Forecasting Corn Futures Volatility in the Presence of Long Memory, Seasonality and Structural Change

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Abstract

Price volatility in the corn market has changed considerably globalization and stronger linkages to the energy complex. Using data from January 1989 through December 2009, we estimate and forecast the volatility in the corn market using futures daily prices. Estimates in a Fractional Integrated GARCH framework identify the importance of long memory, seasonality, and structural change. Recursively generated forecasts for up to 40-day horizons starting in January 2005 highlight the importance of seasonality, and long memory specifications which perform well at more distant horizons particularly with rising volatility. The forecast benefits of allowing for structural change in an adaptive framework are more difficult to identify except at more distant horizons after a large downturn in volatility.

Keywords: corn price volatility, long memory, seasonality, structural change, forecasting

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Introduction

Understanding the structure and developing accurate forecasts of price volatility can serve an essential role in risk management, and option pricing. In futures markets, volatility can influence margin calls. Volatility is also a critical factor in option pricing. Predictability of its direction and magnitude accuracy is helpful for effective commodity derivatives pricing (Myers and Hanson, 1993). Moreover, in hedging, expected volatility is a key factor in determining optimal hedge ratios, and as a measure of relative cost and risk of taking market positions (Haigh, 2005). Unexpected changes in volatility can represent higher risk and higher cost to market participants.

Researchers have spent considerable time developing an understanding agricultural commodity price volatility, but much less attention on developing volatility forecasting. Evidence has emerged that volatility in commodity grain prices is non-constant, time varying, and seasonal in nature (Kendall, 1953; Anderson, 1985; Yang and Brorsen, 1993; Egelkraut and Garcia, 2007). Crain and Lee (1996) identify grain price volatility is highly influenced by changes in government programs, and also argue that volatility is primarily transferred from futures to cash prices. Goodwin and Schnepf (2000) identify the determinants of price volatility for corn and wheat futures markets, including inventories, growing conditions, seasonality. They, among others (e.g. Yang and Brorsen, 1993; Szakmary, 2003), demonstrate that short-term volatility in agricultural prices can be effectively explained by conditional heteroscedastic models.

Two important dimensions of agricultural price volatility have emerged in recent years. Crato and Ray (2000), Jin and Frechette (2004), Baillie, et al. (2007), and Sephton (2009) have identified pervasive patterns of long-term dependence in the volatility of agricultural futures

markets. Long-term dependence is a form of nonlinear dynamics that describes strong correlation patterns at extended lags. While the sources of the long-term dependence are somewhat controversial, Jin and Frechette (2004) argue this dependence can arise from staggered supply and demand information flows, changes in inventory, and trader heterogeneity which exist in futures and cash markets. A second key dimension is a change in price volatility which has appeared in recent years. Resulting price spikes and periods of high volatility are likely related to a changing structure in agricultural markets which are now more global with stronger linkages to the energy complex (Irwin, et al., 2008). Because of growing world demand and biofuel mandates which link agricultural and energy markets, it is likely that heightened volatility will persist in agricultural markets.

In this context, it is apparent that forecasting volatility in agricultural commodity markets is a challenging yet potentially rewarding task. The limited recent research on agricultural price volatility forecasting has focused primarily on short-term forecasting using conditional heteroscedastic models in livestock markets (Manfredo, Leuthold, and Irwin, 2001; Brittain, Garcia, and Irwin, 2011). In contrast, Egelkraut and Garcia (2007), using data through 2001—a relatively stable period, generate reasonably effective intermediate interval forecasts using implied forward volatilities for selected grains. Here, we investigate the usefulness of recently developed methods, which capture long-term dependence, seasonality and structural change, to forecast corn futures price volatility. The basic structure uses a General Autoregressive Conditional Heteroskedasticity (GARCH) framework to address the short-term changes in volatility. Seasonality is included in a Fourier basis framework (Goodwin and Schnepf, 2000). A long memory dimension is estimated using fractional integration developed by Baillie et al (1996), and applied by many researchers to agricultural commodities (e.g., Jin and Frechette,

3

2004). We also incorporate flexible Fourier forms based functions developed by Baillie and Morana (2009) to provide an adaptive framework that allows structural change in the volatility process.

