(0.083)
γ_6					0.024	(0.013)					0.152	(0.075)
δ_7					-0.027	(0.013)					-0.174	(0.085)
γ_7					-0.009	(0.011)					-0.044	(0.058)
δ_8					-0.023	(0.011)					-0.127	(0.089)
γ_8					-0.019	(0.010)					-0.129	(0.074)
AIC	1.902		1.901		1.896		1.900		1.898		1.895	
BIC	1.905		1.904		1.908		1.902		1.902		1.908	
LL	-11018.1		-11008.3		-10961.4		-11003.9		-10992.2		-10959.5	
Q(10)	0.741		0.399		0.992		0.982		0.978		0.997	

Table 2.3. (cont.)

Q(20)	0.818	0.694	0.999	0.987	0.990	1.000
Kurtosis	3.712	3.667	3.584	3.699	3.659	3.596
T	5794	5794	5794	5794	5794	5794

Note: β is the parameter for conditional variance and ϕ is for the unconditional variance. Asymptotic standard errors are reported in parenthesis. AIC and SIC are the Akaike and Schwarz information criteria. Seasonal and structural terms are included based on the lowest AIC value up to four and eight pairs respectively. LL is the value of the log-likelihood function. Q(k) is the Ljung-Box test p-value for k lags on the squared standard residuals. Kurtosis is for the standardized residuals.

Table 2.4. Results for the Soybeans Volatility Models, 1989/1/3 – 2011/12/30

	GARCH		S-GARCH		SA-GARCH		FIGARCH		S-FIGARCH		SA-FIGARCH	
ω	0.023	(0.007)	0.022	(0.006)	0.094	(0.025)	0.148	(0.040)	0.205	(0.054)	0.539	(0.362)
β	0.923	(0.009)	0.937	(0.009)	0.908	(0.017)	0.626	(0.112)	0.524	(0.154)	0.260	(0.189)
d							0.501	(0.101)	0.381	(0.077)	0.210	(0.139)
ϕ	0.068	(0.008)	0.053	(0.008)	0.048	(0.009)	0.170	(0.052)	0.170	(0.099)	0.073	(0.332)
seasonals												
a_1			0.006	(0.004)	0.000	(0.006)			-0.017	(0.051)	-0.049	(0.700)
b_1			-0.017	(0.004)	-0.033	(0.008)			-0.300	(0.067)	-0.379	(0.276)
a_2			-0.008	(0.004)	-0.009	(0.005)			-0.022	(0.075)	-0.011	(0.025)
b_2			0.007	(0.005)	0.011	(0.006)			0.120	(0.074)	0.150	(0.113)
a_3			0.012	(0.005)	0.011	(0.006)			0.013	(0.077)	-0.001	(0.140)
b_3			-0.008	(0.005)	-0.014	(0.006)			-0.141	(0.061)	-0.155	(0.175)
a_4			-0.013	(0.006)	-0.008	(0.006)			0.041	(0.098)	0.046	(0.152)
b_4			0.013	(0.006)	0.017	(0.006)			0.152	(0.101)	0.137	(0.173)
structurals												
δ_1					-0.044	(0.014)					-0.309	(0.398)
γ_1					0.010	(0.006)					-0.017	(0.122)
δ_2					-0.024	(0.010)					-0.140	(0.122)
γ_2					-0.011	(0.006)					-0.152	(0.529)
δ_3					-0.005	(0.005)					-0.027	(0.037)
γ_3					-0.005	(0.007)					-0.052	(0.332)
δ_4					0.000	(0.006)					0.068	(0.229)
γ_4					-0.018	(0.008)					-0.142	(0.423)
δ_5					0.020	(0.008)					0.197	(0.073)
γ_5					-0.011	(0.006)					-0.039	(0.252)
δ_6					0.012	(0.007)					0.057	(0.312)
γ_6					0.025	(0.008)					0.301	(0.154)
δ_7					-0.012	(0.006)					-0.147	(0.647)
γ_7					0.007	(0.006)					0.058	(0.295)

Table 2.4. (cont.)

δ_8			-0.023	(0.008)			-0.237	(0.153)
γ_8			-0.001	(0.005)			-0.046	(0.955)
AIC	1.709	1.705	1.700		1.710	1.705	1.702	
BIC	1.711	1.712	1.716		1.712	1.712	1.718	
LL	-9895.6	-9864.3	-9823.8		-9902.0	-9867.2	-9830.7	
Q(10)	0.541	0.580	0.493		0.435	0.628	0.796	
Q(20)	0.496	0.650	0.743		0.276	0.645	0.793	
Kurtosis	4.841	4.858	4.652		4.856	4.851	4.599	
T	5794	5794	5794		5794	5794	5794	

Note: β is the parameter for conditional variance and ϕ is for the unconditional variance. Asymptotic standard errors are reported in parenthesis. AIC and SIC are the Akaike and Schwarz information criteria. Seasonal and structural terms are included based on the lowest AIC value up to four and eight pairs respectively. LL is the value of the log-likelihood function. Q(k) is the Ljung-Box test p-value for k lags on the squared standard residuals. Kurtosis is for the standardized residuals.

Table 2.5. Mean Squared Errors and Quasi Likelihood (MSE and QL), 2005-2007

		GARCH	S-GARCH	SA-GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
Corn							
MSE	1 day	26.956	-0.67%	**-1.50%**$^{+}$	0.39%	-0.96%$^{+}$	-0.24%$^{+}$
	10 days	28.128	-1.76%$^{+}$	**-2.56%**$^{+}$	0.11%	-2.49%$^{*+}$	-0.88%$^{+}$
	25 days	29.376	-2.04%	-2.76%$^{+}$	-0.48%	**-3.45%**$^{*+}$	0.11%$^{+}$
	40 days	29.673	-1.17%	-1.70%$^{+}$	-0.75%	**-2.97%**	2.21%$^{+}$
QL	1 day	1.097	0.81%	0.39%	**-0.44%**	-0.25%	1.42%
	10 days	1.148	1.68%	3.38%	**-1.42%**	-0.84%	95.06%
	25 days	1.203	1.94%	6.96%	**-2.65%**	-2.21%	6.28%
	40 days	1.213	2.73%	-2.48%	**-3.77%**	-3.34%	35.57%
Wheat							
MSE	1 day	26.975	-0.23%	1.97%	-0.63%$^{*+}$	**-0.77%**$^{+}$	1.38%
	10 days	27.963	-0.63%	1.66%	-1.02%$^{*+}$	**-1.16%**$^{+}$	1.86%
	25 days	28.167	-0.64%	3.28%	-0.82%	**-0.83%**	4.01%
	40 days	26.949	**-0.75%**	3.89%	0.09%	0.04%	5.95%$^{+}$
QL	1 day	1.126	-0.43%	1.09%	-0.61%	**-0.97%**	-0.25%
	10 days	1.156	-0.70%	1.33%	-1.24%	**-1.41%**	-0.66%
	25 days	1.149	-0.67%	4.17%	-1.38%	**-1.40%**	1.28%
	40 days	1.118	**-0.71%**	5.22%	0.02%	0.00%	1.45%
Soybeans							
MSE	1 day	17.09	**-0.90%**$^{+}$	0.10%	0.51%	-0.70%	0.59%
	10 days	17.835	-2.14%	0.66%	-0.33%	**-3.23%**$^{+}$	-0.73%
	25 days	18.586	-3.39%$^{+}$	3.30%	-0.84%	**-5.00%**$^{+}$	-1.89%
	40 days	17.688	-4.43%$^{+}$	7.41%	0.02%	**-5.34%**$^{+}$	-1.99%
QL	1 day	1.330	-0.52%	5.13%	-0.36%	**-1.34%**	6.65%

Table 2.5. (cont.)

10 days	1.361	-1.17%	73.12%	-1.13%	**-3.03%**	9.23%
25 days	1.393	-4.79%	11.04%	-0.89%	**-5.46%**	10.64%
40 days	1.386	-4.66%	33.90%	-0.58%	**-5.16%**	42.14%

Note: 1). The GARCH column reports the MSE and QL values. In other columns we report the percentage improvement over GARCH MSE and QL, e.g. $\frac{MSE_{S-GARCH}-MSE_{GARCH}}{MSE_{GARCH}}\%$.

2). Lowest MSE and QL in bold fonts for each commodity and horizon.

3). * and $^{+}$ indicate forecast error reduction is significant at the 5% relative to GARCH at each horizon respectively for the Diebold-Mariano (1995) and Clark-West (2007) modified MSE tests.

Table 2.6. Mean Squared Errors and Quasi Likelihood (MSE and QL), 2008-2011

Corn		GARCH	S-GARCH	SA-GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
MSE	1 day	91.614	-0.82%$^{+}$	0.12%	-0.11%	**-0.89%**$^{+}$	-0.23%$^{+}$
	10 days	94.479	-1.64%$^{*+}$	0.92%	-0.71%$^{*+}$	**-1.77%**$^{+}$	-0.27%
	25 days	93.726	-0.70%	4.81%	**-0.77%**	-0.36%	2.88%
	40 days	96.338	-0.54%	5.00%	**-1.28%**$^{+}$	-1.06%	3.51%
QL	1 day	1.395	-1.15%	0.09%	-1.22%*	**-2.22%***	-0.97%
	10 days	1.439	-0.89%	7.97%	-2.06%*	**-2.52%***	2.73%
	25 days	1.441	-0.61%	24.76%	**-2.80%***	-1.88%	7.05%
	40 days	1.471	1.23%	33.87%	**-3.09%***	-1.02%	17.26%
Wheat							
MSE	1 day	145.37	0.29%	-0.17%	**-0.45%**$^{+}$	-0.28%	-0.13%$^{+}$
	10 days	150.925	0.01%	-0.25%	**-1.17%**	-1.07%	-0.62%$^{+}$
	25 days	156.299	-0.30%$^{+}$	-0.64%	**-2.07%**	-1.96%	-1.89%$^{+}$
	40 days	157.187	-0.35%	0.52%	**-2.04%**$^{+}$	-1.88%	-1.78%$^{+}$
QL	1 day	1.345	0.00%	0.73%	**-0.62%**	-0.44%	-0.39%
	10 days	1.400	-0.43%	0.31%	-1.46%	-1.35%	**-1.62%**
	25 days	1.486	-1.14%	0.37%	-2.72%	-2.56%	**-4.73%**
	40 days	1.524	-1.56%	1.91%	-3.43%	-3.06%	**-6.43%**
Soybeans							
MSE	1 day	51.447	**-0.09%**	0.62%	0.43%	0.48%	1.58%
	10 days	52.421	0.29%	1.58%	**-0.15%**	0.45%	2.66%
	25 days	54.685	0.11%	2.09%	**-0.45%**	0.17%	2.90%
	40 days	55.687	0.38%	2.99%	**-0.62%**	0.12%	3.55%
QL	1 day	**1.487**	1.17%	2.05%	0.01%	1.31%	2.51%

Table 2.6. (cont.)

10 days	**1.535**	2.53%	4.77%	0.05%	3.03%	4.82%
25 days	1.598	4.18%	9.79%	**-0.71%**	3.60%	6.00%
40 days	1.650	6.56%	15.86%	**-1.31%**	4.13%	7.29%

Note: 1). The GARCH column reports the MSE and QL values. In other columns we report the percentage improvement over GARCH MSE and QL, e.g. $\frac{MSE_{S-GARCH}-MSE_{GARCH}}{MSE_{GARCH}}\%$.

2). Lowest MSE and QL in bold fonts for each commodity and horizon.

3). * and $^{+}$ indicate forecast error reduction is significant at the 5% relative to GARCH at each horizon respectively for the Diebold-Mariano (1995) and Clark-West (2007) modified MSE tests.

Table 2.7. Mincer – Zarnowitz Regression on Out-of-Sample Forecast, 2005-2007

Corn		GARCH	S-GARCH	SA-GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
R^2	1 day	0.052	0.058	**0.067**	0.051	0.059	0.064
	10 days	0.022	0.036	0.044	0.022	0.039	**0.047**
	25 days	0.006	0.022	0.028	0.006	0.027	**0.034**
	40 days	0.006	0.024	0.029	0.006	0.029	**0.037**
F-stat	1 day	9.605	13.463	16.297	6.498	7.559	31.461
	10 days	6.981	5.674	6.782	6.600	3.687	13.958
	25 days	11.462	10.785	12.933	8.756	6.533	24.468
	40 days	9.605	13.463	16.297	6.498	7.559	31.461
Wheat							
R^2	1 day	0.023	0.023	0.014	0.026	0.027	**0.032**
	10 days	0.007	0.009	0.005	0.008	0.009	**0.024**
	25 days	0.010	0.012	0.004	0.013	0.013	**0.025**
	40 days	0.024	0.028	0.007	0.030	0.025	**0.038**
F-stat	1 day	2.573	1.917	6.629	1.441	1.370	11.432
	10 days	6.664	5.072	12.205	3.325	3.339	20.150
	25 days	5.481	4.208	16.250	3.728	4.421	27.929
	40 days	5.606	4.905	14.297	8.832	8.887	19.074
Soybeans							
R^2	1 day	0.029	0.034	0.025	0.030	**0.035**	0.022
	10 days	0.008	0.019	0.003	0.011	**0.026**	0.007
	25 days	-0.001	0.008	0.002	0.000	**0.016**	0.000
	40 days	-0.001	0.012	0.002	-0.001	**0.020**	0.002
F-stat	1 day	3.167	1.752	1.753	5.262	2.853	2.353
	10 days	7.417	3.754	8.188	6.939	1.845	4.410
	25 days	13.923	5.498	29.926	10.547	1.945	8.752
	40 days	13.097	2.839	45.567	12.715	1.804	8.302

Note: The table presents estimates of regressions of real volatility on a constant and volatility forecasts. The F-stat is the joint test on the null hypothesis of $\theta_0 = 0$ and $\theta_1 = 1$. Its 5% critical value is 3.00. The highest regression R^2 are in bold font.

Table 2.8. Mincer – Zarnowitz Regression on Out-of-Sample Forecast, 2008-2011

Corn		GARCH	S-GARCH	SA-GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
R^2	1 day	0.037	**0.040**	0.030	0.038	0.039	0.031
	10 days	0.018	**0.024**	0.005	0.018	0.021	0.009
	25 days	0.019	**0.024**	-0.001	0.017	0.017	0.001
	40 days	0.004	**0.005**	0.001	0.003	0.001	0.000
F-stat	1 day	5.423	2.570	2.133	5.158	1.853	0.952
	10 days	10.385	4.998	8.268	6.889	2.904	4.157
	25 days	7.091	6.185	20.106	2.772	4.475	11.806
	40 days	14.491	12.416	37.175	7.755	8.071	30.266
Wheat							
R^2	1 day	0.033	0.029	0.032	**0.035**	0.034	0.031
	10 days	**0.010**	0.008	0.009	**0.010**	**0.010**	0.009
	25 days	-0.001	-0.001	0.000	-0.001	-0.001	**0.002**
	40 days	-0.001	-0.001	-0.001	-0.001	-0.001	**0.002**
F-stat	1 day	2.801	2.440	1.705	1.700	1.785	1.101
	10 days	9.933	9.284	8.195	4.244	4.444	6.689
	25 days	22.338	20.782	19.504	11.521	11.977	14.009
	40 days	22.692	20.938	24.692	11.998	12.372	16.864
Soybeans							
R^2	1 day	**0.082**	0.081	0.074	0.079	0.075	0.068
	10 days	**0.066**	0.062	0.049	0.065	0.059	0.047
	25 days	**0.032**	0.030	0.019	0.031	0.023	0.022
	40 days	**0.017**	0.014	0.007	0.016	0.008	0.011
F-stat	1 day	1.684	0.807	0.170	2.008	0.389	2.213
	10 days	2.086	1.556	1.074	0.901	0.670	5.008
	25 days	5.166	4.254	7.781	2.516	1.304	13.656
	40 days	7.333	7.405	15.935	4.039	3.437	21.314

Note: The table presents estimates of regressions of real volatility on a constant and volatility forecasts. The F-stat is the joint test on the null hypothesis of $\theta_0 = 0$ and $\theta_1 = 1$. Its 5% critical value is 3.00. The highest regression R^2 are in bold font.

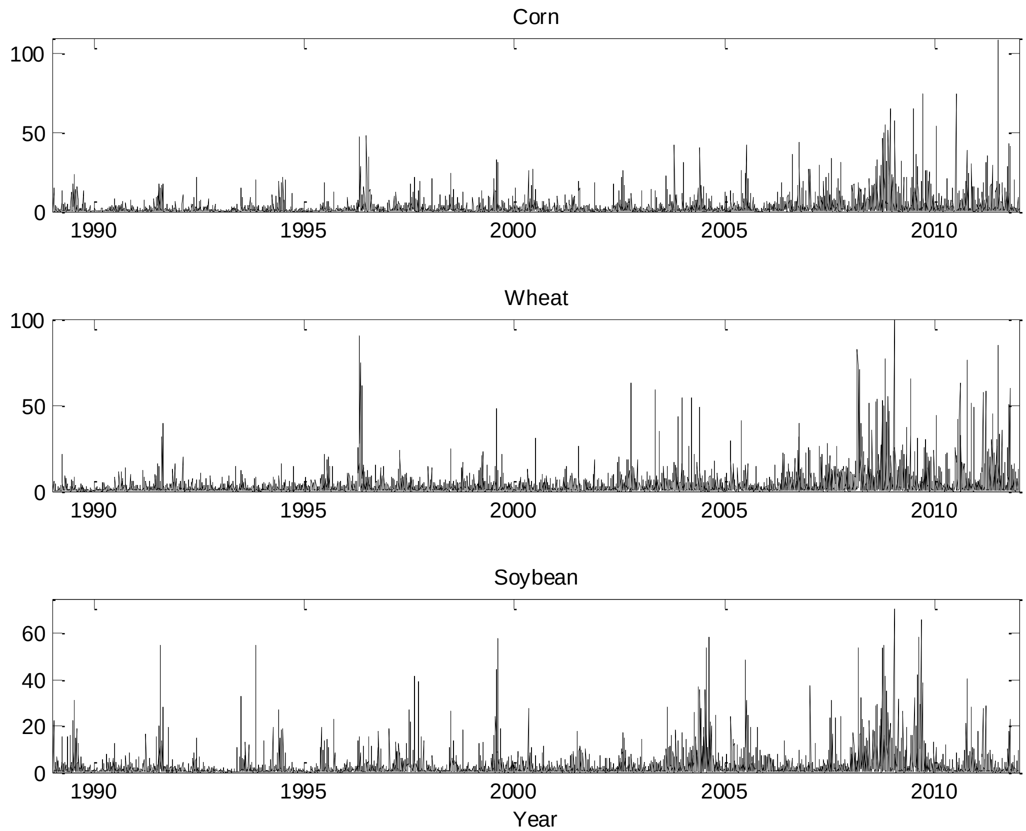

Figure 2.1. Daily volatility for corn, wheat and soybeans futures, 1989 – 2011

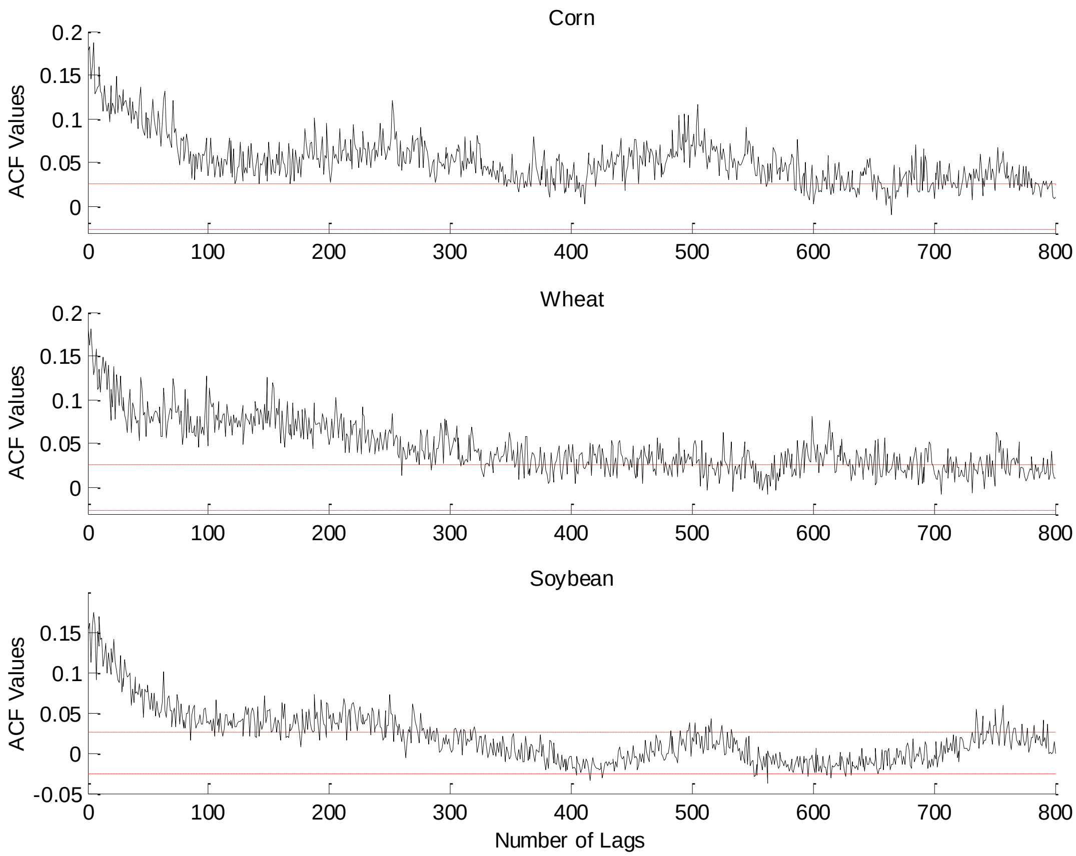

Figure 2.2. Autocorrelation of daily corn, wheat and soybeans volatility, 1989 – 2011

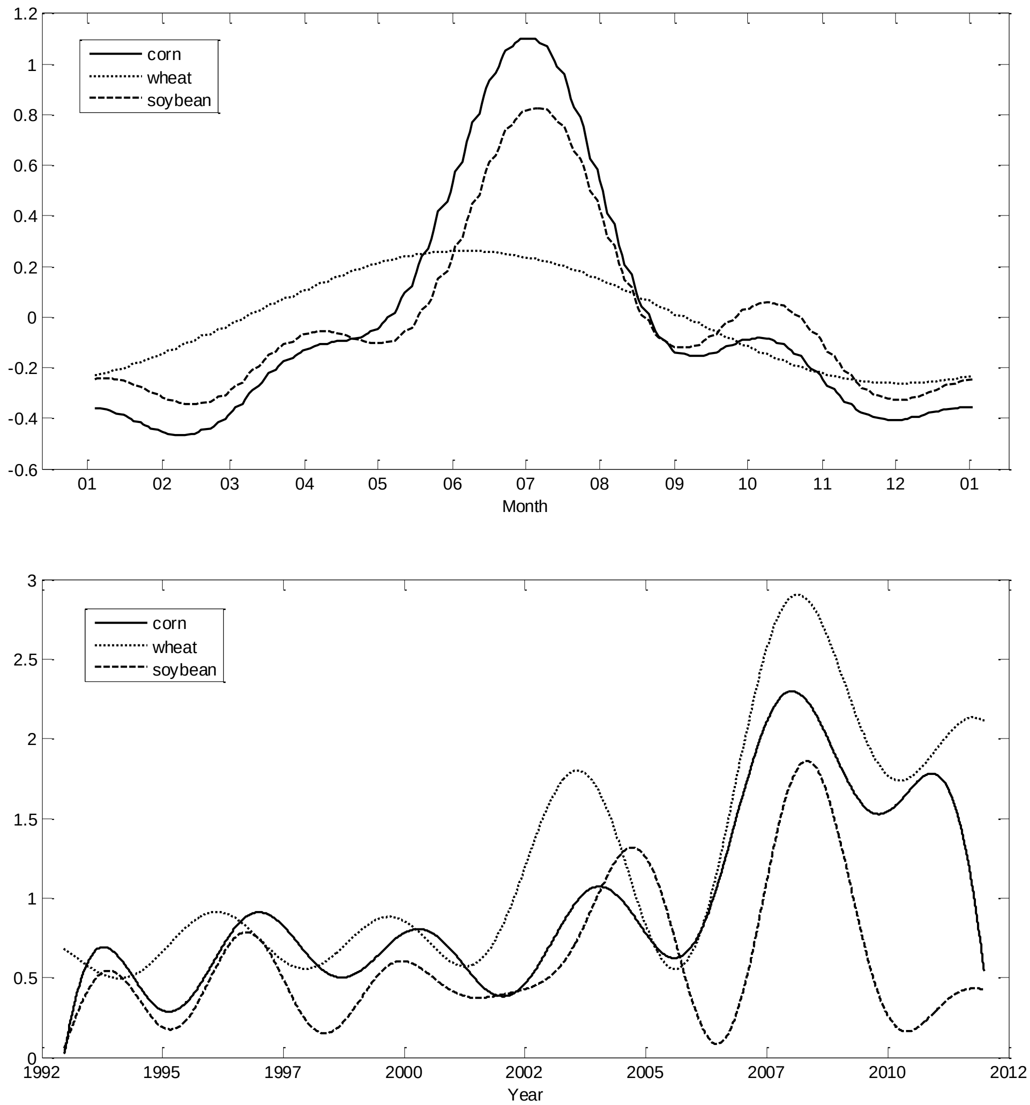

Figure 2.3. Estimated seasonal and structural level shifts

CHAPTER 3

THE BEHAVIOR OF THE BID-ASK SPREAD IN THE ELECTRONICALLY TRADED CORN FUTURES MARKET

3.1 Introduction

The structure of agricultural commodity futures markets has changed in the last decade. Arguably, the transition to electronic trading, which now accounts for more than 90 percent of volume traded in grains, has been a central dimension of the change (Irwin and Sanders 2012). Electronic markets provide an opportunity to reduce transaction costs and improve the speed at which new information enters markets. The emergence of electronic trading has fueled growth in market participation by allowing easier access and by permitting participants to see the order book, which contains bids, offers, and corresponding quantities available for trading. However, transition to electronic markets has also produced concerns. Increased anonymity in trading heightens concerns about adverse selection for liquidity providers (Bryant and Haigh 2004). The speed at which trades are placed also has potential to make markets more volatile, increasing demand for available liquidity and raising costs of immediate order execution, i.e., liquidity costs (Working 1967).