The analysis is performed using daily settlement prices from January 1989 to 2009 for nearby corn futures contracts to generate volatilities. We first estimate and compare the performance of simple GARCH, Fractional Integrated GARCH (FIGARCH), seasonal FIGARCH and seasonal Adaptive FIGARCH models for the entire sample period. Then starting in 2005, we recursively generate daily out-of sample forecasts for 1, 10, 25, and 40 days ahead, using model specifications based on AIC. The out-of-sample period is marked by a rather stable, followed by an increase in volatility, then a turn down, and the ability of forecast procedures was influenced this pattern. Out-of-sample forecasts are evaluated using mean squared errors (MSE) and modified Diebold-Mariano (MDM) procedures.

Literature Review

Research has identified the presence of a long memory pattern in corn price volatility (Crato and Ray, 2000; Jin and Frechette, 2004; Baillie, et al., 2007; Sephton, 2009). In the context of an impulse response function, this means the weights of external shock decay slowly at hyperbolically rate with time.[1] Crato and Ray's tests (2000) identify a long memory property in volatility series. Jin and Frechette (2004) find the long run decay can be well described by fractional integration of past unconditional variance innovations (FIGARCH). Baillie, et al. (2007) further find strong seasonality which if accounted for can mask the magnitude long

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[1] It can as well be shown in autocorrelation function (ACF) $\rho(h)$ between the time t and t-h. For white noise series , $\rho(h) = 0$ the process is said to have no memory. When $\rho(h)$ decays to 0 quickly at a geometric or exponential rate, the series is said to have short memory.

memory effect. Sephton (2009) shows long memory continues to persist when allowing for asymmetric effects conditional on previous returns.

Long memory volatility forecast models have been studied rather extensively in financial and crude oil market. Long-memory alone has been found to capture volatility clustering and persistence better than short-term modeling procedures, particularly at more distant horizons (Vilasuso, 2002; Martens and Zein, 2004; Zumbach, 2004; Kang et al., 2009). For example, Vilasuso (2002) find FIGARCH significantly improves forecasting accuracy at a 10 day horizon for five major exchange markets. There are also substantial gains in shorter forecasting horizons at 1 and 5 days, although not all significant. Kang et al. (2009) find FIGARCH perform significantly better at 1, 5 and 20 days forecast in crude oil markets. Later extensions allowing for asymmetric responses in returns series confirm the usefulness of long memory in forecasting (Degiannakis, 2004; Lux and Kaizoji, 2007; Martens et al., 2009; Scharth and Medeiros, 2009). However, long memory models have not worked well in all situations. Specifically, Lux and Kaizoji (2007) indicate that while long memory models generally work well, cases of drastic failures can emerge related to regime shifts. In periods of large changes in volatility, this limitation of long memory models may be severe.

To overcome this issue, Baillie and Morona (2009) propose an Adaptive FIGARCH (A-FIGARCH) approach to account for both long memory and structural changes in response to large shocks. The intercept or constant component of the FIGARCH model is augmented by a smooth flexible Fourier form developed by Gallant (1984). In this way, A-FIGARCH model considers both stochastic long memory component and deterministic break process component. It does not require pre-testing for the number of break points, nor does it require volatility regimes switches because it is simultaneously estimated. Simulation analysis and empirical results

suggest their framework works well in the presence of embedded breaks, cycles and other changes in conditional volatility (Baillie and Morona, 2009). Compared to other methods to capture the non-linear structural movements, e.g., non-parametric spline functions (Engle and Rangel 2008, Martens, et al., 2009), flexible Fourier forms have the advantage of specification parsimony and require no identification of structural change points. Their shape is estimated with observed data.

Modeling Framework

Following Engle (1982), return series r_t have the predicting error $\varepsilon_t = r_t - E_{t-1}[r_t]$, where E_{t-1} is expectation operator conditional on information at t-1. Assuming market efficiency, the expected return is zero and the realized volatility is the predictive error squared. To model this error, Bollerslev (1986) developed the generalized ARCH (GARCH) model to include both conditional and unconditional variance innovations, which correspond to a learning process. He defines

$$\varepsilon_t = z_t \sigma_t,$$

z_t is iid with zero mean and unit variance. The GARCH process is proposed as

$$\sigma_t^2 = \omega + \alpha(L)\sigma_t^2 + \beta(L)\varepsilon_t^2,$$

where $\omega > 0$, L is backshift operator. $\alpha(L) = \alpha_1 L + \cdots + \alpha_p L^p$ and $\beta(L) = \beta_1 L + \cdots + \beta_q L^q$ are lag polynomials. Restrictions on $\alpha(L)$ and $\beta(L)$ are $\alpha(L) + \beta(L) <1$. Because of its robustness and applicability in many empirical situations, the most widely used specification is a GARCH(1,1) process

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

In this framework, conditional volatility is decomposed into three parts: the long run mean volatility (variance) ω , previous conditional volatility σ_{t-1}^2 and previous unconditional

volatility ε_{t-1}^2. Such formulation has proved to be useful in capturing the clustering effect of volatility series.

Alternatively, GARCH(p,q) can be expressed as the ARMA(p,q) form

$$[1 - \alpha(L) - \beta(L)]\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t,$$

where $v_t \equiv \varepsilon_t^2 - \sigma_t^2$. For GARCH(1,1) process, the impulse response from unconditional innovation h steps back is $\alpha(\alpha + \beta)^h$, which decays exponentially with step h.

To capture the long memory, Baillie et al. (1996) combine the Fractional Integrated ARMA(p,d,q) with GARCH(p,q) model to create FIGARCH(p,d,q) model which takes the form

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

$\phi(L) = 1 - \alpha(L) - \beta(L)$, and 0<d<1, which can also be expressed in ARMA form

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

The conditional variance is

$$\sigma_t^2 = \omega[1 - \beta(1)]^{-1} + \lambda(L)\varepsilon_t^2, \tag{2}$$

And $\lambda(L) = 1 - (1 - \beta(L))^{-1}\phi(L)(1 - L)^d$. The term $(1 - L)^d$ can be extrapolated in terms of hyper-geometric function as infinite polynomials

$$(1 - L)^d = F(-d, 1, 1; L)$$

$$= \sum_{k=0,\infty} \Gamma(k - d)\Gamma(k + 1)^{-1}\Gamma(-d)^{-1}L^k,$$

where $\Gamma(\cdot)$ is Gamma function. It can also be expressed in 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 Gamma function expansion can be used to model the long run decay of volatility autocorrelation.[2] Notice GARCH(p,q) is nested in the FIGARCH(p,d,q) specification. When fractional integration parameter d=0, FIGARCH(p,d,q) reduces to GARCH(p,q).

To allow for regime shifts in the conditional volatility, Baillie and Morana (2009) develop an adapative FIGARCH model. The FIGARCH assumes its conditional mean ω is constant and the effect on persistence of all shocks is equal. However, in many situations it is more common for a few significant and fundamental shocks to a longer more pronounced effect on volatility than small and frequent shocks. To allow for this effect, their model permits the constant term to vary over time using a smooth flexible Fourier form (Gallant, 1984). The A-FIGARCH(p,d,q,k) formulation is similar to FIGARCH(p,d,q) specification,

$$[1 - \beta(L)]\sigma_t^2 = \omega_t + [1 - \beta(L) - \phi(L)(1 - L)^d]\varepsilon_t^2, \qquad (3)$$

but now $\omega_t = \omega_0 + \sum_{j=1}^{k} \left(\gamma_j \cos \frac{2\pi jt}{T} + \delta_j \sin \frac{2\pi jt}{T} \right)$ for each observation t. It reduces to FIGARCH when $\omega_t = \omega[1 - \beta(1)]^{-1}$ is constant. T is usually set as the number of observations. Baillie and Morana (2009) demonstrate even with parsimonious settings of $k = 1$ or 2, the model can capture quite abrupt structural level shifts.