Agricultural economists have studied the cost of order execution in open-outcry markets using bid-ask spread (BAS), a measure of width between prevailing asking and biding prices. However, we know little about the structure and determinants of BAS in electronically-traded agricultural futures markets, a trading platform that will be in use for the foreseeable future.[8] The magnitude and variation of BAS is of broad interest to a wide range of market participants. For an exchange, it is important to maintain liquidity costs at an affordable level to promote viable futures contract trading. Hedgers and other market participants also need to know how liquidity costs vary through time and across different contracts to manage execution costs.

The study of BAS in agricultural futures markets has been hampered by data limitations. In U.S. open outcry futures markets only transaction prices, but not BAS, are recorded. As a consequence, researchers used statistical estimators based on transaction data to infer the BAS faced by market participants (Roll 1984; Thompson and Waller 1987; Hasbrouck 2004). Comparisons of generated BAS estimates often reveal marked differences (e.g., Bryant and Haigh 2004; Frank and Garcia 2011), a problem for researchers and market participants who seek to understand market behavior and identify hedging and trading strategies. Several recent papers have compared BAS in open outcry and electronic trading in different markets (e.g., Shah and Brorsen 2011; Martinez et al. 2011), but these analyses used transaction-price based estimators, and behavior and determinants of observed BAS were not investigated. With electronic trading, BAS is directly observable as traders submit orders and by reconstructing the limit order book from electronic trading records we obtain the actual BAS faced by traders. These electronic data permit an assessment of the structure and behavior of BAS unencumbered by the limitations of previous estimates. Further, the data provide an opportunity to investigate behavior for specific events and at more distant horizons, neither of which have been examined because transactions data were insufficient to estimate BAS using conventional methods.

[8] Trading transaction costs are composed of brokerage fees and liquidity costs. Evidence indicates that brokerage fees have dropped sharply as fully electronic brokers offer commissions for well under $10 per round turn (Irwin and Sanders 2012).

With the growth of electronic markets, market participation has increased and the supply of liquidity has expanded beyond that provided by floor traders at the exchange. One might anticipate that expanded liquidity and faster trading would decrease liquidity costs, reducing BAS to minimum competitive levels. However, in an analysis of LIFFE coffee and cocoa futures markets, Bryant and Haigh (2004) find the opposite and argue that anonymous traders put liquidity providers at an informational disadvantage, creating risk and widening BAS. Moreover, the recent growth in these markets has changed the composition of participants—commodity index traders have assumed a larger part of trading activity and much debate exists over their market impact (e.g., Irwin and Sanders 2011). Large order flows associated with the roll of index trader positions may cause temporal imbalances between liquidity supply and demand and widen BAS (Grossman and Miller 1988). The early findings on liquidity costs in electronic markets and recent changes in trader composition provide added motivation for an examination of liquidity issues in agricultural futures markets.

This paper is the first to study liquidity costs based on observed BAS in electronic agricultural futures markets. Using the Best Bid Offer (BBO) dataset from the CME Group for January 2008-January 2010, we identify the structure and determinants of the BAS for electronically-traded corn futures contracts. The period examined represents a particularly turbulent time in the corn market. Increasing ethanol production from 9 to 13.2 billion gallons in 2008-2010, expanding export demand in 2007/2008, a series of poor growing season weather events, and low ending stock-to-use ratios throughout the period led to high and volatile prices.[9] In addition, the futures market experienced the development of new financial instruments, such as exchange-traded funds which along with electronic trading expanded access to the market.

[9] For instance, the corn futures price almost doubled to $8/bushel in 2008 and then fell below $4/bushel as economic activity declined in the financial crisis.

These changes in price levels and market structure could have a significant impact on liquidity costs.

This dataset enables us to examine aspects of BAS behavior that have been of great interest to researchers and market participants. We begin by documenting patterns in daily BAS, focusing on its magnitude and variation over an extended portion of the contract life. Subsequently, we estimate a three-equation structural model to reflect the relationship of BAS with volume and volatility (Wang and Yau 2000; Martinez et al. 2011). The BAS equation is augmented by other specific determinants of BAS to identify their effects in nearby and deferred contracts. The analysis identifies patterns in liquidity cost behavior which are useful to market participants. Findings indicate that the move to an electronic corn market, with a few exceptions, has resulted in low liquidity costs even in the turbulent 2008-2010 period.

3.2 Literature Review

Studies on liquidity costs in agricultural futures markets focus primarily on the determinants of BAS. Research has identified that BAS is influenced by two fundamental factors—volume and price volatility (Brorsen 1989; Bryant and Haigh 2004; Frank and Garcia 2011; Shah and Brorsen 2011). Almost uniformly across these studies, increases in volume reduce BAS while increases in price volatility increase it. To date, most research has implicitly assumed that liquidity providers are passive agents who only respond to volume and price volatility. Yet liquidity providers change prices and BAS to manage order inventories which can also affect volume and price volatility. This interaction among BAS, volume, and price volatility has received limited attention in studies of agricultural futures markets. Frank and Garcia (2011) find that volume and volatility are endogenous in explaining the determinants of BAS, but they do not investigate the influence of BAS on volume and volatility. Only Martinez et al. (2011) model the interaction in electronic corn futures using a systems framework.[10] However, their BAS estimates are based on transaction-price estimators of BAS and the analysis is performed using 2006 data, reflecting an early stage in the transition to electronic trading. Perhaps as a consequence and in sharp contrast to previous work, Martinez et al. (2011) find that volume and volatility have no effect on BAS in the corn market. In what follows, we first discuss how BAS interacts with price volatility and trading volume and then identify other less commonly considered factors in explaining BAS which are readily investigated with the data.

3.2.1 BAS, Price Volatility, and Volume Relationship

The influence of price volatility and volume on BAS is well recognized. Stoll (1978) and Ho and Stoll (1983) provide the basic inventory theory which predicts that BAS is positively correlated with asset risk. Price volatility creates risk for liquidity providers' order inventories. To manage the added risk, liquidity providers submit less aggressive bid and ask prices which widen the BAS. Ho and Stoll (1983) also demonstrate that the effect of volatility on BAS will be moderated when the number of liquidity providers and concomitant competition increase. The effect of trading volume on BAS emerges from its influence on costs to the liquidity provider. Copeland and Galai (1983) conceptualize that posting a limit order offers a free option to the market. For instance, a limit order on the bid gives sellers a put option to sell at that bid price. In this context the BAS is the value of a short strangle on the bid and ask prices,[11] which is affected by price volatility and the option's time to maturity—the anticipated time to the next transaction at the posted price. With added volume in the market, liquidity providers can quickly open and

[10] In a study of precious metal and financial index futures, Wang and Yau (2001) also investigate the relationship among BAS, volume, and volatility in a dynamic system.
[11] A short strangle involves selling a put and a call at different strike prices. As a numerical example, Copeland and Galai (1983) show for a $100 asset with annualized volatility of 40%, at the money call and put option premiums are $0.123 when there is 5 minutes to the next transaction. The implied BAS is $0.246 with bid and ask prices at $99.877 and $100.123.

close positions which drives down the time between transactions and reduces the time value of the strangle position. As a consequence, BAS declines with increased volume.

Changes in BAS can also influence volume and price volatility. Often, it is assumed that liquidity providers are passive agents who respond only to volume and price volatility. Smidt (1971) and Garman (1976) were among the first to realize that liquidity providers also adjust BAS and bid and ask prices to manage their order inventory. In effect, liquidity providers adjust order inventories to profit from order flows. Higher bid prices increase selling orders and higher ask prices decrease buying orders. As a result, more aggressive bid and ask prices (higher bid and lower ask) narrow BAS, lower execution costs, and attract volume, while less aggressive bid and ask prices (lower bid and higher ask) widen BAS, increase execution costs and reduce volume (Stoll 1978; Ho and Stoll 1983). The effect of BAS on price volatility emerges readily from the realization that the top bid and ask prices provide a spread in which the equilibrium price lies. Hence, in the absence of large information shocks which move prices abruptly, BAS provides a range in which equilibrium prices vary. A wider BAS allows price to vary to a larger degree, increasing price volatility.

It is also important to realize that volume and volatility are likely jointly determined. Harris (1987) argues that price variability and volume respond positively to the arrival of information. Higher trading volume brings information to the market which results in changing prices as traders adjust positions. Similarly, Copeland (1976) and Jennings et al. (1981) argue that transactions from informed traders convey private information which generates price changes and subsequent volume changes in a sequential dynamic manner. This sequential interaction also leads to a positive relationship between volume and price volatility.

Due to order inventory management activities by liquidity providers and the dynamic nature of information arrival, the relationship between BAS, volume, and volatility is expected to be simultaneously determined and dynamic. Information arrival creates volume and price volatility that differentially affect BAS. Added volume drives down BAS, but added volatility increases it. The overall effect is uncertain, and in part will depend on the magnitude of the information shock and the depth in the market. When a market is highly liquid the effect of information arrival is reduced. Additionally, liquidity providers manage position inventories. To manage these positions, they change bid and ask prices when desired and actual inventories diverge. These price changes and concomitant changes in BAS make trading more attractive for other market participants as BAS narrows. Because the "equilibrium price" is presumed to lie between the highest bid and lowest ask, a narrower BAS moderates price volatility. This structure is consistent with the framework proposed by Wang and Yau (2000) and Martinez et al. (2011) which characterizes these interactions in a system of dynamic structural equations.

3.2.2 Further BAS Determinants

Recently, commodity index funds have played an increasingly important role in commodity futures trading. Driven by risk diversification, the last decade has seen considerable growth in commodity index investments to $223.5 billion by the end of 2012.[12] These funds typically establish passive long positions in nearby futures contracts that must be "rolled" due to contract expirations. The roll is accomplished by selling the nearby and buying deferred contracts on specific days in the month prior to expiration of the nearby contract. To illustrate, consider the roll transactions of commodity index funds that track the Standard and Poor's-Goldman Sachs Commodity Index™ (S&P-GSCI) and the Dow Jones-UBS Commodity Index™ (DJ-UBS).

[12] CFTC Index Investment Data Report, December 2012. http://www.cftc.gov/ucm/groups/public/@marketreports/documents/file/indexinvestment1212.pdf

These are the two most widely-followed indices in the industry (Stoll and Whaley 2010). Holding long positions in the March corn contract, funds sell their March positions and buy May contracts on the fifth through ninth trading day in February.[13] If insufficient liquidity exists on the days index funds roll their positions, BAS could temporarily widen. This illiquidity problem is said to arise from the asynchronous arrival of orders which amounts to a temporary mismatch between the supply and demand for liquidity (Grossman and Miller 1988). However, Admati and Pfleiderer (1991) argue that large predictable trades, termed “sunshine trading,” can attract natural counterparties as well as additional liquidity suppliers, which in turn, can reduce the impact of the trade on price and even permit the trader to achieve a more favorable price. Since index funds position changes are systematic and generally reflect the activity of uninformed traders, adverse selection concerns and related risks of holding a position for liquidity providers may be reduced. Similarly, opportunities may exist for liquidity providers to benefit from strategically positioning their trades which can further reduce the cost of order execution. Bessembinder et al. (2012) recently examined the effect of predictable exchange-traded-funds rolls in the crude oil futures market using Commodity Futures Trading Commission (CFTC) proprietary individual trader data. They find strong evidence to support sunshine trading with BAS narrowing during the roll.

In agricultural markets the effect of the roll may differ in the nearby and deferred contracts because trading in agricultural futures is driven by merchandisers hedging needs which primarily involve short futures positions. During the roll period, short hedgers may be naturally attracted to the deferred contracts as index funds build long positions, augmenting the liquidity supply. In contrast, as index funds sell the nearby contract to close their expiring positions,

[13] Aulerich, Irwin and Garcia (2013) find about 60% of all index fund positions were rolled during these five-day windows in 2008-2009.

liquidity providers absorb the short pressure without the natural counterparty short hedger activity. In this environment, BAS in the deferred contract may tighten while it may widen in the nearby contract. Empirical evidence of the commodity index roll effect on BAS in agricultural markets is limited. Shah and Brorsen (2011) perform a *t*-test on the mean BAS between rolling and other periods for Kansas City Board of Trade (KCBT) wheat futures and report no significant difference, but their analysis is restricted to only the nearby contract. Frank and Garcia (2011) find higher volume per transaction in the roll period which contributes to a BAS increase, without directly testing the relationship.

The effect of USDA information releases on BAS has not been systematically examined in agricultural futures markets. In studying earning announcement effects in the stock market, Brooks (1994) divides BAS into the fixed cost of handling incoming orders and the cost from adverse selection of informed traders. He identifies that the adverse selection costs surrounding announcements are large, but revert quickly back to normal levels. Krinsky and Lee (1996) also study earnings announcement effects on BAS and indicate that added volume surrounding the announcement may limit any changes in BAS caused by asymmetric information. Research in agricultural futures markets suggests that the release of USDA reports affects price and increases volatility immediately following the release of the reports (Fortenbery and Sumner 1993; Garcia et al. 1997; Isengildina-Massa et al. 2008; McKenzie 2008; Adjemian 2012). This increase in volatility can lead to increases in BAS on the day of the release as uncertainty may exist about the direction and magnitude of subsequent price adjustments. In this risky context, the importance of informed trading is also anticipated to be high, but limited to the announcement day only, because in an efficient market like corn, with diverse participants, price adjustment to information releases is often completed within the day (Garcia et al. 1997).

A largely neglected factor in BAS behavior is the influence of short-term price trends. Working (1967) observed that liquidity providers recognize price trends and often use a “cut losses and let profits run” strategy in their trading. When on the right side of a price trend they hold the position to accumulate profits. When on the wrong side they offset the position immediately to stop losses. An implication of this strategy is a decrease in liquidity services during price trends. Additionally, an important portion of the volume in futures markets is driven by technical trading strategies which are often based on underlying trends in the price data (Park and Irwin 2007). A common trend-following strategy is to bet that past price momentum will continue in the future and to even increase the trading positions in the presence of perceived trends (Szakmary et al. 2010). The combination of the “cut losses and let profits run” strategy of liquidity traders (which reduces liquidity) and the trend-following strategy of technical traders (which increases the demand for liquidity), can result in a wider BAS during periods of trending prices.

3.3 Structure of BBO Data

Information used in the analysis is the CME Group Best Bid Offer (BBO) data on electronically-traded corn futures for the period January 14, 2008 to January 29, 2010. The BBO dataset provides electronic Globex trading orders for each active contract. It contains the quotes of best bid prices paired with best ask prices with a time-stamp to the nearest second. For each best bid price and corresponding best ask price, the number of contracts available for trading at those prices are specified. When a better bid or ask price enters the market or when the number of contracts available for trading at those prices changes, a new pair of best bid price and best ask price are recorded along with the number of contracts available. An observed BAS is calculated by the difference between a pair of best bid and ask prices, and for a contract the daily average BAS is the mean of all BASs for a trading session.

CME runs both daytime and evening sessions in corn futures, and we focus on the daytime session since it is the most actively traded. We also focus on daily average data for consistency in comparison with prior research. Corn is the most actively traded agricultural commodity contract at the CME. It has five maturities a year: March, May, July, September and December. On each trading day, about ten to twenty contracts are listed for trading with different levels of activity. The number of observations differs dramatically from day to day and across contracts. For nearby contracts, more than forty thousand pairs of best bid and ask prices are typically recorded daily. The minimum allowed price change is one tick, which is 0.25 cents/bushel in the CME corn futures market.

3.4 Empirical Regularities of BAS

To begin, we trace the evolution of BAS through the contract life for five contracts maturing in 2009, which possessed the largest number of trading day observations in the sample. The five contracts are pooled and aligned by days to contract expiration. The minimum, median and maximum daily BASs and volumes are plotted in figure 3.1. BAS exhibits a U-shaped pattern over the life of a contract. In the early stages of a contract's life, trading activity is minimal and is accompanied by a large and volatile BAS. BAS steadily declines as contract expiration approaches and volume increases, and then increases sharply in the expiration month as volume disappears. Closer examination of similar figures for individual contracts (not presented) reveals a pattern of increased trading activity in the nearby contract. March, May, and July contracts exhibit increased trading about two to three months prior to their expiration months. The December contract exhibits an increase in trading as much as five months prior to its expiration month, while the September contract exhibits an increase only two months prior to its expiration month. These findings are consistent with the notion that December is the first new crop contract and actively used for hedging, while the September contract combines old and new crop information and has less trading interest (Smith 2005).

The maturity patterns imply a term structure of liquidity costs, with distant contracts having lower volumes and higher BASs. The term structure has important implications for producers making long-term hedging decisions (Peterson and Tomek 2007). We plot BASs that correspond to a producer hedging production at planting on the December contract in April 2008 and April 2009. In figure 3.2 (a) and (b) we graph BAS by contract for each trading day in April to illustrate the cost structure of placing hedges at distant horizons. For instance, in April 2008 there are 22 trading days and 13 contracts being traded. In figure 3.2(a) contracts are arranged by their maturity date on the horizontal axis, and each column contains the 22 daily average BASs represented by stars for a particular contract. For current year contracts, liquidity costs are rather stable and show little dispersion. For more distant contracts, BAS is higher in terms of both level and variability. At these distant horizons, a clear seasonal pattern emerges with BAS for the December contract being the lowest and least dispersed, followed by a widening BAS from March through September. At about a two-year horizon, the May and September contracts are rarely, if ever, traded which is reflected by large and highly dispersed BASs or the absence of a recorded BAS. These patterns are similar to two other known seasonal patterns in the corn futures market: the term structure of implied volatility (Egelkraut et al. 2007) and variability in spot prices (Peterson and Tomek 2007), strongly suggesting that BASs are affected by expected seasonal volatility.

Trading activity in a contract is greatest in the last 90 trading days prior to maturity. To examine this period in more detail, we combine the average daily BAS for the nine contracts during their last 90 trading days, plotting the median, minimum, and maximum values in figure 3.3. In terms of magnitude, prior to the expiration month BAS generally remains small and well below two ticks—0.5 cents/bushel. From day 90 to about day 50, BAS declines gradually but systematically, reaching a level slightly above one tick. It then remains stable with the median slightly above the minimum value until the expiration month. BAS rises in the expiration month as trading fades, especially in the last week when traders offset positions to avoid delivery. Examination of similar figures for the individual contracts (not presented) reveals that BAS values for the May contract were slightly above those for March, July, and December which was the lowest. BAS for September was more elevated than those of the other contracts consistent lower trading volume.

To examine the short-term dynamics of BAS more closely, we construct two BAS series, both of which exclude data from the expiration month. One series, *NB1BAS*, is the daily BAS in the nearby contract, while the other series, *NB2BAS*, is the daily BAS in the first deferred contract. We change the nearby and deferred contracts to their next maturity contracts on the last trading day prior to the maturity month. Figure 3.4 plots these two series. The deferred BAS series in most periods clearly lies above the nearby series and declines sharply when approaching the nearby period. Exceptions occur in July-August of 2008 and 2009 when the deferred contract is the December contract which is generally the lowest and the nearby contract is the September contract which is generally the highest. Average values for the two series are 0.314 and 0.376 cents/bushel (table 3.2). Pair-wise t-tests show the differences are significant at the 5% level, confirming a term structure effect, and identifying the differences in liquidity costs that can emerge when making short-term hedges in more distant contracts or when taking spread positions across contracts. Comparisons to previous BAS findings based on transaction-price estimators for the corn market provide insight into our electronic estimates. During a relatively stable period, Brorsen (1989) finds the average BASs over a number of contracts is 0.305 cents/bushel for floor-traded corn futures. In contrast, during the transition period to electronic markets in 2006, Martinez et al. (2011) find an average BAS of 0.510 cents/bushel for electronic trading, and 0.550 cents/bushel for floor-traded corn futures.

Commodity index funds roll their positions in the corn market five times a year in February, April, June, August and October. The nearby BAS during the roll period is 0.315 cents/bushel, almost identical to the average for non-roll periods. Interestingly, BAS in the deferred series is 0.368 cents/bushel during the roll period, falling slightly below the average for the non-roll periods in the deferred series. In both series the average volume is higher on roll days than on non-roll days by about 4,000 contracts, which means that in the deferred contracts the index funds represent a larger portion of the volume traded on those days (16.2% in the deferred relative to 7.1% in the nearby). Differences in volume or BAS are not significant based on *t*-tests at conventional levels, suggesting that liquidity demand by commodity index traders had little effect in the market.

To examine the effect of USDA information we consider the release dates of four reports: Crop Production report (PD), World Agricultural Supply and Demand Estimate report (WASDE), Crop Progress report (PS), and Grain Stocks report (GS). The PD report contains U.S. crop production information, including acreage, area harvested and yield. Corn production data are reported monthly from August to November, with final estimates provided in January. The WASDE report provides monthly USDA forecasts of U.S. and world supply-use balances of major grains using PD data. The PS report provides weekly information on planting, crop and harvest progress as well as the overall conditions of selected crops in major producing states during the crop season. The GS, which is issued four times annually in January, March, June and September, contains estimated corn stocks on a state and national level as well as by their on-farm or off-farm position.

Table 3.1 compares the nearby and deferred BASs on USDA announcement and non-announcement days. During the sample period for this analysis, the GS, PD and WASDE reports were released at 8:30 AM EST, after the close of overnight trading and before the beginning of daytime trading.[14] Previous studies show that information is quickly reflected into the market on release days. The PS report is released on Mondays at 4:00 PM after daytime trading has closed, and the BAS reported in the table corresponds to the following Tuesdays. In both series, the GS, PD, and WASDE reports generally result in a higher BAS compared to non-announcement days, with the GS release exerting the most influence. The PD and WASDE differences are significant at 5% in deferred series. BAS on GS report days is significantly higher than non-announcement days in both series at the 1% level. In contrast, BAS for PS report days (i.e., the following trading day) does not differ from non-announcement days. Presumably its information is incorporated quickly in overnight trading or in the early portion of the next trading day.

3.5 Regression Specification

The BAS, volume, and volatility relationship is specified as a dynamic three-equation model in which lagged own variables represent principle dynamics or persistence in the market (Martinez et al. 2011). BAS equation (3.1) includes contemporaneous volume and volatility and other

[14] In July 2012, the USDA started releasing reports during regular trading hours. See Kauffman (2013) for further details.

determinants of liquidity costs identified previously, as well as dummy variables to control for seasonal contract and day-of-the-week effects (Frank and Garcia 2011). Consistent with previous research, it is expected that increases in volume reduce BAS while increases in price volatility increase it (Ho and Stoll 1983; Copeland and Galai 1983). In addition, we incorporate two factors—market depth and futures price spreads—not included in previous studies.[15] Market depth represents the availability of liquidity provided by traders. It is often viewed as an important dimension in explaining execution costs particularly when order size varies appreciably (Black 1971). When the number of available limit orders is large, a market is said to be deep and BAS is less likely to be influenced by incoming order flows. Futures price spreads may also affect BAS. Spread trading is active in corn futures because the price of storage links contracts across maturities, which creates arbitrage opportunities. Widening spreads suggest arbitrage opportunities emerge for spread traders which increases the demand for liquidity and may widen BAS.

Volume equation (3.2) includes contemporaneous BAS and volatility, lagged open interest, and seasonal contract variables. It is expected that a wider BAS, arising from liquidity providers' inventory order management activities, will result in higher execution costs, decreasing trading profitability and reducing volume (Stoll and Ho 1983). A positive relationship between volume and volatility is expected in response to information arrival (Harris 1987) and the sequential trading pattern that emerges (Copeland 1976, and Jennings et al. 1981). Volume is also influenced by the flow of hedging to the market, but on a day-to-day basis it is difficult to measure. Here, we include lagged open interest— total number of outstanding contracts that are held by market participants at the end of each day—and seasonal contract dummy variables to

[15] We would like to thank two anonymous reviewers for these suggestions.

reflect this notion. While the seasonal dummy variables likely reflect differences in hedging behavior in the marketing year, lagged open interest also measures the short-term flow of trading capital into a market which may differ from hedging activity (Bessembinder and Seguin 1993). Notwithstanding, increasing open interest means that trading capital is flowing into the market and provides a relevant indication of subsequent increases in trading volume.

Volatility equation (3.3) includes contemporaneous BAS and volume, seasonal contract dummy variables, dummy variables to reflect USDA announcements, lagged volume, and crude oil volatility. As indicated above, volume and volatility should be positively related, and a wider BAS will allow for larger variability in price. Corn futures volatility is known to be seasonal in nature (Peterson and Tomek 2005; Egelkraut et al. 2007) and affected by USDA announcements (e.g., Fortenbery and Sumner 1993). We include contract dummies to reflect seasonal patterns which should reflect higher volatility in contracts spanning the summer. We add USDA announcement dummy variables to account for report release effects. This effect is not expected to be long lasting since most of the added volatility on announcement days tends to concentrate around the market opening (Garcia et al. 1997). In addition, we incorporate lagged volume since Blume, Easley and O'Hara (1994) show that lagged volume contains private information coming to market, and indicate that contemporaneous volume and volatility can be well explained by lagged volume. Interestingly, research has identified a negative effect of lagged volume on volatility which, given a positive relationship between concurrent volume and price volatility, suggests that traders may over-react to new information. We also include crude oil volatility since strong volatility spillovers from crude oil to corn have been identified in recent years. For example, Trujillo-Barrera et al. (2012) estimate about 10%-20% of corn futures price volatility is attributable to the WTI crude oil volatility in 2006-2011, and during the 2008 financial crisis it increased to as much as 45%.

The structural equations with a definition of the variables are:

$$BAS_{i,t} = f(volume_{i,t}, volatility_{i,t}, BAS_{i,t-1}, RL_t, PD\_WASDE_t, GS_t,$$
$$trend_{i,t}, spread_{i,t}, depth_{i,t}, K_t, N_t, U_t, Z_t, Tue_t, Wed_t, Thu_t, Fri_t) \quad (3.1)$$

$$volume_{i,t} = f(BAS_{i,t}, volatility_{i,t}, volume_{i,t-1}, open\_interest_{i,t-1},$$
$$K_t, N_t, U_t, Z_t) \quad (3.2)$$

$$volatility_{i,t} = f(BAS_{i,t}, volume_{i,t}, volume_{i,t-1}, volatility_{i,t-1},$$
$$Crude\_volatility_t, PD\_WASDE_t, GS_t, K_t, N_t, U_t, Z_t) \quad (3.3)$$

where *i* =1 and 2 stands for the nearby and deferred series, *BAS* is the daily average bid-ask spread in cents/bushel from the BBO, *volume* is the daily trading volume (,000 contracts), *volatility* is the daily standard deviation of the midpoint of reported bid and ask quotes on the electronic platform for the corresponding contract, and *open_interest* is number of outstanding contracts (,000) for the nearby or deferred months from the Commodity Research Bureau (CRB). *Crude_volatility* is the daily high-low range of nearby WTI crude oil futures prices (dollar/barrel) using the nearby contract from CRB. Consistent with the treatment of BAS, rolling to the deferred contract occurs on the last day before maturity month.[16] *RL* is a dummy variable for commodity index roll periods, which equals to 1 for the fifth to ninth trading day of February, April, June, August and October, otherwise zero. Since production reports are always on the same date as the WASDE reports, we create a single dummy variable *PD_WASDE* equal

[16] We follow Wang and Yau (2000) in using the daily price high-low range to represent the daily volatility in crude oil. The high-low range measured in dollars /barrel is consistent with the corn futures volatility measured in cents/bushel.

to 1 on the day of WASDE reports, otherwise zero. *GS* is a dummy variable for grain stock reports. We do not include crop progress reports because the release is always late on Monday and as discussed in our preliminary examination we found little response. To measure short-term price trends, we sum the close-to-open price differences on the previous five trading days, and define a variable *trend* whose value at *t* is the absolute value of lagged summed price changes. *Spread* is based on daily settlement prices from CRB. In the nearby model, it is the difference between the first deferred futures prices and the nearby futures prices, and in the deferred model, it is the spread between the second and first deferred futures prices. *Depth* is defined as the minimum of either the daily average number of ask or daily average number of bid limit orders from the BBO. Depth is commonly defined as the average number of bid and ask limit orders (e.g. Frino et al. 2008; Lepone and Yang 2012), but in agricultural markets, particularly on price limit or near price limit days, this measure may mask liquidity imbalances.[17] To control for observed seasonality, four contract dummy variables *K*, *N, U* and *Z* are included for the May, July, September and December contracts with the March contract in the intercept. We also include weekday dummies *Tue, Wed, Thu* and *Fri* in the BAS equation as studies have identified their importance (e.g., Frank and Garcia 2011).

Estimation is performed separately for the nearby and deferred models. After initial testing, the three equations are estimated as a system to increase efficiency. Several econometric problems may arise. Serial correlation and heteroskedasticity may exist with daily observations although the dynamic nature of the model may mitigate autocorrelation issues. As discussed, BAS, volume, and volatility are likely to be simultaneously determined. In the BAS equation, another possible source of endogeneity exists with market depth as it may respond to changes in

[17] For instance, on a price limit down day, the number of limit orders at the ask swamp the number of bids, because traders do not want to buy contracts. Nevertheless, some transactions occur at that price.

information which influence BAS. We follow a two-step approach to develop our final estimates. In the first step, we assess each equation individually for autocorrelation, heteroskedasticity, and endogeneity. In the second step, we estimate the equations using the GMM-Three Stage Least Squares (GMM-3SLS) method, correcting for the problems identified.

We perform the tests using the General Method of Moments - Instrumental Variables (GMM-IV) method recommended by Baum et al. (2007). Autocorrelation is assessed using the Cumby-Huizinga modified Breusch-Godfrey test in the instrumental variable regressions, with the null of no autocorrelation. Heteroskedasticity is assessed using the Pagan-Hall test. To assess for endogeneity of BAS, volume, volatility, and depth we apply the modified Durbin-Wu-Hausman test (Baum, Schaffer, and Stillman 2007) which requires the identification of instruments. Our strategy follows Angrist and Krueger (2001) and Murray (2006) who point out that using lagged (predetermined) variables is the most common approach in selecting instrumental variables, particularly in specifying dynamic relationships. In the BAS equation, we use lagged depth, lagged volume, and the first difference of volatility as instruments. The choice of lagged volume and differenced volatility follows results by Thompson, Eales and Siebold (1993) and Frank and Garcia (2011). The choice of lagged volume emerges from Blume et al. (1994) who explain that trades bring information to the market, and lagged volume affects contemporaneous volume and volatility. The use of lagged depth as an instrument for depth arises from Ahn et al. (2001) who find market depth exhibits strong state dependence. In the volume equation, we use the lagged BAS and the first difference of volatility as instruments. In the volatility equation, since lagged volume is specified in the equation, we use lagged open interest and lagged BAS as instruments (Martinez et al. 2011). In addition, we test the strength of instruments using the Stock-Yogo test for weak identification. Weak identification refers to the case that excluded instruments explain the endogeneous variables, but the strength is small which leads to bias. The null hypothesis of the Stock-Yogo test is that the bias is unacceptably large at a given level of significance. Test statistics exceeding the critical value point to an effective instrument.

3.6 Regression Results

Table 3.2 provides summary statistics for the 516 daily average observations of the continuous variables used in the statistical analysis. As anticipated, average daily volume in the nearby series (which corresponds to the nearby contracts) is larger than the volume in the deferred series. BAS in the deferred series exceeds BAS in the nearby contract and exhibits more variability. BASs in the nearby and deferred series are 26% and 50% higher than the minimum tick size, 0.25 cents/bushel. Price volatility, price trend, spread, and market depth in deferred contracts differ only marginally from the values in nearby contracts, perhaps a reflection of the linkages that can exist in the constellation of futures prices (Peterson and Tomek 2005). Prior to estimation, the series are tested for non-stationarity using the augmented Dickey-Fuller test and Phillips-Perron test. All series reject the null hypothesis of level non-stationarity at the 1% level.[18]

Tables 3.3 and 3.4 provide the regression results for nearby and deferred series, and table 3.5 contains cross elasticities for relevant variables. Test statistics for endogeneity, serial correlation, weak identification of instrumental variables, and heteroskedasticity are reported in the lower part of tables 3.3 and 3.4. Informatively, no error autocorrelation exists in any of the equations, but significant heteroskedasticity is present in all but the nearby volatility equation.

[18] We test stationarity using the KPSS test. At 5% level, we fail to reject the null of stationary in all cases except market depth in the deferred series. We also assess the series with DF-GLS test which is more powerful than the ADF in small samples, and find that all series are stationary. We conclude that the series are stationary.

The endogeneity tests produce mixed results, with a slightly higher likelihood of finding endogeneity in the nearby models. In the BAS equations, only depth in the nearby and volume in the deferred series are found to be endogeneous. In the volume equations, volatility is endogeneous in both models while BAS is endogeneous in the nearby model. In the volatility equation, both volume and BAS are endogeneous in the nearby model, but endogeneity is not present in the deferred model. Where endogeneity exists, the Stock-Yogo test statistics for weak instruments are reported. The rejection level for the null hypothesis of unacceptably large bias is set at the 5% level. The test statistics are well above the critical values. Since there is no autocorrelation, we conclude the instruments can effectively identify the endogeneous variables. System estimation of instrumental variable regressions calls for the three-stage least squares method. In the presence of different instrumental variables in the equations and heteroskedasticity, we use the GMM-3SLS (Wooldridge 2002), treating variables found not to be endogenous in the testing as exogenous in estimation.

The results suggest that the models fit the data reasonably well. The signs of the coefficients in the BAS, volume, and volatility equations are consistent with expectations and statistically significant in both the nearby and deferred models. The coefficients of the lagged variables are also of expected sign and significance, except in the nearby volatility equation where lagged volume is insignificant. Lagged open interest provides a good indication of subsequent volume traded. Lagged volume negatively affects volatility suggesting traders do over-react to changes in information, but the effect is limited to the deferred model where trading is less active.[19] In the nearby model where trading is active, over-reaction is less likely to occur. Coefficients of lagged dependent variables support the notion of persistence in the market, with

[19] Viewing the volatility equations in an autoregressive distributed lag framework, the over-reactions in the nearby and deferred series are 0.03 and 0.19 percentage points.

the evidence pointing to higher persistence in BAS than in volume and volatility in both the nearby and deferred models. These findings contrast with Martinez et al. (2011) who find no persistence in the volume equation, but greater persistence in the BAS and volatility equations than encountered here. Crude oil volatility significantly affects corn futures volatility in both models, confirming the strong volatility spillover identified by Trujillo-Barrera, Mallory and Garcia (2012).

3.6.1 BAS, Price Volatility, and Volume Estimates

In general, the coefficient signs are consistent with expectations and coefficient estimates are statistically significant. BAS declines as volume increases (Copeland and Galai 1983; Ho and Stoll 1983) and widens as price volatility increases (Ho and Stoll 1983). We focus on the contemporaneous coefficients because they reflect daily effects that are most relevant for market participants. These effects are small in magnitude. A 1% increase in daily volume reduces the nearby BAS by only 0.0002 cents/bushel and the deferred by 0.0003 cents/bushel. Compared to the mean BAS of 0.314 and 0.376 cents/bushel, the percentage changes are below -0.1% (table 3.5). Similarly, a 1% increase in the standard deviation of price leads to a 0.0002 cents/bushel rise in both nearby and deferred BAS series, and percentage changes below 0.1%. These findings support the notion that the electronic corn market is highly liquid as the costs of execution are largely unaffected by normal changes in volume and volatility. Negligible volume effects are consistent with the Copeland and Galai (1983) framework. For a market in which volume traded is substantial, the anticipated time between transactions is already small. Similarly, negligible volatility effects are consistent with Ho and Stoll (1983) who demonstrate that the effect of volatility on BAS is moderated when the number of liquidity providers and concomitant competition increases. These findings highlight a benefit of an electronic platform that opens access to added market participants.

In contrast, the effects of BAS on volume and volatility are relatively more substantial. Volume and volatility are more sensitive to changes in liquidity costs than liquidity costs are to the changes in volume and volatility. A 1% increase in BAS results in a decline 586 contracts in nearby and 371 in deferred contracts, or -1.02% and -1.51% (table 3.5). A 1% increase in BAS increases volatility by 1.09% in the nearby and 1.82% in the deferred models. The finding that volume and volatility are relatively more sensitive to changes in the BAS was also encountered by Wang and Yau (2000) who investigated open outcry financial and metal futures. Martinez et al. (2011) find that BAS plays an insignificant role in price volatility, but a 1% increase in BAS reduces volume by 2.55%. As suggested by Smidt (1971) and Garman (1976), liquidity providers adjust BAS to attract or deter trading in order to manage their order inventory and their behavior affects both volume and volatility.

Compared to the asymmetric effects between volume, volatility and BAS, the relationship between volume and volatility is more balanced. In the volume equations, a 1% change in volatility results in a 0.35% (0.52%) change in volume in the nearby (deferred) model. In the volatility equations, a 1% change in the volume results in a 0.35% (0.49%) change in the nearby (deferred) model. The positive and symmetric interaction of volume and volatility is consistent with the Harris (1987), Copeland (1976), and Jennings et al. (1981) findings of how volume and volatility respond to the arrival of information and the sequential trading patterns that arise as traders adjust their positions.

Estimates of the effects of seasonal contract patterns differ in the three equations as do the day-of-the-week effects in nearby and deferred BAS contracts. Seasonality is most pronounced in the nearby BAS and volume equations, and the deferred volume equation. In BAS equations, since the seasonal and day-of-the-week patterns are represented by dummy variables, these coefficients can be interpreted as a cents/bushel change. For BAS, in most cases the signs and magnitudes are consistent with expectations, but with little economic significance. In the nearby model in which a strong statistically significant pattern emerges, BAS is lowest in the December contract, and then increases through the March, May and July contracts with a modest decline in September. In the deferred model in which statistical significance is limited, the seasonal pattern is roughly the same, except September is the highest as anticipated based on figure 3.4. The existence of lower BAS in December, a contract used heavily for hedging (Smith 2005), corresponds with Working's (1967) observation that hedging attracts speculative liquidity service. The seasonal pattern is also consistent with expectations in volume. The relative volume (March is the base month) increases in the nearby July contract as traders protect themselves against weather shocks and increasing risk. Similarly, trading volume is higher in the December deferred contract as hedgers establish their positions well in advance of harvest. Seasonality also appears in the volatility equations, but it is difficult to identify the specific pattern because most of the coefficients are insignificant. In part this may due to the difficulty in measuring seasonal effects with the standard deviation of intraday prices. It also may result from the close relationship that exists between volume and volatility, and importance of lagged volume, lagged volatility, and crude oil volatility in the equation. Little meaningful day-of-the-week effects exist in the BAS equations. The existence of day-of-the-week effects are somewhat mixed in terms of statistical significance, but their economic impact on liquidity costs is also small.

3.6.2 Further BAS Determinants Estimates

With a few exceptions, the other factors hypothesized to directly influence BAS demonstrate considerable statistical significance, but with small changes on a cents/bushel or percentage basis. Market depth is a significant determinant of BAS only in the deferred contracts. For a 1% increase in depth, BAS decreases by 0.0004 cents/bushel, or 0.10%. The absence of a market depth effect in the nearby model, where trading is most active, suggests the order book is quickly replenished with new limit orders. However, in deferred contracts, where trading is not as large, added depth reduces BAS. Short-term price trends widen the BAS in both nearby and deferred series, providing modest evidence that trading demand of trend-following technical traders and the strategic actions of liquidity providers result in a higher BAS. For an average five-day price trend of 20 cents/bushel, liquidity costs will rise by 0.002 and 0.006 cents/bushel in nearby and deferred contracts, or 0.01% and 0.02%. Similarly, in nearby contracts, a widening of the futures spread by 1 cent causes BAS to widen but by only 0.0021 cents/bushel, or 0.08%. Futures spreads have no significant effect in deferred contracts suggesting that the impact of spreading activity resides primarily in nearby contracts in which trading volume is higher and basis convergence is more predictable.

Several instances occur in which the relative changes in BAS are much larger. A more substantive change arises when commodity index funds roll their positions and USDA announcements are made. In the nearby model, the roll of commodity index positions has a negative but insignificant effect on BAS, but in the deferred model BAS is reduced by 0.0121 cents/bushel, or about 3% (table 3.5). These findings support the notion that "sunshine trading" by large index funds attracts natural counterparties to the market. The added liquidity suppliers more than offset the demand for liquidity arising from the roll of index positions (Bessembinder et al. 2012). As expected the effect is more pronounced in the deferred model. Because the dominant commercial market activity is short hedging, attracting the long side is more important in augmenting liquidity supply. The findings in the nearby model correspond with Shah and Brorsen's (2011) results in the wheat market that index position rolls do not increase the BAS in nearby contracts. From a hedging perspective, the findings also support the view held by Sanders, Irwin and Merrin (2010) that long-only index funds can help ease hedging pressure by traders and producers seeking to establish short positions.

USDA announcements also significantly affect BAS in nearby contracts, with Grain Stock (GS) reports having the biggest influence. On GS report release days BAS increases by 0.039 cents/bushel, about 12% (table 3.5). During the 2008 and 2009 period, changes in market demand and supply resulted in low stock-to-use ratios. In this situation, the market was extremely sensitive to inventory information and liquidity costs increased in response. The relatively large magnitude, after accounting for price volatility and trading volume, suggests added uncertainty in the market may have existed over the trajectory of price adjustments which widened BAS. The effect may have been magnified by the adverse selection cost arising from informed trading (Brooks 1994). Production and WASDE reports (PD_WASDE) have smaller and less significant effects, about one fourth the size of the GS report. On days of WASDE reports, BAS increases by 0.009 cents/bushel in the nearby period, about 3% on average. In the deferred model, announcement day effects are consistently positive and similar in size to those in the nearby model, but are not statistically significant. Examination of data around report release dates revealed that trading prior to and on the release date often declined, but increased sharply on the day after the release. This pattern suggests that traders are uncertain about the content of new information, and increase trading as they interpret its effect on their market positions. It is also consistent with Krinsky and Lee's (1996) findings that limited trading and large increases in BAS around announcement days point to asymmetric information as the cause. Informatively, increases in liquidity costs resulting from USDA announcements are not long lasting. Average BAS values for days following Grain Stock and Production and WASDE reports are 0.314 cents/bushel and 0.302 cents/bushel, respectively, almost identical to those reported in table 3.1 for non-announcement days. The quick reversal corresponds to Garcia et al.'s (1997) finding that price adjustment to new information is limited primarily to within the day. Similarly, it corresponds closely to Brooks' (1994) finding that while the magnitude of an adverse selection announcement effect in liquidity costs can be large, its duration is often short with BAS reverting to normal levels quickly.[20]

3.7 Conclusions

Electronic trading in agricultural commodity futures markets, which now accounts for more than 90 percent of the volume traded in grains, offers a fast and transparent platform that has fueled market participation. However, electronic trading has raised concerns that increased speed and heightened anonymity have raised order execution costs. We study the behavior of the bid-ask spread (BAS), a common gauge of liquidity costs, in the electronically-traded corn futures market during a particularly turbulent period, 2008-2010. We measure BAS by reconstructing

[20] To assess robustness, we compare estimates of the dynamic equations presented in the text to several other formulations: static OLS models (no lagged dependent variable, but a maturity variable to reflect time to expiration), static GMMs using the instruments in the text with (without) specific dummy variable effects, and an equation by equation GMM-IV estimation of the dynamic equations in the text. In all cases, GMM estimates provide smaller coefficients (in absolute value) that are less significant compared to OLS. In the dynamic GMM models, statistical coherence increases, evidence of endogeneity is reduced, and autocorrelation disappears. Similarly, coefficients are more consistent with theoretical expectations. Smallest differences exist between the dynamic GMM model presented in the text and an equation by equation dynamic GMM estimation. Parameter estimates are almost identical, but modest differences emerge in estimated standard errors.

records from the electronic order book, and investigate its behavior, determinants, and interactions with volatility and volume, two key factors influencing liquidity costs, using a dynamic systems framework.

The evidence demonstrates that the electronic corn futures market not only offers speed and accessibility, but with a few exceptions provides sufficient liquidity to maintain order execution costs at low and rather stable levels. The average BAS in the most actively traded nearby and deferred (next nearby) contracts are 0.314 and 0.376 cents/bushel respectively. These values are only marginally higher than the minimum tick of 0.25 cents/bushel. Similarly, while BAS across maturities exhibits a clear seasonal pattern that is consistent with the term structure of price volatility, the differences are small in magnitude in the nearby contracts. However, this pattern is magnified at contract horizons beyond one year. Consistent with the literature, statistical analysis reveals that BAS responds negatively to changes in volume and positively to changes in volatility. However, the responses on a cents/bushel or a percentage basis are negligible. Informatively, larger responses emerge when examining the effects of changes in BAS on volume and volatility. These findings demonstrate that market participants are indeed sensitive to how transactions cost changes influence their trading volume and returns and also indicate that maintaining BAS at low and stable levels can moderate within-day price variability.