Seasonality s_t in volatility also can be represented by the Fourier pairs, $s_t = \sum_{i=1}^{m}(a_i \cdot \cos \frac{2\pi it}{252} + b_i \cdot \sin \frac{2\pi it}{252})$ (Goodwin and Schnepf, 2000). In the case of the corn futures prices, which has been shown to have higher volatility in the middle of the year (Figure 1), an inverse cosine function may provide an adequate and parsimonious representation. The sin ($\cdot$) function is included to capture possible leptokurtosis. Combining the adaptive and seasonal models leads to a seasonal A-FIGARCH (SA-FIGARCH) specified as

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

$$[1 - \beta(L)]\sigma_t^2 = \omega_t + s_t + [1 - \beta(L) - \phi(L)(1 - L)^d]\varepsilon_t^2. \tag{4}$$

In the empirical analysis, the period for the seasonality is chosen as 252, which corresponds to the number of days in business year, and to large spike in the pattern demonstrated by the long-run decay in the autocorrelation function. The number of adaptive and seasonal triangular functional pairs is determined by Akaike Information Criterion (AIC).

Quasi Maximum Likelihood Estimation method (QMLE) proposed by Bollerslev and Wooldridge (2002) is used. QMLE has the advantage of being consistent when a normal log-likelihood function is maximized but the assumption of error normality is violated. The limiting distribution is still normal if the sample is large enough. Since the series shows signs of kurtosis and spikes, the QMLE method seems appropriate. To evaluate forecast accuracy, mean squared errors (MSE) are calculated: $MSE = \frac{1}{n}\sum_{i=1}^{n}(\sigma_{f,t}^2 - \sigma_{a,t}^2)^2$. $\sigma_{f,t}^2$, $\sigma_{a,t}^2$ are volatility forecast and actual volatility for day t, n is number of forecast data points. The Harvey et al. (1997) modified Diebold-Mariano statistic (MDM) is used to test for equal forecast accuracy, based on the squared error loss function. The MDM corrects for autocorrelation in forecast values, and is reasonably robust to non-normality. The MDM follows t-distribution with n-1 degrees of freedom under the null hypothesis of similar forecast accuracy.

We start by estimating the simple GARCH(1,1) model, then include components of long memory effect (FIGARCH(1,d,1)), seasonal level shifts (S-FIGARCH(1,d,1)) and long term structural change (SA-FIGARCH(1,d,1)). Before generating forecast results, we first estimate the four models for the entire sample period to illustrate their general performance. Then we generate forecast from the four models recursively. Finally we compare their forecast ability.

We conduct two sets of forecast difference tests. First, each forecast model at each forecast horizon is compared to a benchmark GARCH(1,1). This is motivated by a desire to

determine whether additional complexity leads to improved forecasts, and by Hansen and Lunde (2005) who find that it is difficult to out-perform a simple GARCH(1,1). Second, at each horizon, the model with the lowest MSE is compared to other specification to see if the gains are significant.

Data Description

The data used are daily corn futures settlement prices for contracts traded at the Chicago Board of Trade (CBOT). The data are transformed following standard procedures (Vilasuso, 2002; Jin and Frechette, 2004; Baillie, et al., 2007; Sephton, 2009; Kang et al., 2009). The price series runs from January 3, 1989 through December 31, 2009. The daily percentage returns, $r_t \equiv 100(ln(f_t/f_{t-1}))$, are derived from the futures prices f_t. Since contracts only last for a limited period, the next nearby contract is blended 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 price for day t and t-1. On next day (t+1), we switch to the nearby contract and the return is calculated using the settlement price for the new contract for day t+1 and t. The process continues with subsequent contract prices to generate a continuous returns series. Daily realized volatility (variance) is calculated as the square returns r_t^2, a simplification consistent with market efficiency. With approximately 252 observations a year, the number of observations is 5292.

Figure 2 plots the daily returns and volatility, and Table 1 provides summary statistics. Daily returns fluctuate around a zero mean and median, which is consistent with market efficiency. The min and max values are similar in magnitude, suggesting distribution of returns is symmetric around zero and skewness is close to zero at -0.02. There is also weak kurtosis in

returns. While difficult to observe directly in Figure 2, recall the recurring average seasonality which peaks in the summer identified in Figure 1. In more recent years, there have been extremely high spikes and persistence in volatility. The most dramatic changes in volatility occurred during 2008 when the corn price increased sharply to record highs and then dropped precipitously in response to the overall decline in the economy related to the subprime crisis.