With a few exceptions, the effects of other factors anticipated to affect BAS are statistically significant, but small on a cents/bushel or percentage basis. For instance, in the nearby model, seasonality emerges with lower BAS in the December contract, a contract used heavily for hedging (Smith 2005), which is consistent with Working's (1967) observation that hedging attracts speculative liquidity service. However, this difference in cents/bushel is not large. Much larger cents/bushel and percentage changes in BAS occur during commodity index trader roll periods and on USDA report release days. The roll period findings point to a sunshine trading effect with added liquidity entering the market in anticipation of commodity index traders' predictable behavior, while the announcement effects identify the importance of unexpected information and adverse selection on order execution costs.

Our findings are consistent with Brorsen's (1989) analysis of the open-outcry corn market in terms of the magnitude of the BAS in a relatively stable and actively traded market. They differ substantially from Martinez et al.'s (2011) findings which identified significantly higher liquidity costs in both open-outcry and electronic markets and failed to demonstrate any relationship among BAS, volume and volatility during the transition to an electronic platform. Importantly, our findings also differ because they are based on a more comprehensive model and representative dataset that permit us to identify the dynamic interactions among BAS, volume, and volatility and to investigate other BAS determinants. Overall, our analysis reveals that the move to an electronic corn market with added liquidity providers has resulted in low liquidity costs even in a period recognized as being particularly volatile. The analysis also provides insights into the factors that affect and fail to affect liquidity costs in meaningful economic ways and has identified differences in liquidity costs that may be important to hedgers seeking to manage their short- or long-term price risks.

Further research is needed to investigate the quality of electronic trading in agricultural futures markets. We need to verify the relationships encountered here for other electronically-traded agricultural commodities. Additionally, we know only a little about intra-day interactions, and even less about the effect of the emerging algorithmic traders on liquidity costs. Recently, CME reported that 26% of the volume in agricultural futures markets is generated by algorithmic trading. What effects do these traders, who often employ high frequency automated trading strategies and order placement systems, have on price volatility and liquidity costs? Importantly, the structure of trading also is expanding toward around the clock access. As the evening session increases in its importance, how will the migration of liquidity providers to these trading sessions influence the BAS? Identifying these relationships and answering these questions will permit a clearer understanding of how markets and institutions adapt to changes in market fundamentals and trading environments and allow market participants to make more informed choices.

3.8 References

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3.9 Tables and Figures

Table 3.1. Average Nearby and Deferred BAS on USDA Report Announcement and Non-Announcement Days

	Crop Production (PD)	WASDE	Grain Stock (GS)	Crop Progress (PS)	Non-Announcement Days
Nearby	0.324	0.318	0.357 ***	0.319	0.312
Deferred	0.418 **	0.400 **	0.451 ***	0.366	0.375
Observations	12	25	8	72	412

Note: Average BAS is calculated separately for days with Crop Production reports (PD), WASDE reports, Grain Stock reports (GS), Crop Progress reports (PS), and days with no announcements (Non-Announcement). The units are cents/bushel. The asterisks reflect the level of significance (***,**,* at 1%, 5% and 10%) for unpaired *t*-test of the difference in average BAS on report announcement and non-announcement days. The sum of the observations across announcement and non-announcement days exceeds the number of observations in the sample because some reports are released on the same day.

Table 3.2. Summary Statistics

	BAS	*Volume*	*Volatility*	*Trend*	*Spread*	*Depth*	*Open Interest*	*Crude Volatility*
Nearby								
Mean	0.314	57.54	2.56	19.83	12.54	49.07	354.24	3.43
Std. Dev.	0.043	28.58	1.59	16.34	3.49	20.53	148.98	1.72
Min	0.258	1.63	0.00	0.00	3.02	3.45	27.63	0.84
Max	0.509	196.44	11.82	103.5	20.74	135.92	597.47	12.32
Deferred								
Mean	0.376	24.67	2.58	20.38	10.95	46.59	270.23	
Std. Dev.	0.061	28.28	1.59	16.55	4.00	18.38	147.72	
Min	0.264	1.56	0.00	0.00	-2.49	1.84	92.70	
Max	0.691	149.94	11.96	103.25	20.91	127.89	608.17	

Note: There are 516 daily observations. *BAS* is the daily average bid-ask spreads in cents/bushel. *Volume* is the daily total volume for the nearby and deferred series in thousands of contracts per day. *Volatility* is the daily standard deviation of the mid-quote of intraday bid and ask prices in cents/bushel. *Trend* is the absolute value of past 5-day cumulative close-to-open price changes in cents/bushel. The daily nearby (deferred) *spread* is the difference between the first (second) and the nearby (first) futures prices in cents/bushel using settlement prices. *Depth* is defined as the minimum of the daily average number of ask or daily average number of bid limit contract orders. *Open interest* is the number of outstanding contracts in thousand contracts per day. *Crude volatility* is the high-low range of corresponding nearby WTI crude oil futures.

Table 3.3. Regression Results for the Nearby Model

	BAS		*Volume*		*Volatility*	
	Estimate	t value	Estimate	t value	Estimate	t value
Intercept	0.1321***	6.17	63.067***	4.65	-1.8964*	-1.75
BAS_t			-186.508***	-4.09	8.9094**	2.54
$volume_t$	-0.0004***	-7.20			0.0156**	2.41
$volatility_t$	0.0060***	6.57	7.803***	7.71		
BAS_{t-1}	0.5065***	7.57				
$volume_{t-1}$			0.171***	4.32	-0.0059	-1.44
$volatility_{t-1}$					0.1700***	3.08
$Open\_interest_{t-1}$			0.067 ***	9.33		
$depth_t$	-0.0001	-0.71				
$trend_t$	0.0001**	2.47				
$spread_t$	0.0021***	4.40				
$Crude\_volatility_t$					0.1757***	3.76
RL	-0.0017	-0.76				
PD_WASDE	0.0092*	1.73			0.4023	1.47
GS	0.0379**	2.31			-0.0792	-0.16
K	0.0050*	1.76	2.933	1.24	-0.0843	-0.46
N	0.0110***	3.95	6.060**	2.37	-0.0130	-0.08
U	0.0054	1.10	-16.103***	-4.07	0.3147	1.05
Z	-0.0083***	-2.86	2.123	0.97	0.1110	0.68
Tue	0.0056*	1.91				
Wed	0.0023	0.84				
Thu	0.0067**	2.53				
Fri	0.0065**	2.32				
d.f.		497		506		503
Endogeneity test	*volume*	0.30	*volume*	-	*volume*	9.88***
	volatility	0.01	*volatility*	6.61***	*depth*	-
	depth	8.77***	*BAS*	8.82***	*BAS*	7.92***
Heteroskedasticity		83.56***		39.77***		20.02**
Autocorrelation		1.53		2.18		0.68
Weak identification		61.15**		84.24**		35.39**

Note: The asterisks ***,**,* indicate significance at the 1%, 5% and 10% levels. Test statistics are reported for each test. *BAS* is the daily average bid-ask spreads in cents/bushel. *Volume* is the daily total volume for the nearby and deferred series in thousands of contracts per day. *Volatility* is the daily standard deviation of the mid-quote of intraday bid and ask prices in cents/bushel. *Trend* is the absolute value of past 5-day cumulative close-to-open price changes in cents/bushel. The daily nearby (deferred) *spread* is the difference between the first (second) and the nearby (first) futures prices in cents/bushel using settlement prices. *Depth* is defined as the minimum of the daily average number of ask or daily average number of bid limit contract orders. *Open interest* is the number of outstanding contracts in thousand contracts per day. *Crude volatility* is the high-low range of corresponding nearby WTI crude oil futures. *RL* is a dummy variable for days that index funds roll their positions. *PD_WASDE* and *GS* are dummy variables for USDA report release dates. *K*, *N*, *U*, *Z* are dummy variables for contracts (May, July, September, December). *Tue, Wed, Thu* and *Fri* are weekday dummy variables.

Table 3.4. Regression Results for the Deferred Model

	BAS		*Volume*		*Volatility*	
	Estimate	t value	Estimate	t value	Estimate	t value
Intercept	0.2675***	8.35	20.684***	3.26	-3.4315***	-4.39
BAS_t			-98.636***	-6.49	12.5224***	5.80
$volume_t$	-0.0011***	-6.80			0.0517***	10.91
$volatility_t$	0.0072***	5.98	5.026***	7.12		
BAS_{t-1}	0.3760***	5.43				
$volume_{t-1}$			0.251***	4.11	-0.0185***	-4.77
$volatility_{t-1}$					0.1419***	2.87
$Open\_interest_{t-1}$			0.070***	7.08		
$depth_t$	-0.0008***	-6.55				
$trend_t$	0.0003***	4.00				
$spread_t$	0.0002	0.49				
$Crude\_volatility_t$					0.0752*	1.83
RL	-0.0115***	-3.64				
PD_WASDE	0.0102	1.16			0.3284	1.29
GS	0.0144	0.59			0.1226	0.19
K	0.0053*	1.71	3.640***	3.38	-0.1802	-1.12
N	0.0000	0.01	0.641	0.43	-0.1839	-0.99
U	0.0079*	1.93	-0.355	-0.33	0.0120	0.07
Z	0.0018	0.30	13.375***	3.80	-0.4207	-1.64
Tue	-0.0003	-0.09				
Wed	-0.0006	-0.17				
Thu	0.0029	0.94				
Fri	-0.0002	-0.05				
d.f.		497		506		503
Endogeneity test	*volume*	7.46***	*volume*	-	*volume*	1.76
	volatility	0.02	*volatility*	7.60***		-
	depth	0.05	*BAS*	0.62	*BAS*	0.42
Heteroskedasticity		99.83***		72.93***		21.02**
Autocorrelation		0.22		0.72		0.18
Weak identification		48.16**		71.68**		-

Note: The asterisks ***,**,* indicate significance at the 1%, 5% and 10% levels. Test statistics are reported for each test. *BAS* is the daily average bid-ask spreads in cents/bushel. *Volume* is the daily total volume for the nearby and deferred series in thousands of contracts per day. *Volatility* is the daily standard deviation of the mid-quote of intraday bid and ask prices in cents/bushel. *Trend* is the absolute value of past 5-day cumulative close-to-open price changes in cents/bushel. The daily nearby (deferred) *spread* is the difference between the first (second) and the nearby (first) futures prices in cents/bushel using settlement prices. *Depth* is defined as the minimum of the daily average number of ask or daily average number of bid limit contract orders. *Open interest* is the number of outstanding contracts in thousand contracts per day. *Crude volatility* is the high-low range of corresponding nearby WTI crude oil futures. *RL* is a dummy variable for days that index funds roll the positions. *PD_WASDE* and *GS* are dummy variables for USDA report release dates. *K, N, U, Z* are dummy variables for contracts (May, July, September, December). *Tue, Wed, Thu* and *Fri* are weekday dummy variables.

Table 3.5. Estimated Cross Elasticities for the Structural Model

Equation	*BAS*	*Volume*	*Volatility*	*Trend*	*Spread*	*Depth*	*RL*	*GS*	*PD_WASDE*	*Open Interest*	*Crude Volatility*
Nearby											
BAS	-	-0.07	0.05	0.01	0.08	-	-	12.07	2.93	-	-
Volume	-1.02	-	0.35	-	-	-	-	-	-	0.43	-
Volatility	1.09	0.35	-	-	-	-	-	-	-	-	0.24
Deferred											
BAS	-	-0.07	0.05	0.02	-	-0.10	-3.06	-	-	-	-
Volume	-1.51	-	0.52	-	-	-	-	-	-	0.76	-
Volatility	1.82	0.49	-	-	-	-	-	-	-	-	0.10

Note: The elasticities correspond to the primary variables with significant coefficients in tables 3.3 and 3.4.

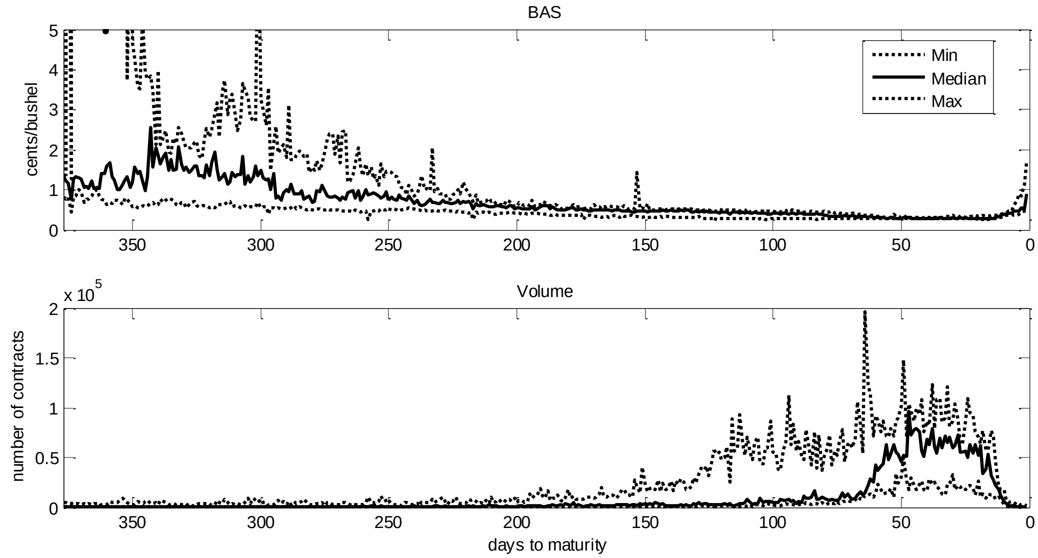

Figure 3.1. Maturity pattern of BAS and daily volume in 2009 contracts

Note: The BAS is truncated at 5 cents/bushel. The minimum tick size is 0.25 cents/bushel.

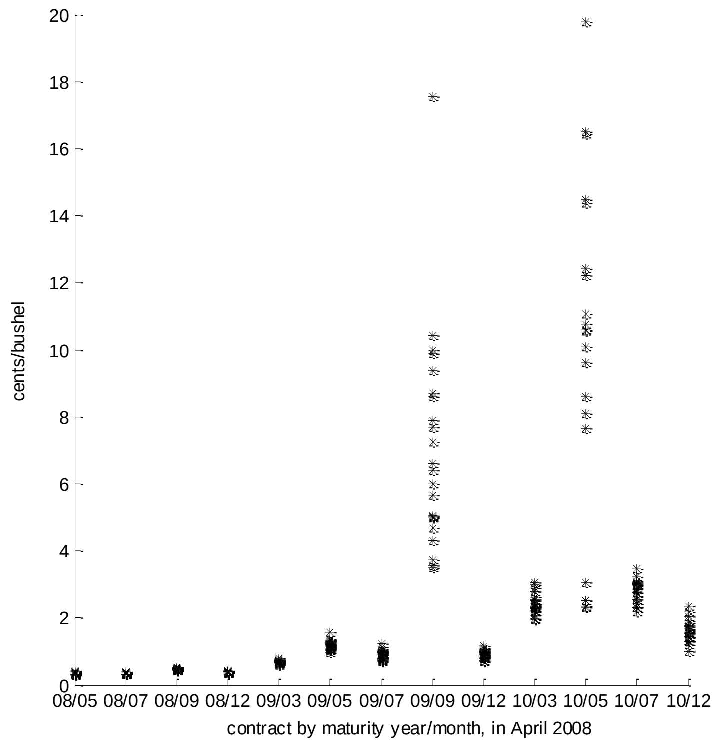

Figure 3.2 (a). BAS term structure April 2008 (N=22)

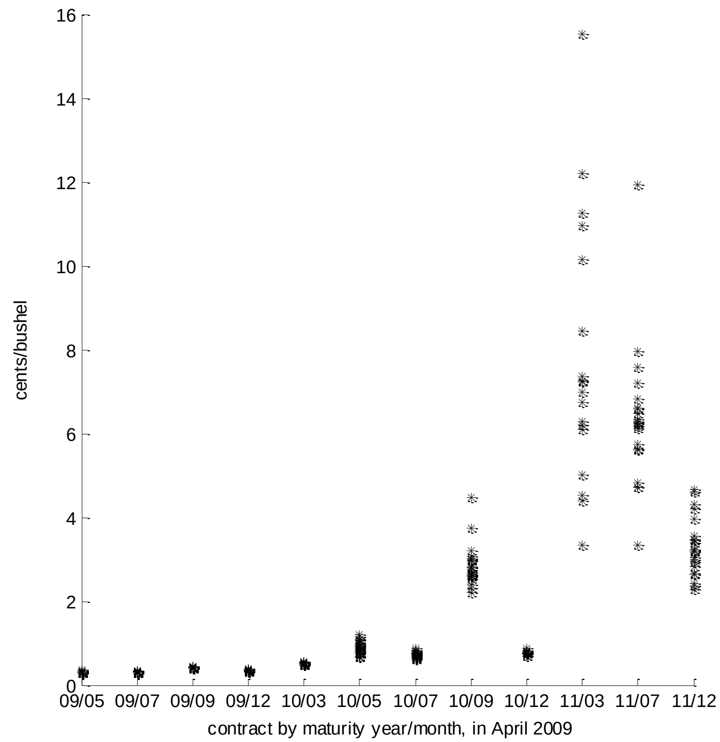

Figure 3.2 (b). BAS term structure April 2009 (N = 21)

Note: N is the number of trading days in April 2008 and April 2009. The minimum tick size is 0.25 cents/bushel.

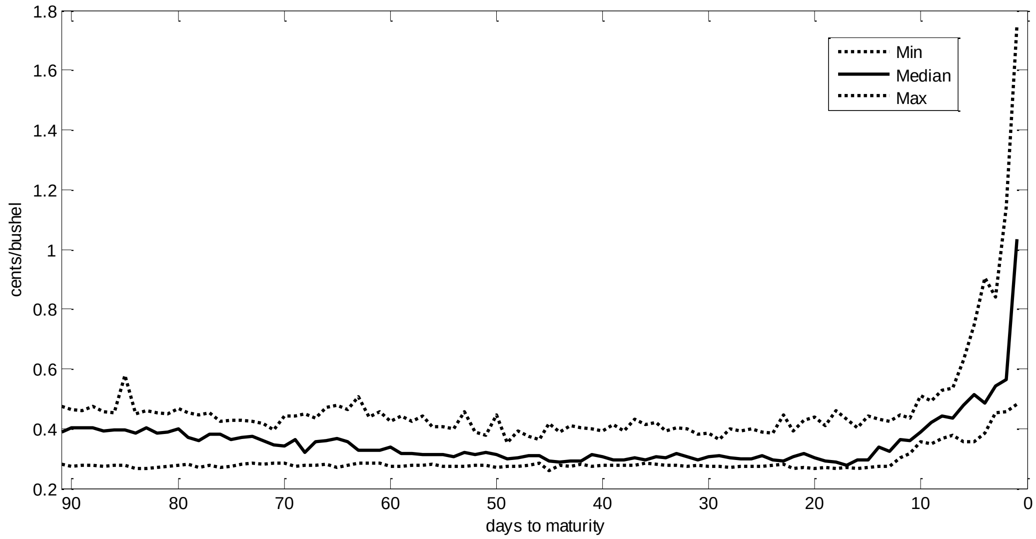

Figure 3.3. BAS in the last 90 trading days of 2008 and 2009 May, July, September and December contracts and the 2009 March contract

Note: The minimum tick size is 0.25 cents/bushel.

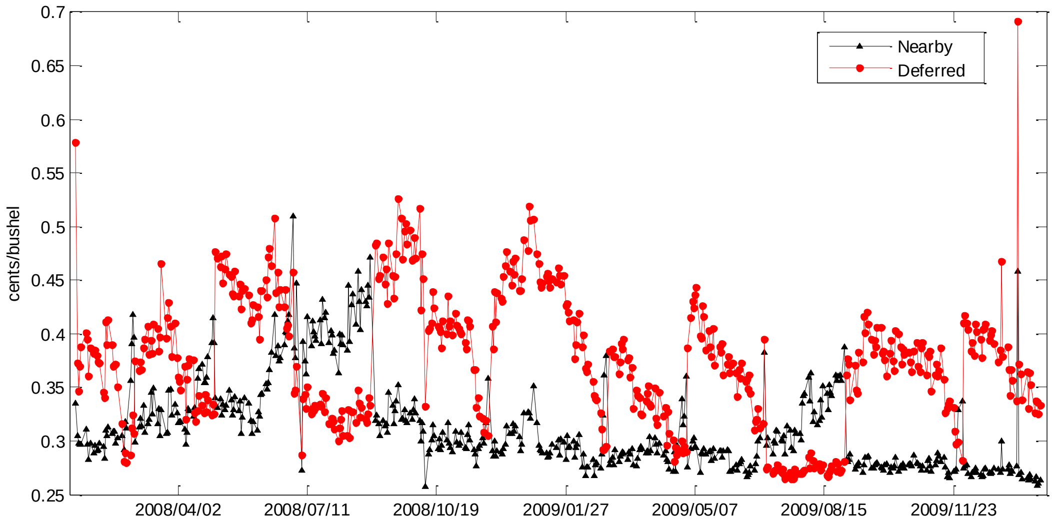

Figure 3.4. Daily average BAS for the nearby and deferred contracts

Note: Horizontal axis represents the minimum tick size, 0.25 cents/bushel

CHAPTER 4

ARE COMMODITY FUTURES GETTING NOISIER? – THE IMPACT OF HIGH FREQUENCY QUOTING

4.1 Introduction

Agricultural commodity futures markets have almost completely transitioned from an open outcry to an electronic trading platform. More than 90% of trading volume in major grains futures markets now occurs on electronic platforms (Irwin and Sanders 2012). Electronic markets are organized as a central open limit order book. Traders at each computer terminal can observe the current market, and participate by posting and revising their limit orders or placing market orders. While evidence is emerging that electronic markets provide an opportunity to moderate transaction costs (Wang et al. 2014), the transition also raises the potential for high speed activities that were not physically possible under a human open-outcry pit trading mechanism. As traders using high speed automated computer algorithms have emerged in electronic markets, they have caused concern over market quality, e.g. the price risk in order execution.

High frequency traders (HFTers) use predefined high speed computer algorithms to automatically execute orders and revise existing quotes (Easley et al. 2012). These algorithms can react to market changes in milliseconds or even microseconds. Because of their short reaction time, HFTers employ automated algorithms with little human monitoring. According to several Chicago Mercantile Exchange reports (CME Group 2010a and 2011), 16% of the total agricultural futures volume was generated by automated algorithms in January 2010, which increased to 26% by the end of 2010. Notably, 49% and 50% of the order messages in these two periods were generated by automated algorithms, suggesting that orders may have been placed to implement strategic trading objectives.

A notable change following the emergence of high frequency trading (HFT) is the way that liquidity is provided in electronic markets. Many HFTers function as liquidity providers (Fabozzi et al. 2011; Easley et al. 2012; Menkveld 2013). High frequency liquidity providers act like competitive scalpers in open outcry market and post limit orders on both bid and ask sides to gain the bid-ask spread (BAS) (Menkveld 2013), only at a faster speed incomparable with human actions. In effect, these traders arbitrage small price differences that emerge in the bid-ask spread and can make markets more effective. Another subset of HFTers also has emerged, referred to as predatory algorithms (Easley et al. 2012).[21] Predatory algorithms place strategic orders to trigger and exploit predictable price movements in the market microstructure. The strategic behavior of predatory algorithms transforms liquidity provision into a tactical game. In the presence of predatory algorithms, high frequency liquidity providers may have to cancel posted limit orders, and even liquidate positions to cut losses (Easley et al. 2012). The outcome is price quotes are updated at a high frequency rate (Hasbrouck and Saar 2013). Quote durations can be as short as several milliseconds, which are referred to as flickering quotes (Baruch and Glosten 2013). Following Hasbrouck (2013), we refer to this phenomenon as high frequency quoting. One feature of high frequency quoting is it generates more bid/ask quotes than transaction volume, which is shown in the higher portions of order messages compared to volume in CME futures markets.

[21] Predatory trading was first defined by Brunnermeier and Pedersen (2005) as trading activity that "induces and/or exploits the need of other investors to reduce their positions", which "leads to price overshooting and a reduced liquidation value for the distressed trader." Predatory algorithms is predatory trading in nature, but is most likely to occur at short time intervals as firms take advantage of locating computers near trading facilities.

High frequency quoting has caused concerns that automated high speed trading may harm market quality because liquidity can suddenly disappear, making it more costly for other traders to execute orders. The additional cost comes from the uncertainty of flickering quotes and is incurred by traders who manually place market orders. Consider an individual who intends to place a market order. A trader observes an ask price P_0 from time t-1 to t and decides to place an order to buy at P_0 (figure 4.1). However, during the t to t+1 period when the order is submitted, quotes from a HFTer are canceled and the ask price moves to P_1. In such a situation, the market order will either not be filled or be executed at a higher buying price P_1. Even if price remains at P_0 in t to t+1, when the HFTer cancels the limit orders, market depth is reduced which may result in a larger price impact.[22] As stated by a Wall Street Journal report, "*If the traders using those programs pull back from the market, then big 'buy' or 'sell' orders (from other traders) are effectively placed into a vacuum, leading to sudden, big swings.*"[23]

As a consequence, high frequency quoting can add excess noise (or volatility) to a market. Viewed in the context of figure 4.1, ask prices can fluctuate quickly between P_0 and P_1 for no apparent fundamental reason. In recent years agricultural futures markets have experience heightened volatility. Clearly, increased volatility has been related to changing fundamental supply and demand conditions in the underlying commodities, but little is known about the impact of automated trading and quoting noise. Despite limited information, public concerns that electronic markets are becoming noisy and unstable have led regulators to take steps to

[22] In the CME Globex trading platform, market orders are accompanied with a price protection band which prevents transaction price from further changes. For example, in corn futures, the price band is 20 ticks (5 cents/bushel), which means a market order can at most move price by 5 cents/bushel for each trade. More details on price protection band can be found in CME Rulebook 588.H. at http://www.cmegroup.com/rulebook/CBOT/I/5/5.pdf. https://www.tradingtechnologies.com/en/support/knowledge-base/1/1509/. CME has reduced the band in a list of financial indices futures in September 2012 but not in agricultural futures, http://www.cmegroup.com/tools-information/lookups/advisories/electronic-trading/20120904.html.

[23] 'Mini "Crashes" Hit Commodity Trade', Wall Street Journal, May 5th, 2011.

restrict the high speed traders.[24] Prior to pursuing costly regulatory policies, a primary question to ask is—How much does high frequency quoting affect execution uncertainty by adding noise?

This paper is the first to study the economic impact of high frequency quoting in agricultural futures markets. We refer to this impact as quoting noise, because it reflects the price uncertainty of order execution brought about by high frequency quoting. We ask two questions. First, does quoting noise exist and has it been increasing through time? Second, what is the economic magnitude? In other words, how much price risk will traders incur in order execution because of high frequency quoting? Answering these questions has significant policy implications on HFT regulation in the agricultural futures market.

We measure the noise by excess price variance and correlation in bid/ask price co-movement, which are directly related to high frequency quoting. Both measures are estimated from a wavelet-based short-term volatility model developed by Hasbrouck (2013). The method decomposes the quoted price into long-term price changes from fundamental information and short-term variations that are more related to high frequency quoting. In an efficient market, price follows a random walk process based on the arrival of information. Random walk implies the expected price variance increases linearly with time. In the presence of high frequency quoting, excess variance is measured by comparing the short-term price variance to that expected from a random walk process. From a variance decomposition perspective, we quantify the level of excess variance by comparing short-term price change variance with the normal variance level implied by fundamental information. Bid/ask co-movement discrepancy is also estimated using wavelet correlation from short- to long-term time scales to assess the degree that bid/ask price changes are related. Because HFT primarily involves posting and canceling limit orders within

[24] 'CFTC Moves to Rein In High-Speed Traders', Wall Street Journal, August 22nd, 2013.

short time intervals, we investigate high frequency quoting noise at second and sub-second time scales to reflect the HFT impact.

We answer the two research questions by analyzing the excess variance and bid/ask price discrepancy in the electronically-traded corn futures market for 2008-2013. Since 2009, this market has accounted for more than 90% of corn volume traded with a significant amount of automated trading. We use the Best Bid Offer (BBO) data from the CME group to calculate the volatilities. The BBO data contain all the records of quote activities at the top of the limit order book, and are time stamped to the nearest second. To investigate high frequency activities at sub-second scales, the millisecond time stamps are simulated using the Bayesian Markov Chain Monte Carlo method developed by Hasbrouck (2013). We estimate volatility on time scales ranging from 250 milliseconds to 34.13 minutes. On average at 250 milliseconds, excess variance is about 90% higher than normal and bid/ask price changes are related with a correlation of 67%. In terms of economic magnitude, net excess volatility – the square root of variance – is negligibly small at the 250 millisecond scale, ranging from 2.8% to 10.3% of a tick size and declines in the 2008-2013 period. For longer time scales, average excess variance declines below 5% in slightly more than 2 minutes and average correlation reaches 99% at the 32 second scale. These measures suggest that high frequency quoting noise is economically small and declining through the period.

In the following sections, we briefly review the limited relevant studies in agricultural futures markets as well as the more studied financial markets. Then we present the short-term volatility model and excess variance estimation formulas. Next, we describe the data, procedures and research design. Finally, we report and interpret the results.

4.2 Relevant Literature

There is very limited research on high frequency trading in agricultural futures markets. Only the CME Group has documented activities of automated trading for selected markets in January and the fourth quarter of 2010. The CME Group tracks traders registered in Automated Trading Systems, and records their volume and order messages. For aggregate agricultural futures, on average in January 2010, automated traders sent 17.5 messages to obtain 1 traded contract of volume, while for non-automated traders, the rate was only 3.3 messages/volume. The message/volume rates increased for both groups in the fourth quarter of 2010 with an average of 32.1 messages/volume for automated traders, which was still much higher than the 10.9 messages/volume for non-automated traders. The corn futures market was the only individual agricultural commodity specifically documented in the reports. The proportion of volume from automated traders increased from 26% to 32%. The proportion of order messages from automated traders increased from 48% to 65%, more than the proportional increase in volume. Message/volume rates in the two periods were 25.9 and 23.5 for automated traders and 9.6 and 6.0 for non-automated traders.[25] This evidence suggests that in agricultural and particularly corn futures markets, automated trading algorithms are likely to have employed high frequency quoting strategies, resulting in higher message/volume rates compared to non-automated traders. However, the CME reports did not identify the noise arising from high frequency quoting.

There are several studies on the quality of electronically-traded agricultural futures markets, but none consider the impact of high frequency quoting. Wang et al. (2014) study

[25] In January 2010 corn futures, CME reported the total number of messages was 4830845 and 48% of them (2323517) were from AT. It is suspected that the last digit was omitted because the message/volume rates were unrealistically small at 2.59 and 0.96 respectively in AT and non-AT. Multiplying the message numbers by 10 yields message/volume rates at 25.9 in AT and 9.6 in non-AT, which are more consistent with the observations in aggregate agricultural futures markets and in the fourth quarter of 2010 for corn futures markets.

liquidity cost measured by the bid-ask spread (BAS) on the electronically traded corn futures market. But their measure of daily average BAS does not capture the quoting noise at shorter time scales. Martinez et al. (2011) and Janzen et al. (2013) compare the quality of price discovery in an outcry market to electronic trading. They use methods to decompose transaction price volatility into parts that arise from fundamental information and transitory mispricing caused by microstructure frictions (Hasbrouck 1993, 1995; Gonzalo and Granger 1995). Smaller portions of transitory volatility suggest better market quality. However their studies do not reflect the impact of high frequency quoting directly because they rely on transaction prices to infer the transitory frictions and efficient prices. Since the amount of transactions is small compared to quoting activities in the order book, analysis based on transaction price may overlook the noise that can emerge in the quoting process.

More research on HFT exists in financial markets which sheds light on their activity. Easley et al. (2012) report that over 70% of U.S. cash equity and over 50% of futures transactions involve HFT. Strategies of HFTers are diverse and two important categories are predatory algorithms and liquidity-providing HFTers. Predatory algorithms profit by exploring opportunities from market microstructure. Due to the trading mechanism, certain actions are likely to trigger predictable market reactions. For example, Clark-Joseph (2013) identifies the existence of 'exploratory trading' in the S&P500 futures market. Predatory algorithms first test the market using small transactions to learn price responsiveness, and then place subsequent orders based on that information to profit from the predicted incoming orders. Other examples of predatory algorithms also exist including quote stuffing, quote dangling, liquidity squeezing et al. (Easley et al. 2012), which follow the same idea of exploring predictable market reactions. This behavior contrasts with liquidity-providing HFTers who gain the BAS by posting limit orders on both the bid and ask sides. Menkveld (2013) performs a case study using detailed records of a HFT firm. Findings reveal that the HFTer functions as competitive liquidity provider and earns profit from the BAS. When there are price moves, the HFT firm tends to lose money.

Interactions of predatory and liquidity-providing HFTers turn liquidity supply into a tactical game. Predatory algorithms can cause unwarranted price changes which can translate into losses for the liquidity-providing HFTer. Baruch and Glosten (2013) model the strategy of a liquidity-providing HFTer in the presence of a predatory HFTer. In their theoretical model, high frequency liquidity providers need to quickly cancel or replace posted limit orders to reduce risk. High frequency quoting becomes the optimal strategy for a liquidity-providing HFTer in equilibrium, which results in short quote durations. Observations from other studies confirm the existence of high frequency quoting. Hasbrouck and Saar (2013) use stock market data with order messages time-stamped in millisecond to describe the whole order book activity. They find 90% of submitted limit orders are canceled with some orders only lasting for 2-3 milliseconds.

There is very limited empirical study on the high frequency quoting noise. Only Hasbrouck (2013) develops a wavelet-based short-term volatility model to estimate noise from top-of-the-book bid/ask prices using a stock market Best Bid Offer (BBO) dataset. Noise is measured by excess variances and bid/ask price discrepancies, which are estimated across different lengths of time scales from 50 milliseconds to 27.3 minutes. Observations from each day in April are combined to form monthly series which are used to estimate excess variance for each April in 2001-2011. The level of excess variance is the highest at 50 milliseconds and decreases with time scale. It eventually disappears at the longest 27.3 minutes scale. Highest noise is identified in 2004-2006, which is a period of transition to electronic trading and adaption to a new regulation policy (Reg NMS). For 150 representative stocks, average excess variance at 200 milliseconds scale is 7.5 times of the normal level implied from a random walk. After the transition is completed and Reg NMS is implemented, excess variance persists but falls to a lower and stable level. In 2008-2011, average excess variance is 4.2 times the normal level. Hasbrouck (2013) further breaks down the 150 stocks into five groups by trading volume and reports the average estimates for each group in April 2011. Results show high frequency quoting noise is lower in highly traded stocks. At 200 milliseconds, from the most- to least-traded group, excess variance increases from 1.3 to 10.4 times the normal level, while bid/ask price correlation decreases from 0.65 to 0.11.

More HFTer participation does not necessarily mean worse market quality, e.g. higher noise. Baruch and Glosten (2013) show theoretically that while it is optimal for an individual liquidity-providing HFTer to quickly post and cancel limit orders, at an aggregate level the best bid/ask prices may change little. If there are sufficient participants, new limit orders from other liquidity-providing HFTers will enter the market when existing ones are cancelled. When canceled orders are immediately replaced, top-of-book bid/ask prices can remain almost unchanged. As a result, high frequency quoting noise can be small even in the presence of HFT. The theory explains Hasbrouck's (2013) findings that excess variance is lower in deeply traded stocks and in 2008-2011 despite more HFT in recent years. Easley et al. (2012) also make the empirical observation that liquidity-providing HFTers and low frequency traders can strengthen their positions by using strategies to reduce the impact of predatory algorithms, e.g. monitor order flows to infer potential disruptions. They further predict that predators (predatory algorithms) and prey (liquidity-providing HFTers and other low frequency traders) will adapt and evolve toward a market equilibrium characterized by stable liquidity and effective price discovery. In a review of previous findings, Fabozzi et al. (2011) summarize that more competition between liquidity-providing HFTers adds liquidity to the market and reduces liquidity cost. In this context, they argue that the noise from high frequency quoting can be viewed as a cost of maintaining bid/ask spreads at a low level and price discovery effective.

4.3 Wavelet Based Short-Term Volatility

The short-term volatility model (Hasbrouck 2013) is constructed in a variance decomposition framework. The variance decomposition serves as the baseline for evaluating the noise from high frequency quoting. To begin, suppose during a time interval *s*, there are *n* quotes. For the interval from time *t*-*s* to *t*, price deviations are $R(n,t,s) = p_i - S(n,t)$, where $S(n,t) = \frac{\sum_{i=0}^{n-1} p_{t-i}}{n}$ is the mean price. The corresponding mean squared price deviation in *s* is $MSD(n,t) = \sum_{i=0}^{n-1}[R(n,t,s)]^2/n$. Let the length of interval *s* increase at dyadic pattern (i.e., increasing at power of 2, e.g., 1, 2, 4, 8 seconds). Starting with an interval length s_1, a series of sampling time scales can be defined as $s_j = s_1 2^j$, $j = 1, 2, \ldots J$. In a random walk, price innovations follow a stationary and stochastic process. The expected $MSD(n,t)$ equals the variance of the deviations $R(n,t,s)$ for corresponding time scale s_j, which is finite and invariant given the length of interval.

Two measures of price variance can be defined, a rough variance and a wavelet variance. The rough variance σ_j^2 represents cumulative price variations for a specified time scale s_j.

$$\sigma_j^2 \equiv E[MSD(n,t)] = Var[R(n,t,s)]. \qquad (4.1)$$

Correspondingly, wavelet variance is defined as the increment of price variance moving from s_{j-1} to s_j.

$$v_j^2 = \sigma_j^2 - \sigma_{j-1}^2. \tag{4.2}$$

Wavelet is a mathematical method that describes variation patterns related to changes in time scale. Hasbrouck (2013) names v_j^2 as wavelet variance because it emphasizes price variance changes arising as the time scale increases. For convenience of economic interpretation, we further define the square root of σ_j^2 and v_j^2 as rough and wavelet volatility (σ_j and v_j), which are in units of cents/bushel, the value used in the corn futures market.

Rough variance measures the total price variance at a given time scale length and can be split into two parts. One part corresponds to information arrival. Information leads price to follow random walk, which implies the informational variance increases linearly with time. The other part corresponds to market microstructure frictions which are not related to information (Stoll 2000). Frictions can arise from costs for immediate transactions, e.g. the BAS (Stoll 2000), discreteness of minimally allowed price changes–tick size, and high frequency quoting which generates noise in quoted prices and aggravates frictional variance by frequently posting/canceling orders at high speed. Because of strategic interactions between predatory and liquidity-providing HFTers, price movement in short time intervals will exceed the level implied from a random walk due to high frequency quoting (Easley et al. 2012).

The relative portions of informational and frictional variances can change as the time scale expands. Since price follows a random walk, the informational variance contained in that scale increases monotonically. In contrast, frictional variance is likely to be more stable. In order to attract transactions, liquidity-providing HFTers can only post and revise quotes within the range defined by the prevailing best ask and bid prices because quotes outside the top of order book will not likely match incoming market orders. As a result, frictional variance is influenced by the size of BAS. In a liquid market, frictional variance is likely to be small due to stable liquidity costs. Hasbrouck (2013) argues that the price range for high frequency quoting should not be substantially larger than the magnitude of BAS. Following the expansion of time scale, informational variance continues to increase while frictional variance stabilizes. Thus, at short horizons (e.g. at 1 or 2 minutes scale), the relative size of frictional variance to informational variance can be large. In particular, quoting noise from HFT tends to concentrate in the extremely short scales like seconds and sub-second levels. But the long-term price variance (e.g. at 20 to 30 minutes scale) is dominated by fundamental information and price changes that exceed the size of BAS.

Because long-term price variance is dominated by information, wavelet variance at the longest time scale (v_J^2) reflects the effect of fundamental information. To see this point, at the two longest time scales s_{J-1} and s_J, rough variances σ_{J-1}^2 and σ_J^2 contain the same amount of frictional variance because it stabilizes at long time scales. Wavelet variance $v_J^2 = \sigma_J^2 - \sigma_{J-1}^2$ strips off the common frictional variance from the longest time scale s_J and represents the variance purely from fundamental information. From a variance decomposition perspective v_J^2 represents purely informational variance from the random walk. The degree of excess variance can be evaluated by comparing variances at smaller time scales to the random walk implied variance, which gives a measure of high frequency quoting noise.

To compare variances from different time scales with the benchmark v_J^2, we need to find the time scaling factors. For a purely random walk process, let the price variance per unit of time be σ_u^2. In this hypothetical case there is no frictional variance. Hasbrouck (2013) demonstrates that σ_u^2 has the following relationship with the wavelet variance

$$v_j^2 = 2^{j-2} s_1 \sigma_u^2 / 3 \tag{4.3}$$

and with rough variance

$$\sigma_j^2 = 2^{j-1} s_1 \sigma_u^2 / 3. \tag{4.4}$$

The scaling relationship between wavelet and rough variances across averaging intervals establishes the foundation for assessing excess quoting variance. Hasbrouck (2013) proposes two measures. The first one is the wavelet variance ratio defined as

$$V_{j,J} = 2^{J-j} v_j^2 / v_J^2. \tag{4.5}$$

This is the wavelet variance from each time scale divided by the random walk implied variance adjusted for time scale. The second measure is similarly defined. The rough variance ratio is rough variances divided by the same denominator

$$VR_{j,J} = 2^{J-j-1} \sigma_j^2 / v_J^2. \tag{4.6}$$

Both wavelet and rough variance ratios assess the degree of excess high frequency variance. If price is a random walk process, then based on the scaling relationship from equations (4.3) and (4.4), both variance ratios $V_{j,J}$ and $VR_{j,J}$ always equal unity for each interval, $j = 1 \ldots J$. The more the variance ratios exceed 1, the higher the excess variance. Notice $v_j^2 = \sigma_j^2 - \sigma_{j-1}^2$ strips off the frictional variance contained in time scale j-1 and measures the net increment of frictional variance from time scale change $s_j - s_{j-1}$. Thus v_j^2 provides a better reflection of the level of frictional variance at each time scale as it expands from s_1 to s_J. For this reason we rely on $V_{j,J}$ as the major gauge of excess variance and use $VR_{j,J}$ for complementary information.

Short-term variances have direct economic interpretations since they quantify the high frequency quoting noise. Consider a trader who intends to place a market order. From the time she decides to place an order until the order is executed, she faces all the price variation risks within the time s_j. This type of risk is measured by the rough variance which contains both informational and frictional variations. Wavelet variance identifies the incremental effect of time scale changes. For many reasons, an order can take time to execute (e.g. more time to make decision, or a delay in electronic traffic to route an order message). If order execution time expands, the additional price risk is represented by wavelet variance.

We propose a measure of the economic impact of high frequency quoting at each time scale by comparing the standard deviation of net excess variance to the tick size on a percentage basis. This measure reflects the degree of variability that a trader can expect relative to the minimum change in prices allowed by the exchange for a particular time scale. To develop this measure we need to scale back the informational variance from s_J to s_j, and subtract it from estimated variance υ_j^2 and σ_j^2, which are composed of both frictional and informational variances. Because of the monotonic characteristics of informational variance, scaling can be accomplished by dividing the wavelet variance at longest scale υ_J^2 – which consists of only informational variance – by the scaling factors of 2^{J-j} and 2^{J-j-1}, in equations (4.5) and (4.6). The random walk implied variances can be calculated as $\hat{\sigma}_j^2 = \upsilon_J^2/2^{J-j-1}$ and $\hat{\upsilon}_j^2 = \upsilon_J^2/2^{J-j}$. Subtracting the scaled informational variance from υ_j^2 and σ_j^2 provides the net excess variance at that time scale, and their standard deviations put them into monetary values which we compare to the tick. The net excess wavelet and rough variances are $\upsilon_j^2 - \hat{\upsilon}_j^2$ and $\sigma_j^2 - \hat{\sigma}_j^2$, and we report their standard deviations $\sqrt{\upsilon_j^2 - \hat{\upsilon}_j^2}$ and $\sqrt{\sigma_j^2 - \hat{\sigma}_j^2}$, which are in cents/bushel. Similar to variance ratios, we rely on the net excess wavelet volatility because it captures the frictional variance for that particular scale s_j.

In addition to the two measures on excess high frequency variance, Hasbrouck (2013) proposes a third statistic based on bid/ask price co-movements. The wavelet correlation between bid and offer quotes is defined as

$$\rho^j = v_{b,o,j}^2 / \sqrt{v_{b,j}^2 v_{o,j}^2} \tag{4.7}$$

where $v_{b,o,j}^2 = \sigma_{b,o,j}^2 - \sigma_{b,o,j-1}^2$. $v_{b,o,j}^2$ and $\sigma_{b,o,j}^2$ are the wavelet and rough covariances between bid and ask prices at time scale s_j. $v_{b,j}^2$ and $v_{o,j}^2$ are respectively the wavelet variance of bid and ask prices at s_j. Wavelet correlation intends to assess the degree that bid and ask prices co-move with each other across time scales. Hansen and Lunde (2006) illustrate that when price is purely driven by fundamental information with no frictional noise, bid and ask prices should shift in the same direction and by the same amount. If bid and ask prices follow closely in moving up and downs in a ‘lock step’ pattern, the wavelet correlation equals to 1. In the presence of market friction, discrepancies can occur and the bid/ask movements tend to be separated. In the sub-second scales, high frequency quoting noise is the major force that separates bid/ask co-movement. Other factors like volume and price volatility can also affect the bid/ask co-movement through their impact on the BAS. However, Wang et al. (2014) study a broad range of determinants of daily BAS and find their impacts are small. Particularly in nearby contracts, daily BAS is stable and impervious to changes in its determinants. Thus reduced wavelet correlation mainly reflects the high frequency quoting noise. The larger the deviation from 1 in the correlation ρ^j, the higher is the quoting noise.

4.4 Data Description and Preparation Procedures

We use the BBO data in electronically traded corn futures from the CME. The BBO dataset provides electronic Globex trading orders for each active contract. It contains the best bid prices paired with best ask prices (the top-of-book quote) with a time stamp to the nearest second. When a better bid or ask price enters the market or when the number of contracts available for trading at those prices changes, a new pair of best bid price and best ask price are recorded along with the number of contracts available. Similar data have been used by Hasbrouck (2013) to generate short-term volatility estimates in the electronic stock market. The BBO data in the CME futures have even better quality. Because there is only one centralized limit order book for commodity futures in CME, there is no fragmentation problem compared to the stock market, where errors can arise from affiliated markets routing orders to the central one.

We study corn futures because it is the most actively traded agricultural contract and the only individual agricultural market with reported automated trading by CME Group. The sample period is from January 14, 2008 to November 29, 2013, with more than 90% of total volume is from electronic trading (Irwin and Sanders 2012). Since CME reports more than half of the quote messages were from automated programs in January 2010 and it substantially increased in the fourth quarter of 2010, it is quite likely that HFT existed in this period and their activity has increased with time. Corn futures have five maturities a year: March, May, July, September and December. On each trading day, about ten to twenty contracts are traded. The number of bid/ask quote records differ across contracts. But typically, for a nearby contract, more than forty thousand pairs of quote records are recorded each day. CME runs both daytime and evening sessions in corn futures, and we focus on the daytime session since it is the most actively traded.

In this period, more than 90% of volume is traded in daytime session. The minimum allowed price change is one tick, which is 0.25 cents/bushel in the CME Group corn futures market. The tick size is much wider than the uniformly adopted tick size of 0.01 cents/share in stock markets.

The BBO data do not provide sub-second time stamps, but do identify all quotes in sequential order within each second through a trading session. Figure 4.2 displays the quote records from the 2010 March corn futures contract during the first 5 seconds interval from 9:30:01 am to 9:30:05 am, January 29, 2010. A total of 70 pairs of matching bid and ask prices are recorded. Within each second, there are multiple records listed in order. The 19 quote records stamped at 9:30:01 am take place in the 1 second interval from 9:30:01 am to 9:30:02 am.