The long memory dimension in corn futures volatility is demonstrated using ACF plots.[3] Figure 3 provides the ACF plots for volatility through 800 lags for both periods studied. The ACF structure is quite similar in shape to the figure reported by Baillie et al. (2007). With regards to the structure of volatility, several points are informative. First, as anticipated, autocorrelations differ from zero (the horizontal dash lines identify the boundaries) at very distant daily lags which is a sign of long-memory. Second, local peaks in the autocorrelations occur repeatedly at a frequency of 252 days, which coincides with the number of days in which contracts are traded in a business year. This repeating pattern is consistent with pronounced seasonality. Finally, the ACFs appear to be strong in the beginning, decay slowly and smoothly. This may be attributable to an increased persistence caused by the large information shocks in more recent times. Combining the information in Figures 1-3 identifies the presence of long memory, seasonality, and a changing of structure in market.

Estimation Results

Table 2 reports the estimated results of each model for the entire period. Both GARCH and FIGARCH indicate high levels of persistence; the summation of the GARCH and ARCH parameters (β and ϕ) is close to one. In the FIGARCH model, the fractional integration

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[3] Several statistics exist capable of showing the long-memory property in volatility series. See Crato and Ray (2000), Smith (2004), and Elder and Jin (2007). Since observed long memory in corn volatility is not contentious, we focus primarily on the autocorrelation functions which are more informative in modeling the structure of volatility.

parameter d is above one-half, meaning the process is not weakly stationary—long memory is present but with undefined variance. The values of the log-likelihoods and the information criteria are virtually identical; making it difficult to differentiate statistically the models. In both the S-FIGARCH and the SA-FIGARCH, seasonality is best captured by two Fourier pairs. Closer examination of the seasonality results revealed that both sine functions (a_1 and a_2) are non-significant and extremely small in size compared to cosine terms, so only only the two cosine terms remain. The estimated seasonal pattern is plotted in Figure 4, which is consistent with the realized historical pattern discussed; the procedure seems to effectively recover seasonality in the corn volatility. Inclusion of seasonality reduces long memory estimate in S-FIGARCH model; the parameter d drops by more than one third and is close to value reported by Baillie et al. (2007) after eliminating the seasonal effect.

The importance of the structural change variables emerges in the SA-FIGARCH estimates. A maximum of five pairs of triangular functions are examined and their appropriateness assessed using AIC. We limit the number of pairs to five, which is larger than the four pairs used by Baillie and Morana (2009) in their simulation, but smaller than the eight pairs used in their empirical application. Given the shorter time span of our data, the use of more than five pairs seems at odds with the intent that the structural terms reflect large fundamental changes. For the entire period, five pairs are identified in the SA-FIGARCH. A log likelihood test of their joint significance rejects the null at the 1% level. Inclusion of the structural change variables doesn't seem to affect the seasonality parameters, but the long memory parameter d declines by more than a quarter from its value in the S-FIGARCH model. Also, their inclusion does affect the traditional ARCH and GARCH parameters (β and ϕ), reducing them in size and influencing their statistical significance, suggesting that the multiple pairs may be absorbing the

short-run volatility. The fitted structural change dimension of the conditional volatility is plotted in Figure 4. The fitted structure is consistent in general terms with the earlier discussion of realized volatility, but more sensitive than anticipated—perhaps a result of the large number of pairs identified. The level of the conditional volatility exhibits an increasing pattern which levels-off around 2004 through 2006, then begins to increase at first gradually and then dramatically. The volatility seems to peak in 2008 and then decline sharply in 2009.

Overall, the results emphasize the importance of long memory, seasonality, and structural change in corn price volatility. They also identify the sensitivity of the long memory parameter to omitted factors whose absence influences the correlation patterns at extended lags.

Forecast Results

Out-of-sample daily forecasts are recursively generated for the period, 2005/1/3 – 2009/12/31. Forecasts are made for 1 day, 10 days, 25 days and 40 days ahead. Each day the next observation is added to re-estimate model and forecast. The forecasts cover a highly volatile period, which as discussed are characterized by a relatively stable but slightly increasing period, followed an extreme period reflecting the sharp increase and later decline in corn prices, followed by a somewhat more stable period (Figure 5). We analyze forecast performance in three periods— 2005-2007, 2008, 2009—which correspond to this pattern. The structure of the performance analysis can be viewed as a simplified approximation of real-time forecasting in which an analyst might carefully monitor the models' forecast performance on a regular basis.