4.4.1 Simulation of the Sub-second Time Stamp in the BBO Data

To study the high frequency quoting noise at the sub-second time scale, we use the Bayesian Markov Chain Monte Carlo (MCMC) procedure proposed by Hasbrouck (2013) to simulate the sub-second time stamps (See details in Appendix A). Hasbrouck (2013) assumes that quote updates arrive in a Poisson process of constant intensity, which is a widely used assumption in limit order book modeling literature (Foucault et al. 2005; Biais and Weill 2009; Rosu 2009). Then for the total number of records n in a particular time interval, the time length between any two updates follows a uniform distribution due to the randomness of updates. The number of records n defines the posterior distribution for the time length between updates, and the discrete probability density function is 1 for each second. The millisecond time stamps are simulated by making n random draws for that second. The n simulated stamps are then sorted into an ascending order and matched to each record.

Hasbrouck (2013) compares actual records time-stamped to milliseconds with estimates from simulated time stamps. The simulation produces a good fit to the real time stamps. At 50 milliseconds, correlation between wavelet variances estimated using real and simulated time is 0.78. It rises to 0.98 at 200 milliseconds scale. The less compelling performance at smaller time scale is due to the sensitivity of time alignment. Because there are fewer observations at the smaller time scales, ascribing observations from one time interval to another can make a bigger difference in calculating the variance for that interval. For example, moving records from the first 0.5 second to the next 0.5 second may change variance estimates at the half second scale but does not affect the 1 second scale.

4.4.2 Concentration of Intraday Quoting Activities

In commodity futures markets, trading activity is usually higher at the beginning and ending periods of a trading session. For example, in corn futures, Lehecka et al. (2013) find both volume and volatility are strongly U-shaped in the daytime trading session. Quote activity shares similar intraday concentrations. In figure 4.3, we plot intraday bid/ask quotes of the 2010 March corn futures contract in each minute for the 19 trading days in January 2010. The median, 10% and 90% quantiles are consistently U-shaped.

The pattern of quote concentration affects variance estimates. Higher trading activity and volatility at the market open often reflect price adjustment in response to the accumulated overnight information rather than the normal information arrival rate. Similarly, higher trading levels before the market close reflect adjustment to the expected overnight information after market closure. Since trading concentrations at neither the open nor the close reflect the normal information arrival rate during trading session, records in both periods need to be removed for accurate estimation of rough variance. Hasbrouck (2013) recommends excluding records in the first and last 15 minutes to remove the effects of these deterministic patterns. We follow his strategy in this analysis. The daytime trading session is from 9:30 am to 1:15 pm for corn. After removing the first and last 15 minutes with higher quote activity, we keep the records from 9:45 am to 1:00 pm.[26]

4.4.3 Removing Inter-day Price Jumps and Limit Move Days

Another potential problem emerges when combining observations from each day to construct one nearby series for a contract. Information arrives not only during trading sessions, but also when the market is closed. As a result, the price at the market open often jumps from the previous day's closing price. Combining intraday records across days can create spikes and jumps where the data are merged. For example, the upper panel of figure 4.4 combines the best bid prices of the 2010 March contract in the 58 trading days from 12/1/2009 – 2/26/2010, after discarding the first and last 15 minutes for each day. Significant downward trends and inter-day price changes can be observed. On one occasion, the price made a limit move at the market open and dropped from 4.2 to 3.8 dollars/bushel in two days. Inter-day price jumps lead to biases in estimating wavelet correlation and variance ratios and create artificially high bid/ask wavelet correlations from the trending pattern. Jumps also exaggerate variance estimates by incorporating open-close price changes from overnight information, which complicates measuring variance ratios.

[26] Since May 2012, CME Group has changed corn futures trading hours several times, such as extending the ending time to 2 pm (May 2012) and shortening it back to 1:15 pm (April 2013). For details of the changes, see Kauffman (2013) and Lehecka et al. (2013). We use the 9:45 am–1:00 pm time window to consistently compare in the full sample period.

To remove the jump between the last price observation of day *k* and the first price of day *k*+1, we subtract the first-last price gap from the price series of day *k*+1 for all prices in day *k*+1. In this way, the first price of day *k*+1 equals the last price of day *k* and the inter-day price jump is removed. The combined price series should follow a random walk in the two-day window because connecting two random walk series with the same distribution produces a random walk series. We perform the procedure sequentially to combine prices from multiple days into one series.

We also exclude observations involving limit price moves. In many days the price makes a limit move and stays as a straight line. Three examples can be found in the upper panel of figure 4.4, which are 12/21/2009, 1/12/2010 and 2/8/2010. Price discovery stops arbitrarily and price variance is zero, which fails to reflect the actual informational variance. We use the intraday high-low range and inter-day open-close difference to select days that price possibly reaches limit moves. Then we check each selected day whether the price just hits the price variation bound or stays at the bound as a straight line. Only if price stays a straight line do we exclude observations in that day. In total, we exclude 42 days in the nearby corn futures series.

The lower panel of figure 4.4 plots the combined series of the 2010 March contract after removing inter-day price jumps and three limit move days. Compared to the original series, the price high-low range reduces from over 70 cents/bushel to less than 35 cents/bushel, which gives a better estimate of price variance during trading sessions. The observed downward price trend is also eliminated which can reduce the bias in wavelet correlation estimates.

4.5 Research Design

We use prices from the nearby contract until the maturity month because they are usually the most actively traded in the corn futures market. Wang et al. (2014) show the level of trading volume in the nearby period is stable until the maturity month, and then begins to migrate to the next maturity contract. As most volume is generated in the nearby period, HFTers are more likely to participate in a deeper market where it is easier to attract transactions.[27]

We estimate the short-term volatility model using the simulated millisecond time stamps. We start from s_1=250 milliseconds and reach the longest length at $s_J \approx 34.13$ minutes, where J=14 and s_j increases dyadically. The two sub-second scales – 250 and 500 milliseconds – are particularly relevant in examining the effect of high frequency quoting. We do not use smaller intervals, e.g. 125 milliseconds, because Hasbrouck (2013) shows in his BBO data, wavelet variances based on the simulated time conform better to the real time stamps at larger time scales, e.g. above 200 milliseconds. The upper time scale limit needs to be sufficiently long to allow frictional variance to stabilize and fundamental information to dominate price variance. For these reasons, we set the upper limit at 34.13 minutes, which is the closest length to the 27.3 minutes upper scale selected by Hasbrouck (2013). Rough volatility at this time scale should be sufficiently larger than the average BAS and variance ratios are expected to stabilize irrespective of using longer upper time scale length. As a robustness check, we also compare the variance ratios with others from using 17.07 minutes and 68.27 minutes as upper limits to check if it stabilizes as expected.

[27] Consider the December 2009 corn futures contract, its nearby period is from mid-September to mid-December. To avoid the reduced trading in maturity month, we use observations from September 1st to November 30th 2009. We use the same strategy on other contract maturities as well.

We take two steps to answer the research questions. First, we estimate the short-term volatility model with a selected nearby contract and interpret the results. We combine observations from each day to construct continuous bid/ask series and estimate the rough and wavelet variances, variance ratios and wavelet correlations. Hasbrouck (2013) takes a similar approach by combining stock market data in April 2011 to obtain monthly short-term volatility estimates. From the estimates, we examine the magnitude of high frequency quoting noise with economic interpretations on the estimated variance ratios, correlations and volatilities.

Second, we study high frequency quoting noise for each nearby contract through the sample. Continuous bid/ask series are constructed in the nearby period for each contract. In tracking the nearby contract series, we rely on wavelet variance ratio $V_{j,J}$, rough variance ratio $VR_{j,J}$ and wavelet correlation ρ^j at sub-second levels because high frequency quoting impact is higher at the smallest time scales. We plot $VR_{j,J}$, $V_{j,J}$ and ρ^j through the sample period to identify annual or seasonal patterns. The net excess volatility is compared with the tick size to examine its changes through time.

We use the Maximal Overlapping Discrete Wavelet Transformation (MODWT) method developed by Percival and Walden (2000) to calculate the variance estimates (Appendix B). Wavelet variances can also be calculated directly by the formula of MSD and equation (4.2). However it is less efficient because taking maximal overlapping wavelet transformations averages all possible time alignments. For example, for a 1 second scale variance, it calculates not only the 1 second intervals from t-1 to t, but also other alignment possibilities such as t-0.5 to t+0.5. In this computation, we use the discrete Haar wavelet filter as recommended by

Hasbrouck (2013) for its simplicity and robustness. Variance estimations are carried out separately for the bid and ask series.

4.6 Results

We report results in two parts. First an illustration is made on the short-term volatility estimation results. Next we examine variations of variance ratios and wavelet correlation through the period.

4.6.1 An Illustration of Quoting Noise Estimates

We begin with an illustration using the 2010 March contract. The data combine the nearby daily observations for 12/1/2009 – 2/26/2010 as demonstrated in the data preparation procedures. The bid series is plotted in the lower panel of figure 4.4. In total there are 2670281 bid/ask quote records, an average of about 4 records per second. We choose this period because CME reports significant automated trading activity in January 2010 which is covered in this nearby contract. The average BAS is 0.272 cents/bushel, which is calculated as the difference between ask and bid prices following Wang et al. (2014).

Table 4.1 contains the estimated rough and wavelet volatilities, variances, variance ratios and wavelet correlations at time scales from 250 milliseconds to 34.13 minutes. Volatilities, variances and variance ratios are the average of bid and ask series since their results are almost identical. Rough and wavelet volatilities (σ_j and ν_j) are square roots of rough and wavelet variances, respectively, and are in cents/bushel. The two variance ratios are calculated using equations (4.5) and (4.6). They are generally consistent in magnitude across time scales and decline at longer time scales. At the longest scale the wavelet variance ratio converges to 1 and rough variance ratio $VR_{14,14}$ differs by only 2.7%. Wavelet correlation begins at 0.642 and converges quickly to 1. The patterns are consistent with expectations and similar to the results of Hasbrouck (2013) on stock market data.

Rough and wavelet volatilities can be directly interpreted from their economic units. For a hedger placing a market order, execution price can change from the observed price during the time of order execution. Rough volatility is the standard deviation of price changes during execution. If an order is executed within 250 milliseconds, execution price has a standard deviation of σ_0=0.014 cents/bushel. When the execution window expands to exactly 250 milliseconds, price standard deviation increases to σ_1=0.022 cents/bushel. If it takes a hedger 34.13 minutes to decide and make the transaction, average price standard deviation is 1.452 cents/bushel. If an order takes an additional 250 milliseconds to be completed, the additional price volatility occurring in this interval is measured by wavelet volatility v_1=0.017 cents/bushel. As expected, the additional volatility increases with time scale. At the longest time scale *J*=14, the additional price volatility occurring in 17.07 minutes ($s_{14} – s_{13}$) is v_{14}=1.013 cents/bushel. It also represents the average price standard deviation purely from fundamental information in the 17.07 minutes interval.

Both wavelet and rough variance ratios show excess variance at small scales, which indicates the existence of high frequency quoting noise. From the generally declining pattern of variance ratios, the highest noise is identified in the sub-second scales. Wavelet variance ratio suggest that variance at the 250 milliseconds scale is $V_{1,14}$ = 2.272 times of the normal variance level implied from fundamental information. At 500 milliseconds, the ratio is still high at $V_{2,14}$ = 1.926. Because HFT primarily occurs in the millisecond environment, excess variance at the two sub-second intervals (250 and 500 milliseconds) indicates high frequency quoting impact exists.

The impact dissipates quickly. Starting from the 32 seconds scale, the net excess variance is less than 5% of the normal variance as the wavelet variance ratio falls to $V_{8,14}$ = 1.049. Rough variance ratio shows a similar structure. $VR_{1,14}$ = 1.871 and $VR_{2,14}$ = 1.898 identify excess variance at sub-second scales. Net excess rough variance also falls quickly toward unity and reaches below 5% at the 2.13 minute scale.

Despite the high variance ratios up to the 1 second time scales, the magnitude of high frequency quoting noise is small. Solving backward, the random walk implied wavelet and rough volatilities at 250 milliseconds are $\hat{\upsilon}_1$=0.011 and $\hat{\sigma}_1$=0.016 cents/bushel, which are about two thirds of the estimated wavelet volatility υ_1=0.017 and rough volatility σ_1=0.022. We compare the net excess wavelet ($\sqrt{\upsilon_j^2 - \hat{\upsilon}_j^2}$) and rough ($\sqrt{\sigma_j^2 - \hat{\sigma}_j^2}$) volatility to the tick size.[28] The net excess volatility enlarged by high frequency quoting is small compared to the minimally allowed price change. From 250 milliseconds to 1 second time scales, the net excess wavelet volatility is 5.1% to 7.1% and net excess rough volatility is 5.9% to 11.5% of the tick size. Up to the 1 second level, though variance ratios are the highest across all time scales, the economic impact of excess high frequency quoting variance is small.

Wavelet correlations similarly demonstrate the quoting noise quickly disappears following time scale increase. The co-movement discrepancy between bid/ask prices is higher at smaller time scales. At 250 milliseconds, ρ^1=0.642 suggesting almost 40% of the bid/ask quotes are moving in the other direction or lagging behind changes on the other side. The correlation quickly increases to nearly 90% at the 2 second time scale. By the 32 second scale, bid/ask series

[28] We use the tick size for comparison, but other reference prices such as the magnitude of limit price movements or average daily prices could have been used. We selected the tick size for its simplicity and because it remains constant, making comparisons through time easier.

move together at 99%. Wavelet correlations corroborate the finding in variance ratios that the price movement discrepancies primarily exist at sub-second scales and disappear for intervals above half minutes.

As a robustness check, we compare variance ratios calculated using 34.13 minutes as the upper limit with two alternative upper limits of 17.07 and 68.27 minutes (Appendix C). The biggest differences are at the smallest scale of 250 milliseconds ($V_{1,J}$ and $VR_{1,J}$), and decrease with time scale to $V_{J,J}$ and $VR_{J,J}$. Focusing on the 250 milliseconds scale with the largest difference, rough and wavelet variance ratios are $V_{1,13}$ =2.144 and $VR_{1,13}$ =1.765 using 17.07 minutes as upper limit. When using 34.13 minutes as upper limit, both variance ratios slightly increase to $V_{1,14}$ =2.272 and $VR_{1,14}$ =1.871. The increase is even smaller when using 68.27 minutes as upper limit which are $V_{1,15}$ =2.349 and $VR_{1,15}$ =1.934. Because frictions are limited by the size of BAS, frictional variance stabilizes following time scale expansion. At the 34.13 minutes upper limit, σ_{14} = 1.452 cents/bushel is five times of the BAS. It is likely to be long enough for frictional variance to stabilize and results in smaller variance ratio changes to 68.27 minutes than to 17.07 minutes. At other time scales for j = 2…13, differences between $V_{j,14}$ ($VR_{j,14}$) and $V_{j,15}$ ($VR_{j,15}$) are even smaller. The comparison results suggest variance ratios stabilize at the 34.13 minutes upper limit. Thus in the following analysis, we use the 34.13 minutes upper limit with J=14.

4.6.2 High Frequency Quoting Noise through Time

To examine changes in the high frequency quoting noise through time, we follow the same procedure by estimating the short-term volatility models for each contract. Variance ratios and wavelet correlations for each contract are calculated and average values are generated for 2008-

2013 period (Table 4.2). Average wavelet variance ratios for all 30 contracts are 1.90, 1.56 and 1.46 from 250 millisecond to 1 second scales, which means variances at these three scales are on average 90%, 56% and 46% higher than normal level. The highest variance ratios consistently appear at the 250 milliseconds scale. Average correlations for the period are 0.67, 0.75 and 0.82 for the 250 millisecond, 500 millisecond, and 1 second scales. Lowest wavelet correlation consistently appears at 250 milliseconds and ranges from 0.36 to 0.91. Consistent with estimation results for the 2010 March contract, average wavelet and rough variance ratios quickly fall below 1.05 at 2.13 and 4.27 minutes respectively, and average wavelet correlation reaches 99% at 32 seconds.[29] We focus on the three shortest time scales and plot their variance ratios and wavelet correlations in figure 4.5.[30]

In figure 4.5, variance ratios identify the existence of excess high frequency variance through the period which appears to decline slightly. Focusing on the 250 milliseconds, wavelet variance ratio $V_{1,14}$ ranges from 1.20 to 2.74. 70% of the ratios are within the range of 1.5 to 2.5. Through time, the level of excess variance exhibits no large change, but appears to decline. Annual averages of $V_{1,14}$ are 2.10, 2.26, 1.97, 1.67, 1.60 and 1.79 for the six years. Average rough variance ratio $VR_{1,14}$ is 1.64 for the period, providing a lower estimate of excess variance. Its annual averages are 1.79, 1.92, 1.62, 1.39, 1.48 and 1.65, showing a similar pattern to the wavelet variance ratios.

[29] Detailed results are not shown but available upon request.
[30] We also estimate the short-term volatility model with data including the first and last 15 minutes. As expected, fundamental price variance represented by the 34.13 minute time scale is higher because of accumulated and expected overnight information. As a result, estimated variance ratios are lower. In the example of 2010 March contract, wavelet variance ratio at 250 millisecond scale drops from 2.27 to 2.18. In another example of the more volatile 2011 July contract that covers May and June, nearby wavelet variance ratio at 250 milliseconds drops from 1.33 to 1.28. The change suggests the excluded time exhibits higher fundamental volatility and is not affected as much by high frequency quoting.

Wavelet correlations show the bid/ask price co-movement discrepancy improves through sample, with only occasional breaks. Wavelet correlation moves negatively with variance ratios and gives a consistent indication of the noise level. The correlation coefficient between ρ^1 and $V_{1,14}$ is -0.35 for the 30 contracts. The occasionally few low spikes of correlation also correspond to peaks of the variance ratio, e.g. 2010 September and 2011 March contracts. At 250 milliseconds, annual average correlations ρ^1 are 0.50, 0.68, 0.64, 0.75, 0.71 and 0.77, which resemble variance ratios and improve over time.

To understand these variation patterns, we plot in figure 4.6 the wavelet variances estimated at the 250 and 500 milliseconds, 1 second and 34.13 minutes, which are used to calculate the wavelet variance ratio. Variance from fundamental information is represented by variance at 34.13 minutes and exhibits both annual and seasonal patterns. It is higher in 2008, 2011 and 2012 when price is volatile, years when inventories were tight and adverse weather conditions prevailed. It dampens in 2009, 2010 and 2013 when price is stable because of ample harvest and storage. The well-established seasonal pattern with higher summer volatility in the corn futures market (Egelkraut et al. 2007) also appears. Estimated fundamental variance is higher for July and September contracts, which span the summer time of May, June (July maturity) and July, August (September maturity). Both annual and seasonal patterns are consistent with expectations.[31]

[31] We also compare the wavelet variance at 34.13 minutes scale with traditional volatility estimates since both intend to measure volatility from fundamental information. We use the daily price return volatility to calculate a realized volatility measure for the contracts in the nearby period as $\sum_{i=1}^{I} r_i^2 /I$. r_i^2 is the squared return of intraday close/open prices and I is the number of days in that nearby contract used to normalize total volatility to a daily basis. We find two measures are generally consistent with each other in direction, with a correlation of 0.41 (Figure D1, Appendix D). Both exhibit similar seasonality and annual patterns that are higher in 2008, 2011 and 2012. Differences primarily emerge in that price return volatility in 2008 is much higher than other years while wavelet variance reports 2008 and 2011 are equally volatile. This is because price return volatility contains the entire price trend from open to close. However, in wavelet variance, the effect of price trend is kept in the filtered series (see the filtered

Wavelet variance at small time scales is less variable. From 250 milliseconds to 1 second, wavelet variances show similar annual and seasonal patterns to the 34.13 minutes scale. We use the coefficient of variation (CEV) to compare their stability. CEVs are 0.56, 0.55 and 0.54 for wavelet variances at three small scales, lower than that of 0.63 at 34.13 minutes. Though the difference is seemingly small, it makes a big difference in variance ratio because of a scaling factor at 2^{J-j}. The implication is variance changes to a lesser degree than fundamental variance at small scales.

The comparison sheds light on the pattern of variance ratios. Because of the different stability, variance ratio peaks when fundamental variance is low. Higher variance ratios are generally observed in contracts with low fundamental variance, e.g., the May and July contracts of 2009, March, May and September contracts of 2010 and July, September contracts of 2013. Due to the common seasonality pattern in variances which neutralize each other, little seasonality is found in variance ratios. The Samuelson hypothesis (1965) predicts price volatility may grow as contract nears expiration. For March and December contracts with one more month in the nearby period, it implies a lower average fundamental volatility than other contracts and can lead to higher variance ratios. However the absence of a seasonal pattern gives little evidence that Samuelson hypothesis has any effect on variance ratios. September contracts often have higher variance ratios. Previous research (Smith 2005; Wang et al. 2014) identifies the September contract has less trading because it combines old and new crop information which reduces hedging interest. Its BAS is higher than other maturities (Wang et al. 2014) and sets a wider range for high frequency quoting. As a result, September contract variance ratios are higher because of the relatively higher frictional variance.

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price in Figure B2, Appendix B). Thus, the wavelet variance estimate at 34.13 minutes is less likely to be influenced by price trend than return volatility, which leads to the difference.

The magnitude of net excess volatility decreases through time. Figure 4.7 plots the net excess wavelet volatility at 250 milliseconds as a percentage of the tick size. We calculate net excess volatility $\sqrt{\upsilon_j^2 - \hat{\upsilon}_j^2}$ and $\sqrt{\sigma_j^2 - \hat{\sigma}_j^2}$ at 250 milliseconds because its variance ratio is the highest for all contracts. Both measures are close, and decline slightly through the period. Net excess wavelet and rough volatility range from 2.8% to 10.3% and 3.4% to 12.6% of a tick, with mean values of 6.2% and 7.2% respectively. The annual averages for 2008-2013 are 9.4%, 6.3%, 4.8%, 6.9%, 5.2% and 4.5% for net excess wavelet volatility and 11.2%, 7.6%, 5.3%, 6.9%, 6.5% and 5.7% for net excess rough volatility. The size of net excess volatility is small compared to the minimum allowed price change, which suggests the high frequency quoting noise in economic terms is not substantial.

4.7 Conclusion

Agricultural futures markets have transitioned from open outcry to electronic trading. HFTers have emerged as an important group of participants in electronic futures markets. High frequency quoting – quickly canceling posted limit orders and replacing them with new ones – emerges as the strategy for high frequency liquidity providers to cope with high frequency predatory trading algorithms. Much concern has arisen that bid/ask limit orders from high frequency quoting are unstable and liquidity can disappear when other traders manually place market orders. High frequency quoting can add noise to prices and increase order execution uncertainty, which harms market quality due to added price variation at execution. In this paper we investigate the high frequency quoting noise in bid/ask price quotes using corn futures market from 2008-2013. Noise is measured by the level of excess variance and bid/ask price co-movement discrepancy at time scales as small as 250 milliseconds. With the Best Bid Offer (BBO) dataset time-stamped to the nearest second, we simulate sub-second time stamps using a Bayesian framework (Hasbrouck 2013). Quoting noise is estimated using the wavelet-based short-term volatility model developed by Hasbrouck (2013).

Evidence from the ratio of excess variance and bid/ask price correlations confirms the existence of high frequency quoting noise, particularly at the sub-second levels. Highest noise is consistently identified at the 250 millisecond scale, with an average short-term variance 90% higher than normal level implied by a random walk. Over time, the annual average ratio of excess variance declines from 110% in 2008 to 79% in 2013. Little seasonal pattern exists except the September contract often has higher noise due to less trading interest and higher BAS. In terms of economic magnitude, net excess volatility – the square root of variance – is negligibly small at the 250 millisecond scale, ranging from 2.8% to 10.3% of a tick size and declines in the 2008-2013 period. Bid/ask price co-movement exhibits a sample average correlation of 0.67 at 250 milliseconds and improves annually from 0.50 in 2008 to 0.77 in 2013. For longer time scales, average excess variance declines below 5% in slightly more than 2 minutes and average correlation reaches 99% at the 32 second scale. These measures suggest that high frequency quoting noise is economically small and declining through the period.

In comparison with findings in financial markets by Hasbrouck (2013), high frequency quoting noise in corn futures market is close to the levels for highly traded stocks. At the 200 millisecond scale, Hasbrouck finds in April 2011, rough variance ratios are 1.3 and 1.57 for the two groups of stocks with highest volume. These are close to the average rough variance ratio of 1.64 in corn futures market. Wavelet correlations for these two stocks groups are 0.65 and 0.49, which are close to the corn futures market average of 0.67. Compared to the average of 4.2 in

2008-2011 for all stocks, variance ratios in the corn futures market are less than half, which suggests quoting noise in corn futures market is smaller than in the stock market. Through time, the level of excess variance in both the corn and stock markets are relatively stable post-2007. Notably, the tick size in the corn futures market (0.25 cents/bushel) is larger than that in the stock market (0.01 cents/share). While average excess variance and correlation measures compare favorably to the most actively traded stocks, the tick size difference suggests quoting noise in the corn futures market might be reduced even further since larger tick size is one source of market frictions.

In light of HFT activities which appear to have increased in recent years, the overall findings lead to the question: Why hasn't high frequency quoting noise worsened through time. One explanation comes from Baruch and Glosten (2013). They argue that in the presence of an increasing number of liquidity-providing HFTers the best bid/ask prices change little. In effect, when one HFTer cancels a posted limit order, it is immediately replaced by new orders from other HFTers. As a result, in the corn futures market as well as in deeply-traded stocks, high frequency quoting noise is relatively small. This is also consistent with the observation by Easley et al. (2012) that predators (predatory algorithms) and prey (liquidity-providing HFTers and other low frequency traders) will adapt to each other and evolve into a balanced equilibrium.

In response to the perception that predatory HFTers have contributed to heightened volatility in recent years, our findings lend little support to this perception as high frequency quoting noise is small in magnitude, almost disappears at the half minute scale, and has been rather stable or even declining through time. Similarly, as shown in a robustness check, including the first 15 minutes of trading—a time when considerable information enters the market—in the analysis leads to a slight reduction in excess variance measures. This suggests even at smaller time scales that information rather than high frequency quoting may be driving volatility. At longer time intervals, observed higher volatility is more likely caused by changing market information. However, since information is transmitted faster electronically, higher intraday volatility may exist, a pattern less likely to be pronounced in the presence of added liquidity found in an electronic platform (Wang, et al. 2014).

Future research is needed on other less deeply-traded commodity futures to broaden our understanding. As identified in Hasbrouck (2013), markets with less activity may suffer from more pronounced high frequency quoting noise. Attention should be paid to less-traded commodities like livestock and "softs" (cotton and coffee et al.). Studies using trader-specific data are also needed to complement findings in this study and to identify the distribution of returns from HFT. But for the moment this data are not available. Nevertheless, it appears that in the corn futures market different traders adjust to provide sufficient liquidity with a limited level of noise. As such, this study offers little support for policy proposals to curb high-speed activities in the corn futures market.

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4.9 Tables and Figures

Table 4.1. Volatility Estimates for the 2010 March Corn Contract, December 2009-February 2010

Level, j	Time scale	Rough Volatility σ_j	Rough Variance σ_j^2	Ratio $VR_{j,J}$	Wavelet volatility v_j	Wavelet Variance v_j^2	Ratio $V_{j,J}$	Correlation ρ^j
0	<250 ms	0.014	0.0002					
1	250 ms	0.022	0.0005	1.871	0.017	0.0003	2.272	0.642
2	500 ms	0.031	0.0010	1.898	0.022	0.0005	1.926	0.730
3	1 sec	0.043	0.0019	1.818	0.030	0.0009	1.738	0.825
4	2 sec	0.058	0.0034	1.688	0.040	0.0016	1.558	0.890
5	4 sec	0.078	0.0061	1.534	0.053	0.0028	1.379	0.933
6	8 sec	0.105	0.0110	1.378	0.070	0.0049	1.223	0.962
7	16 sec	0.141	0.0199	1.246	0.095	0.0090	1.114	0.980
8	32 sec	0.192	0.0369	1.148	0.130	0.0169	1.049	0.991
9	64 sec	0.263	0.0692	1.075	0.179	0.0320	1.003	0.997
10	2.13 min	0.365	0.1332	1.037	0.253	0.0640	1.000	0.999
11	4.27 min	0.515	0.2652	1.033	0.363	0.1318	1.029	1.000
12	8.53 min	0.733	0.5373	1.047	0.522	0.2725	1.060	1.000
13	17.07 min	1.040	1.0816	1.053	0.738	0.5446	1.060	1.000
14(=J)	34.13 min	1.452	2.1083	1.027	1.013	1.0262	1.000	1.000

Note: The rough and wavelet volatilities (σ_j and v_j) are in cents/bushel, calculated as the square root of rough and wavelet variances (σ_j^2 and v_j^2). Variances are estimated from bid/ask series separately. Here we report the mean of bid/ask series since their results are almost identical. $VR_{j,J} = 2^{J-j-1}\sigma_j^2/v_J^2$ is the rough variance ratio, and $V_{j,J} = 2^{J-j}v_j^2/v_J^2$ is the wavelet variance ratio. J=14 is the maximum time scale. ρ^j is the wavelet correlation between bid and ask series.

Table 4.2. Average Volatility Estimates for the Nearby Corn Contracts, 2008-2013

Level, j	Time scale	Rough Volatility σ_j	Rough Variance σ_j^2	Ratio $VR_{j,J}$	Wavelet volatility v_j	Wavelet Variance v_j^2	Ratio $V_{j,J}$	Correlation ρ^j
0	<250 ms	0.021	0.0004					
1	250 ms	0.032	0.0010	1.642	0.024	0.0006	1.900	0.675
2	500 ms	0.045	0.0020	1.603	0.031	0.0010	1.565	0.748
3	1 sec	0.062	0.0038	1.534	0.043	0.0018	1.464	0.824
4	2 sec	0.085	0.0072	1.445	0.058	0.0034	1.357	0.883
5	4 sec	0.116	0.0134	1.346	0.079	0.0062	1.246	0.927
6	8 sec	0.158	0.0249	1.252	0.108	0.0116	1.158	0.958
7	16 sec	0.217	0.0470	1.173	0.149	0.0221	1.095	0.979
8	32 sec	0.301	0.0905	1.121	0.209	0.0435	1.069	0.990
9	64 sec	0.421	0.1772	1.090	0.294	0.0867	1.059	0.996
10	2.13 min	0.590	0.3486	1.068	0.414	0.1714	1.046	0.998
11	4.27 min	0.826	0.6824	1.045	0.578	0.3338	1.022	0.999
12	8.53 min	1.157	1.3383	1.021	0.810	0.6559	0.997	0.999
13	17.07 min	1.631	2.6593	1.006	1.149	1.3210	0.990	0.999
14(=J)	34.13 min	2.318	5.3720	1.003	1.647	2.7127	1	0.999

Note: The rough and wavelet volatilities (σ_j and v_j) are in cents/bushel, calculated as the square root of rough and wavelet variances (σ_j^2 and v_j^2). Variances are estimated from bid/ask series separately. Here we report the mean of bid/ask series since their results are almost identical. $VR_{j,J} = 2^{J-j-1}\sigma_j^2/v_J^2$ is the rough variance ratio, and $V_{j,J} = 2^{J-j}v_j^2/v_J^2$ is the wavelet variance ratio. J=14 is the maximum time scale. ρ^j is the wavelet correlation between bid and ask series. All statistics are averages of nearby contract estimates.

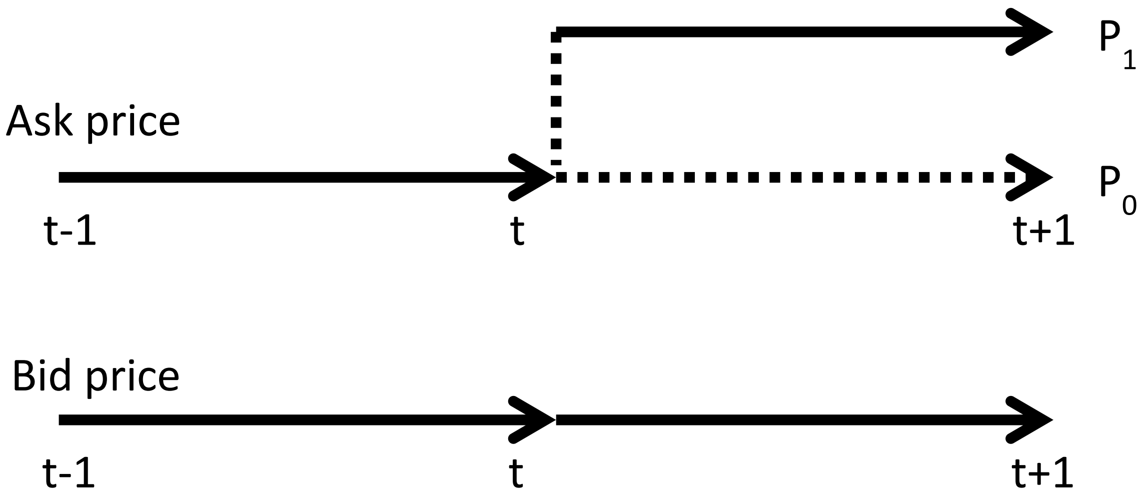

Figure 4.1. Illustration of High Frequency Quoting Impact

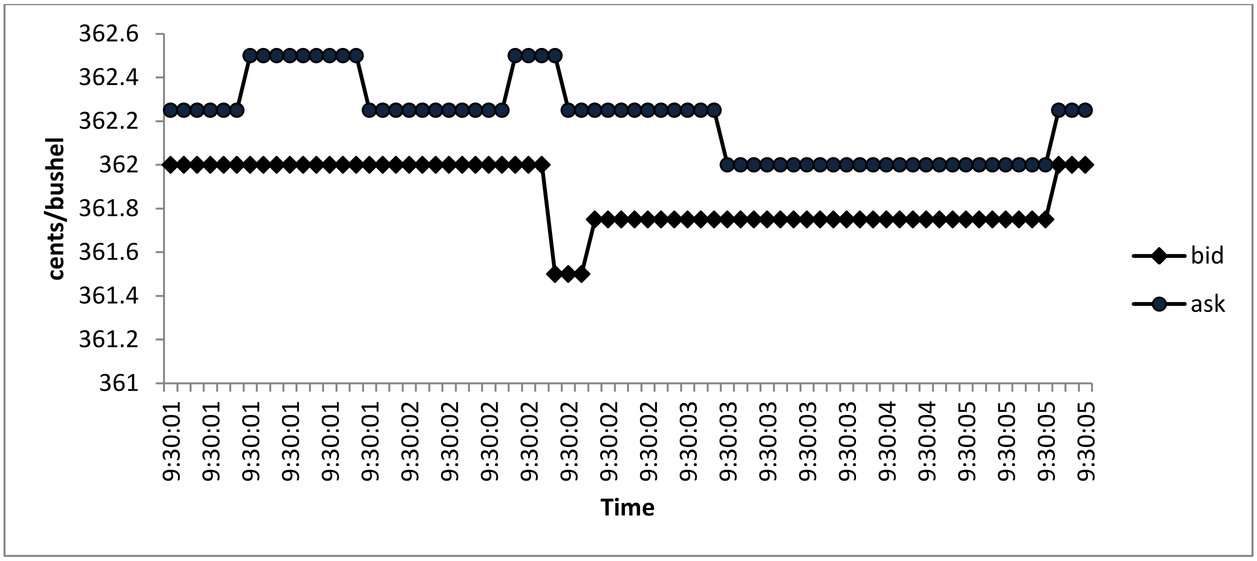

Figure 4.2. 2010 March Corn Contract Price Quotes, 9:30:01 am – 9:30:05 am, 1/29/2010

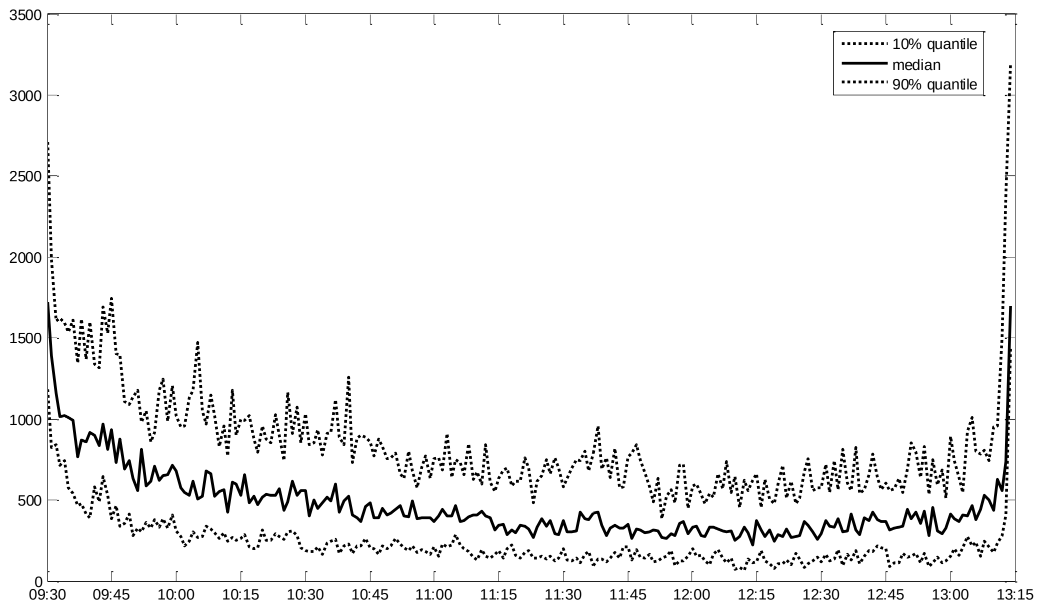

Figure 4.3. Number of Bid/ask Quotes in the 2010 March Corn Contract, 1/4/2010-1/29/2010

Note: The graph plots the total number of bid/ask quotes in each minute of the trading session. There are 19 trading days in January 2010. We show the median (solid line), 10% and 90% quantile boundaries (dotted lines) of the 19 trading days.

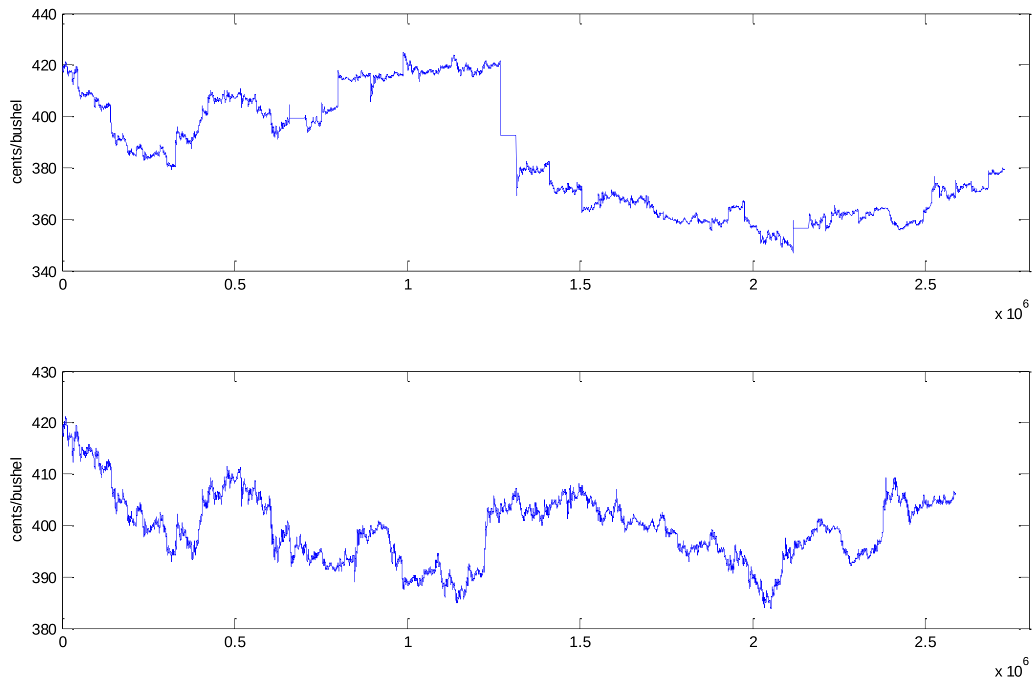

Figure 4.4. 2010 March Corn Contract Bid Prices, 12/1/2009-2/26/2010

Note: The upper panel is the original bid prices combined in the nearby 2010 March corn contract. The lower panel is bid prices after removing inter-day price jumps and price limit move days.

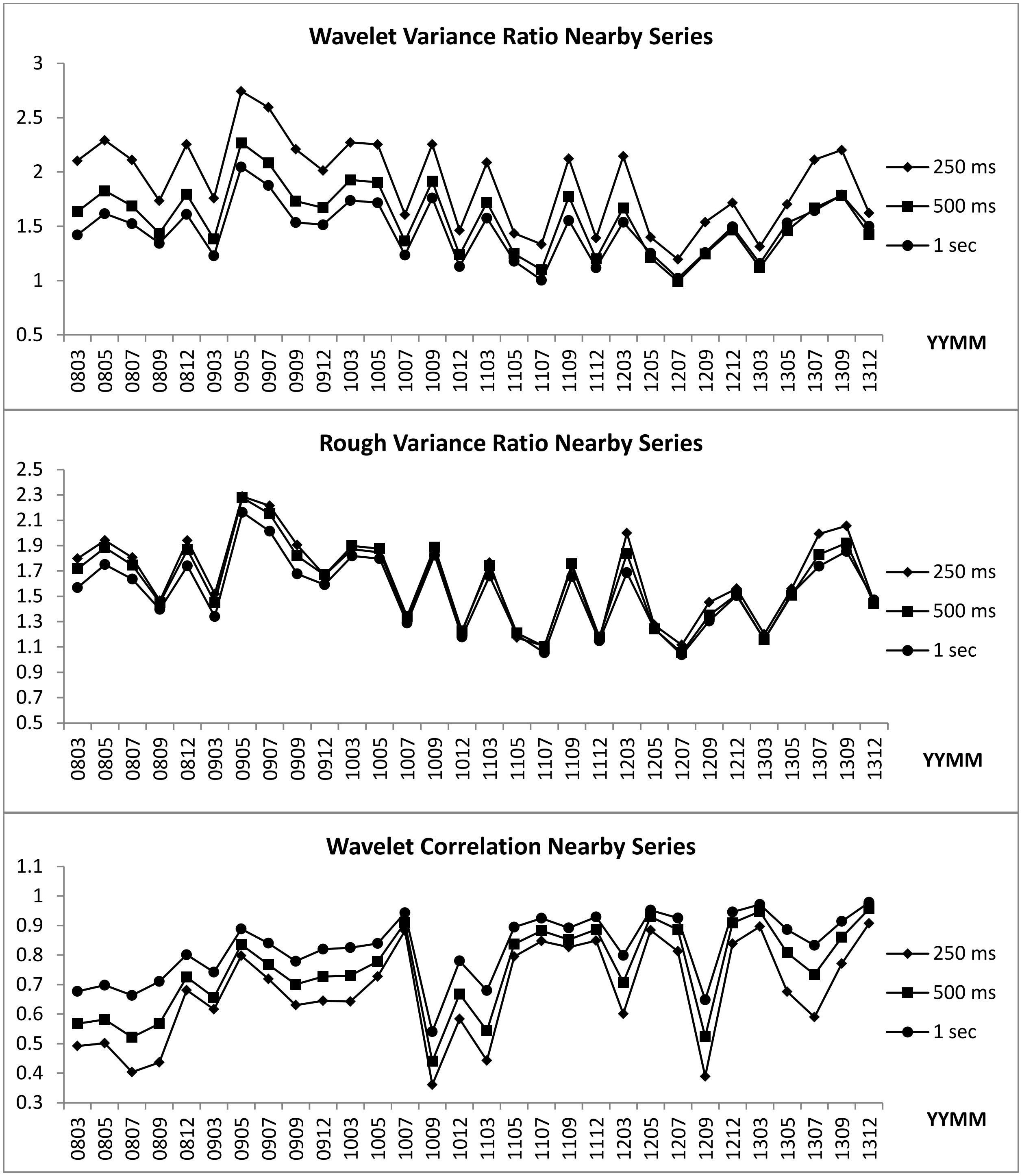

Figure 4.5. Variance Ratios and Wavelet Correlations for Nearby Contracts, 2008-2013

Note: Variance ratios and wavelet correlations are estimated for series of each nearby contract. Three lines connecting dots represent the 250 milliseconds, 500 milliseconds and 1 second level estimates. *J*=14 is the maximum time scale.

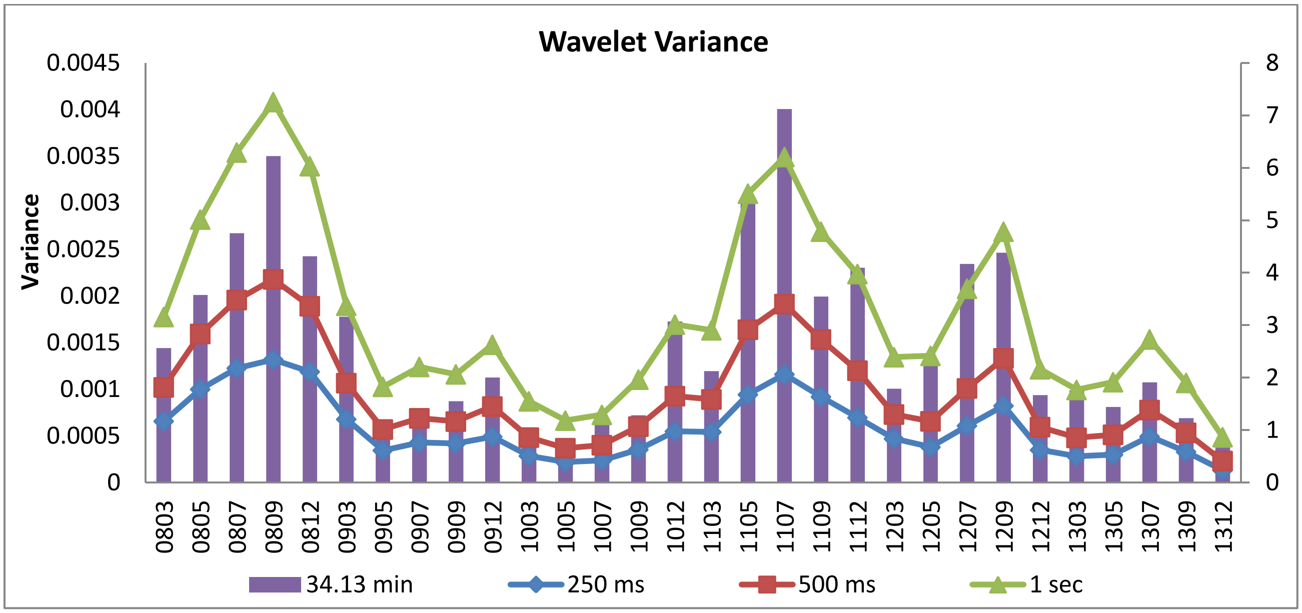

Figure 4.6. Wavelet Variance at Selected Time Scales

Note: The columns represent wavelet variance at the 34.13 minute scale. Its unit corresponds to the right-side y-axis in squared cent/bushel. Three lines connecting dots represent the 250 milliseconds, 500 milliseconds and 1 second level wavelet variance, corresponding to the left-side y-axis.