The forecast results for the three periods are presented in Table 3. For each period, the forecast model with the lowest MSE at each horizon is in bold font. Results of the forecast difference test results relative to the GARCH(1,1), and relative to the best forecast at a specific

horizon for each period are also provided. The most striking feature of the results are the differences in MSE across the three periods which correspond to the extreme behavior of the corn market during the forecast period. MSE values are less than 30 during 2005-2007 while larger than 110 in 2008, and near 90 in 2009.

The performance of the models differs across the three periods and forecast horizons. During the relative stable 2005-2007 period (Figure 5), the seasonal S-FIGARCH provides forecasts with the lowest MSEs at every horizon. While these differences are only modest compared to the other FIGARCH forecasts, the 10 and 25 day forecasts are significantly smaller than the GARCH predictions. In the absence of structural change, the seasonally adapative model provides little benefit.

During the extremely volatile 2008 period, none of the models work well, but the simple FIGARCH dominates the other specifications at all forecast horizons, particularly at longer horizons where the strongest significance in the forecast difference tests appears. Interesting during this period, both non-seasonal models out-perform the models with seasonality. Closer examination of the realized volatility revealed that the structural change broke the rather reliable seasonal pattern so that the most volatile time in 2008 occurred in the later part of the year (Figure 6). As identified, this high level of volatility is consistent with the timing of the changes in financial markets which spilled over to many commodities including corn. Another factor which likely influenced the performance of the simple FIGARCH was the observed effect that inclusion of the seasonality on estimates of d (Table 2). In the absence of seasonality the long memory parameter was considerably larger. In effect, the simpler FIGARCH specification, unencumbered by seasonality, was able to capture the increasing volatility that emerged at the

end of the period.   Examination of the recursively estimated *d* values during this period supported this notion as they increased in size and significance.

During 2009, which was less extreme than 2008 but still more volatile than 2005-2007, the seasonal FIGARCH re-assumes its relatively better performance. It produces the lowest MSEs at the 1-, 10-, and 25-day horizons, and differs statistically from both the GARCH and FIGARCH specifications at the 1- and 40-day horizons. Interestingly, the structural change also begins to work better, particularly at the 40-day horizon which may correspond to its ability to capture the downturn identified in Figure 4.

Conclusions and Discussion

We investigate the ability to forecast corn price volatility at several short and long-term horizons, using information from futures prices from January 1989 through December 2009. Based on characteristics of corn volatility, we recursively estimate GARCH-type models that allow for long memory, seasonality, and structural change in the conditional volatility.   Beginning in 2005, we then assess their forecasting ability using mean squared error at 1-, 10-, 25-, and 40-day horizons in a recursive manner. The forecast analysis is performed in three periods to reflect the changing patterns in realized volatility, and in broad terms can be viewed in the context of an analyst monitoring real-time forecasts.

Several general points emerged from the analysis. First, long memory, seasonality, and structural indeed play important roles in corn volatility. In the presence of seasonality and structural change, long memory declines in importance, but is still significant. This finding supports the notion that long memory is influenced by a failure to account for structural change

and other factors which can affect decay in autocorrelation, but still is consistent with Baillie et al (2007) who argue that long memory is a key component to understanding volatility patterns. Second, at the very short 1-day horizon, it is hard to differentiate between the simple GARCH and the other long memory specifications, except during the 2009 period when the S-FIGARCH model has a lower and significantly different MSE. However, at longer horizons the various FIGARCH specifications, particularly the seasonal S-FIGARCH, perform considerably better. This result is consistent with Vilasuso (2002), Martens and Zein (2004), Zumbach (2004) and Kang et al. (2009) who find long memory on average will forecast better, especially at distant horizons in periods dominated by rising persistence.