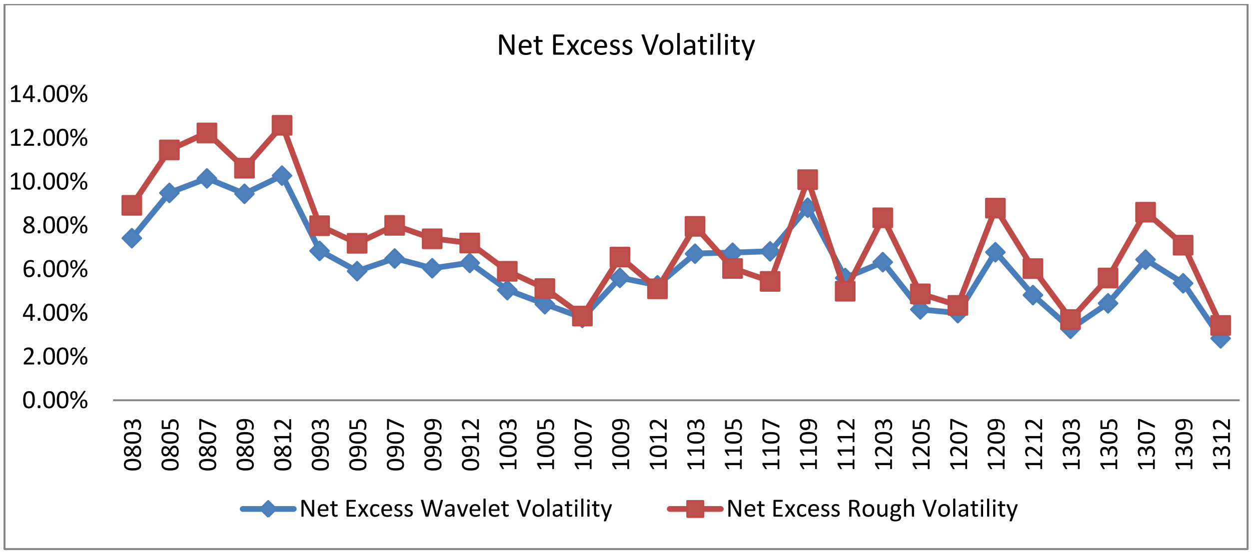

Figure 4.7. Net Excess Wavelet and Rough Volatility

Note: Net excess wavelet and rough volatilities are calculated as $\sqrt{v_j^2 - \hat{v}_j^2}$ and $\sqrt{\sigma_j^2 - \hat{\sigma}_j^2}$, where j=1 for the 250 millisecond scale. The left axis corresponds to the net excess volatility as a percentage of the tick size, 0.25 cents/bushel.

CHAPTER 5

CONCLUSIONS

In recent years, large changes have transformed grain futures markets. Biofuel mandates and tight stock levels have led to heightened volatility which is likely to continue in the foreseeable future. Heightened volatility poses additional price risk to market participants. At the same time, electronic markets have emerged as the major trading platform, accounting for more than 90% of trading volume. Compared to open outcry markets, electronic markets offer faster and easier access with prices that are directly observable in the order book. These changes in futures markets have attracted a broader range of participants like index funds traders (CIT) and high-speed and high-frequency traders using automated programs (HFTers). But electronic trading has also raised concerns that increased speed and anonymity have increased order execution cost and added execution price uncertainty. In this context, I investigate three aspects of futures market behavior to improve our understanding in the grain futures markets.

In the first paper, I examine the sources of long memory in three major grains futures volatility and assess the performance of long memory models in volatility forecasting. Using data from corn, soybeans, and wheat futures contracts for 1989-2011, statistical tests and estimation results support the notion that much of the observed long memory patterns in grain price volatility arises from seasonality and structural breaks. After accounting for both factors, a smaller but still significant long memory effect exists in corn and wheat volatility, but it disappears in soybeans. In forecasting, our findings offer marginal support for the benefits of using long memory models. The loss functions are only slightly smaller than their corresponding non-long memory models in both periods of calm and heightened volatility. Long memory models also generate the fewest rejections of unbiasness in both situations, but all forecasts demonstrate a large degree of bias and a low degree of statistical coherence. Direct modeling of structural breaks through the adaptive semi-parametric method generally failed to produce smaller errors, and in certain cases lead to extremely large errors. The limited success of the adaptive method in a forecasting context may reflect estimation error that can emerge in over-parameterized models, or from the sharp and spiky nature of structural breaks. Nevertheless, we observe the importance of modeling seasonality in forecasting grain markets volatility, which is consistent with a rather extensive literature explaining seasonal patterns in agricultural markets as well as the limited volatility forecasting research. On balance, a combination of both long memory and seasonality generates the best forecast structure.

In the second paper, I study the behavior of bid-ask spread (BAS), a common gauge of liquidity costs, in the electronically-traded corn futures market during a particularly turbulent period, 2008-2010. The BAS is measured from reconstructing records in the electronic order book. I investigate its behavior, determinants, and interactions with volatility and volume, two key factors influencing liquidity costs, using a dynamic systems framework. The average BAS in the most actively traded nearby and deferred (next nearby) contracts are 0.314 and 0.376 cents/bushel respectively. These values are only marginally higher than the minimum tick size, 0.25 cents/bushel. Similarly, while BAS across maturities exhibits a clear seasonal pattern that is consistent with the term structure of price volatility, differences in nearby contracts are small in magnitude. However, this pattern is magnified at contract horizons beyond one year. Consistent with the literature, statistical analysis reveals that BAS responds negatively to changes in volume and positively to changes in volatility. However, the responses on a cents/bushel or a percentage basis are negligible. Informatively, larger responses emerge when examining the effects of changes in BAS on volume and volatility. With a few exceptions, the effects of other factors anticipated to affect BAS are statistically significant, but small on a cents/bushel or percentage basis. Larger impacts occur in commodity index trader roll periods and on USDA report release days. Overall the results suggest the move to an electronic corn futures market has led to low and stable liquidity costs even in a period of market turbulence.

In the third paper, I investigate the high frequency quoting noise in bid/ask price quotes using corn futures from 2008-2013. Noise is measured by the level of excess variance and bid/ask price co-movement discrepancy at time scales as small as 250 milliseconds. With the Best Bid Offer (BBO) dataset time-stamped to the nearest second, we simulate sub-second time stamps using a Bayesian framework (Hasbrouck 2013). Quoting noise is estimated based on the wavelet-based short-term volatility model developed by Hasbrouck (2013). Evidence from the ratio of excess variance and bid/ask price correlations confirms the existence of high frequency quoting noise, particularly at the sub-second levels. Noise quickly decreases as time scale increases and disappears at the half minute scale. Over time, annual average ratio of excess variance generally follows a declining pattern from 2.10 in 2008 to 1.79 in 2013. In terms of economic magnitude, net excess volatility – square root of variance – is negligibly small at 250 milliseconds, ranging from 2.8% to 10.3% of a tick size and declines in 2008-2013. Bid/ask price co-movement exhibits a sample average correlation of 0.67 at 250 milliseconds and improves annually from 0.50 in 2008 to 0.77 in 2013. Measures of excess variance, net excess volatility, and bid/ask correlation suggest that high frequency quoting noise is economically small and declines through the period. Despite more HFTers in recent years, the results suggest the corn market has evolved toward an equilibrium that moderates high frequency quoting noise.

In general, the three studies reveal two messages. First, structural changes in fundamental markets such as biofuel mandates play a significant role in the recently heightened volatility. These changes have contributed to the level of volatility observed in the long memory phenomenon in grain prices. As a result, long memory models can provide a parsimonious specification to generate better volatility forecast. Second, based on findings in chapter 3 and 4, the transition from open outcry to electronic trading has been in general beneficial in the corn futures market. The electronic market provides sufficient liquidity to maintain a low and rather stable BAS with few exceptions. Additionally, while the electronic market attracts HFT which introduces noise in bid/ask quotes, the magnitude of the effect in economic terms appears to be small.

Electronic futures markets offer speed and accessibility, which have attracted a wider range of participants including CITs and HFTers. Many other issues remain to be answered with regards to these new participants. This dissertation has focused on the impact on execution cost. Further aspects like how these new participants affect price discovery is still unknown. Moreover, trader-specific data may help reveal impacts of different trading strategies and provide insights into the price discovery process.

APPENDIX A

PROCEDURES ON SIMULATING MILLISECOND TIME STAMP DATA

Recall that for a one second interval there will be *n* quote records. The time length between any two updates follows a uniform distribution because the quote updates follow Poisson process. Take for example the 2010 March contract at 9:30:01 am, 2010 (Figure 4.2), where *n* the number of observations is 19. A new quote occurs with a probability density function of *unif*(0,1) within the 1 second period. We make *n*=19 random draws following *unif*(0,1) distribution which represent sub-second time stamps. The 19 sub-second time stamps are then sorted in ascending order and matched to each observed quote. In the following table, simulated sub-second time stamps are listed with the prices. Similarly, for the next second, 9:30:02 am with *n*=16 observations, we make 16 random draws and match the sorted time stamps to each quote record. We perform one simulation for each second, because averaging time stamps from multiple random draws will eventually lead to an equally spaced time length of 1/*n* between quotes, which would violate the randomness of quote updates.

Table A.1. Simulated Time Stamps

time	Ask price	Sub-second time
9:30:01	362.25	0.121
9:30:01	362.25	0.156
9:30:01	362.25	0.190
9:30:01	362.25	0.191
9:30:01	362.25	0.226
9:30:01	362.25	0.369
9:30:01	362.5	0.376
9:30:01	362.5	0.385
9:30:01	362.5	0.428
9:30:01	362.5	0.461
9:30:01	362.5	0.482
9:30:01	362.5	0.561
9:30:01	362.5	0.583
9:30:01	362.5	0.590
9:30:01	362.5	0.645

9:30:01	362.25	0.669
9:30:01	362.25	0.856
9:30:01	362.25	0.882
9:30:01	362.25	0.982
9:30:02	362.25	0.007
9:30:02	362.25	0.008
9:30:02	362.25	0.012
9:30:02	362.25	0.062
9:30:02	362.25	0.073
9:30:02	362.25	0.077
9:30:02	362.25	0.173
9:30:02	362.5	0.239
9:30:02	362.5	0.278
9:30:02	362.5	0.524
9:30:02	362.5	0.568
9:30:02	362.25	0.583
9:30:02	362.25	0.819
9:30:02	362.25	0.853
9:30:02	362.25	0.870
9:30:02	362.25	0.896

APPENDIX B

PRICE DECOMPOSITION USING MODWT PROCEDURE

The purpose of the procedure is to decompose time series into add-up components which represent variations at different time scales. As a simple illustration, figure B.1 plots a simulated random walk price series for 30 seconds. The red bold lines are the average price for each non-overlapping 5 seconds interval. This series can be decomposed into two parts—variations within 5 seconds and at the 5 seconds time scale. For each 5-second interval, price deviations $R(n,t,s) = p_i - S(n,t)$ represent the within 5-second variation component. The average prices are the 5-second scale component, which can be further separated into longer time scale variations like 10, 20 seconds. However, this simple separation method is not efficient because it fails to consider all possible time interval alignments, e.g., a 5-second interval can be the 5^{th} to 10^{th} second as well as 7^{th} to 12^{th} second. As a result, the extracted components are rough with jumps, e.g., the 5-second scale component.

The Maximal Overlapping Discrete Wavelet Transformation (MODWT) (Percival and Walden 2000) procedure is an efficient method which takes maximal overlapping wavelet transformation averages at all possible time alignments. Because observations in price series are discrete, we use the discrete Haar wavelet function as the signal filter. The Haar wavelet function is defined as $\varphi(s) = \begin{cases} 1/s_1 & 0 \le s < 0.5s_1 \\ -1/s_1 & 0.5s_1 \le s < s_1 \\ 0 & otherwise \end{cases}$, for a time scale s_1. Notice that it is a zero-mean filter symmetric over the time scale. It isolates the mean value of a series which corresponds to extracting price deviations from the mean of each time scale. A set of Haar filters covering time scales from s_1 to s_J are defined as $\{ \varphi(s_1), \varphi(2s_1), \ldots, \varphi(2^J s_1)\}$. In practice, the set of filters are sequentially applied to extract variations from the raw price series.

As an illustration, we apply the MODWT procedure on the price series of the 2010 nearby March contract. In figure B.2, we plot price variations at the 250 millisecond (j=1), 32 second (j=8), 34.13 minute (j=14) time scales as well as post-filtered raw price in the end. The high-low range of variations increase as scale expands from j=1 to 14. The variance at 34.13 minutes is used as the benchmark measure of information driven volatility. The filtered series are smooth, showing the efficiency of MODWT procedure. Adding variations from each scale back to the filtered price recovers the original price series in the lower panel of figure 4.4.

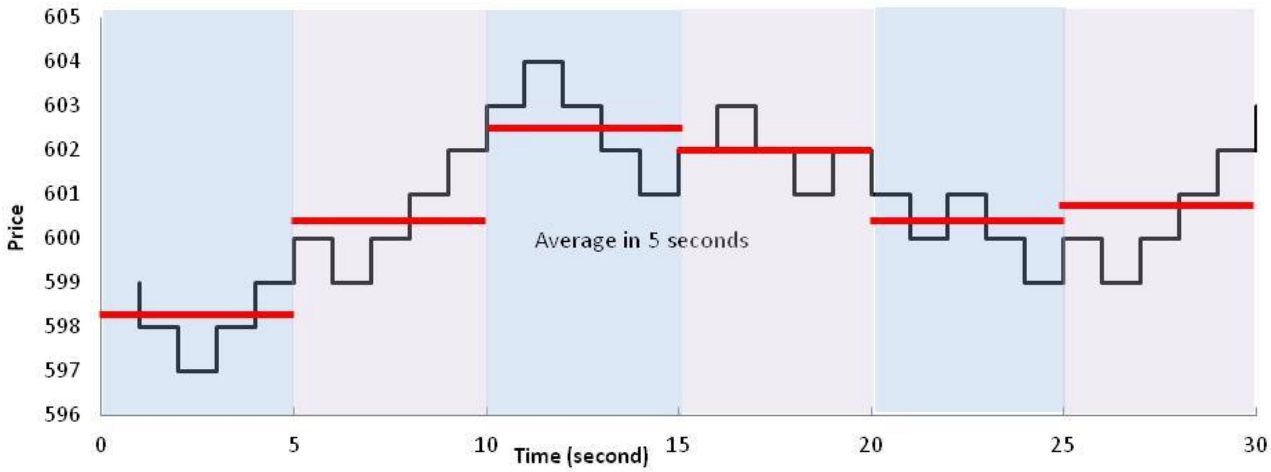

Figure B.1. Price Variations Within and at 5-second Time Scale

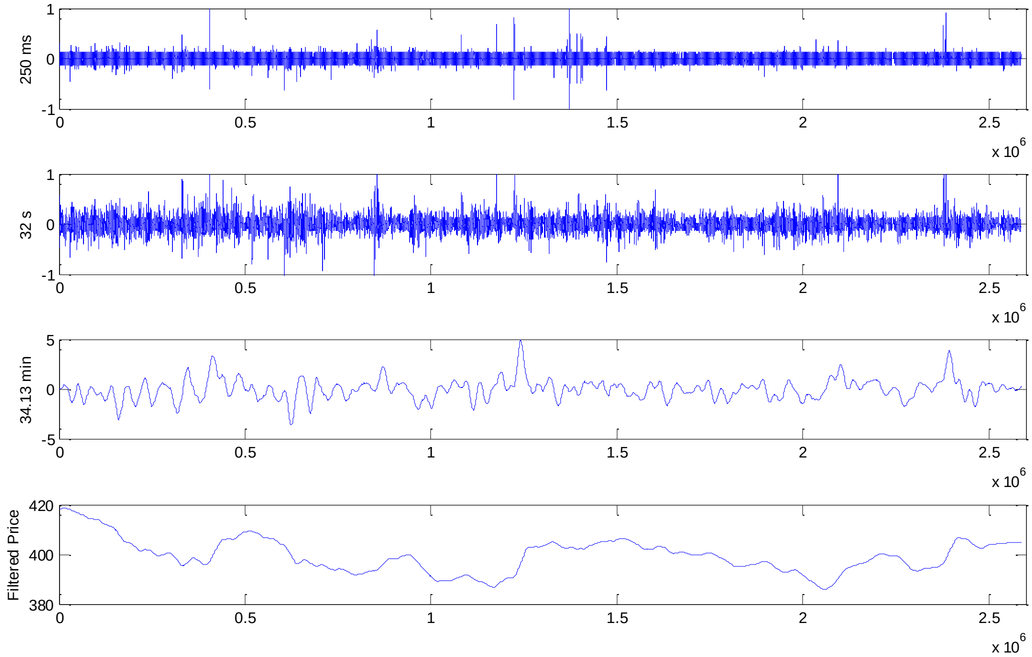

Figure B.2. Application of the MODWT to the 2010 March Contract Bid Prices, 1/4/2010-1/29/2010

APPENDIX C

SHORT-TERM VOLATILITY MODEL WITH ALTERNATIVE UPPER TIME SCALES

Table C.1. Volatility Estimate for the 2010 March Contract, December 2009 – February 2010, *J*=13

Level, j	Time scale	Rough volatility σ_j	Rough Variance σ_j^2	Ratio $VR_{j,J}$	Wavelet volatility v_j	Wavelet Variance v_j^2	Ratio $V_{j,J}$	Correlations ρ^j
0	<250 ms	0.014	0.0002					
1	250 ms	0.022	0.0005	1.765	0.017	0.0003	2.144	0.642
2	500 ms	0.031	0.0010	1.791	0.022	0.0005	1.817	0.730
3	1 sec	0.043	0.0018	1.716	0.030	0.0009	1.640	0.825
4	2 sec	0.058	0.0034	1.593	0.040	0.0016	1.470	0.890
5	4 sec	0.078	0.0061	1.447	0.053	0.0028	1.301	0.933
6	8 sec	0.105	0.0110	1.301	0.070	0.0049	1.154	0.962
7	16 sec	0.141	0.0199	1.176	0.095	0.0090	1.051	0.980
8	32 sec	0.192	0.0369	1.083	0.130	0.0169	0.990	0.991
9	64 sec	0.263	0.0692	1.015	0.179	0.0320	0.946	0.997
10	2.13 min	0.365	0.1332	0.979	0.253	0.0640	0.943	0.999
11	4.27 min	0.515	0.2652	0.975	0.363	0.1318	0.971	1.000
12	8.53 min	0.733	0.5373	0.988	0.522	0.2725	1.000	1.000
13(=*J*)	17.07 min	1.040	1.0816	0.994	0.738	0.5446	1.000	1.000

Note: The rough and wavelet volatilities (σ_j and v_j) are in cents/bushel, calculated as the square root of rough and wavelet variances (σ_j^2 and v_j^2). Variances are estimated from bid/ask series separately. Here we report the mean of bid/ask series since their results are almost identical. $VR_{j,J} = 2^{J-j-1}\sigma_j^2/v_J^2$ is the rough variance ratio, and $V_{j,J} = 2^{J-j}v_j^2/v_J^2$ is the wavelet variance ratio. *J*=13 is the maximum time scale. ρ^j is the wavelet correlation between bid and ask series.

Table C.2. Volatility Estimate for the 2010 March Contract, December 2009 – February 2010, *J*=15

Level, j	Time scale	Rough volatility σ_j	Rough Variance σ_j^2	Ratio $VR_{j,J}$	Wavelet volatility v_j	Wavelet Variance v_j^2	Ratio $V_{j,J}$	Correlations ρ^j
0	<250 ms	0.014	0.0002					
1	250 ms	0.022	0.0005	1.934	0.017	0.0003	2.349	0.642
2	500 ms	0.031	0.0010	1.963	0.022	0.0005	1.991	0.730
3	1 sec	0.043	0.0018	1.880	0.030	0.0009	1.797	0.825
4	2 sec	0.058	0.0034	1.745	0.040	0.0016	1.611	0.890
5	4 sec	0.078	0.0061	1.586	0.053	0.0028	1.426	0.933
6	8 sec	0.105	0.0110	1.425	0.070	0.0049	1.265	0.962
7	16 sec	0.141	0.0199	1.289	0.095	0.0090	1.152	0.980
8	32 sec	0.192	0.0369	1.187	0.130	0.0169	1.085	0.991
9	64 sec	0.263	0.0692	1.112	0.179	0.0320	1.036	0.997
10	2.13 min	0.365	0.1332	1.073	0.253	0.0640	1.034	0.999
11	4.27 min	0.515	0.2652	1.068	0.363	0.1318	1.064	1.000
12	8.53 min	0.733	0.5373	1.082	0.522	0.2725	1.096	1.000
13	17.07 min	1.040	1.0816	1.089	0.738	0.5446	1.096	1.000
14	34.13 min	1.452	2.1083	1.061	1.013	1.0262	1.034	1.000
15(=*J*)	68.27 min	2.023	4.0925	1.031	1.409	1.9853	1.000	1.000

Note: The rough and wavelet volatilities (σ_j and v_j) are in cents/bushel, calculated as the square root of rough and wavelet variances (σ_j^2 and v_j^2). Variances are estimated from bid/ask series separately. Here we report the mean of bid/ask series since their results are almost identical. $VR_{j,J} = 2^{J-j-1}\sigma_j^2/v_J^2$ is the rough variance ratio, and $V_{j,J} = 2^{J-j}v_j^2/v_J^2$ is the wavelet variance ratio. *J*=15 is the maximum time scale. ρ^j is the wavelet correlation between bid and ask series.

APPENDIX D

COMPARISON OF WAVELET VARIANCE WITH PRICE VOLATILITY FOR NEARBY CONTRACTS

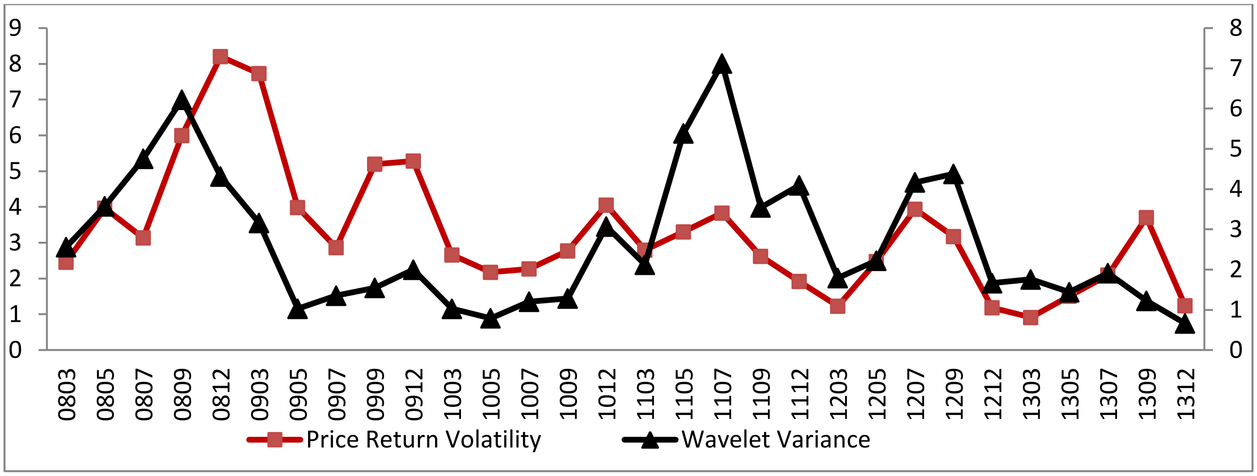

Figure D.1. Wavelet Variance and Price Return Volatility

Note: Wavelet variance is on the 34.13 minutes scale. Price return volatility is the realized volatility for each nearby contract. It is calculated as $\sum_{i=1}^{I} r_i^2 /I$, where r_i^2 is the squared return of intraday close/open prices and I is the number of days in that nearby contract. The right axis is in squared cents/bushel corresponding to wavelet variance. The left axis is in squared percentage corresponding to price return volatility.