Third, both the seasonal (S-FIGARCH) and the seasonal adjusted (SA-FIGARCH) point to the importance of seasonality in forecasting corn volatility, except during the extreme conditions at the end of 2008 where its regular pattern was disturbed by the subprime crisis. The importance of seasonality is consistent with a rather extensive literature explaining the patterns in the corn volatility (e.g. Goodwin and Schnepf, 2000) as well as the limited volatility forecasting research (Egelkraut, et al 2007). Fourth, despite statistical differences in estimation over the entire sample, there is little to separate the S-FIGARCH and SA-FIGARCH in terms of their forecasting performance. The similar performance is somewhat surprising given the structural change in market volatility that emerged in the corn market. In terms of the procedures used here, a key to the similarity in performance may arise from the apparent interaction between the traditional ARCH and GARCH parameters (β and ϕ) and the structural change parameters as evidenced in estimation. Inclusion of the long-run structural change dimension of conditional volatility seems to absorb the short-run effects, with little improvement in the forecasting. Interestingly, this occurred in both in more volatile periods where the number

of pairs in the Fourier form reached five, and in the relatively stable period where the number of pairs was three (Figure 5). This suggests that the framework may have difficulty disentangling the short- and long-term effects for data used here. Perhaps, a less volatile, longer time span is required. For instance, Baillie and Morana (2009) in their innovative work used weekly data starting 1928 to 2007 to separate the short- and long-term effects, and demonstrate forecasting improvement.

Finally, the fact that forecasting performance was limited should not dissuade researchers from further efforts. The forecasting analysis here was framed in a long-term, recursive framework consistent with recent literature in agricultural markets that focused on long memory in volatility and the presence of dramatic market structural change. In a forecasting framework which does not focus on long memory, other procedures as simple as rolling-window estimation may lead to better forecasts at least in more nearby horizons. In addition, composite forecast models between the long- and short-term dimensions of volatility may lead to improved performance. However, it should be noted that volatility forecasting is indeed a challenging task which will not become easier in global markets that linked directly to the energy complex.

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Table 1 Summary Statistics of Volatility and Returns, 1989/1/3 - 2009/12/31

	Mean	Median	Std Dev	Kurtosis	Skewness	Minimum	Maximum	N
vol	2.31	0.66	4.99	47.04	5.49	0	75.03	5292
return	-0.025	0.00	1.52	5.66	-0.017	-8.10	8.66	5292

Table 2 Results for Volatility Models, 1989/1/3-2009/12/31

	GARCH(1,1)		FIGARCH(1,d,1)		S-FIGARCH(1,d,1)		SA-FIGARCH(1,d,1)	
ω	0.020	(0.01)	0.132	(0.03)	0.263	(0.05)	0.535	(0.135)
$\beta^\dagger$	0.917	(0.01)	0.688	(0.075)	0.551	(0.07)	0.345	(0.161)
$\phi^\dagger$	0.076	(0.01)	0.223	(0.043)	0.278	(0.06)	0.174	(0.14)
d			0.549	(0.09)	0.341	(0.04)	0.227	(0.043)
Seasonals								
a_1					-		-	
b_1					-0.427	(0.063)	-0.470	(0.072)
a_2					-		-	
b_2					0.125	(0.043)	0.127	(0.052)
Structurals								
δ_1							-0.233	(0.077)
γ_1							0.143	(0.167)
δ_2							-0.243	(0.122)
γ_2							0.072	(0.145)
δ_3							-0.123	(0.167)
γ_3							-0.039	(0.103)
δ_4							-0.140	(0.136)
γ_4							-0.038	(0.086)
δ_5							-0.080	(0.069)
γ_5							-0.099	(0.083)
AIC:	1.716		1.716		1.709		1.707	
SIC:	1.719		1.719		1.713		1.717	
LL	-9077.78		-9078.69		-9037.85		-9018.83	
Q(10)	0.695		0.524		0.814		0.756	
Q(20)	0.237		0.166		0.244		0.200	
Kurtosis	4.26		4.257		4.203		4.141	
T	5292		5292		5292		5292	

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

Table 3 Mean Squared Error (MSE) and MDM Results

MSE for 2005-2007

	GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
1 day	27.0	27.1	**26.8**	26.8
10 days	28.2*	28.2*	**27.7†**	27.8
25 days	29.4*	29.3	**28.6†**	28.8
40 days	29.7	29.5	**29.0**	29.4

MSE for 2008

	GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
1 day	113.2	**113.0**	113.9	114.3
10 days	119.2**	**118.3††**	120.8	121.0
25 days	117.1	**116.3**	124.7**	123.8*
40 days	122.1***	**120.0†††**	129.7	127.2

MSE for 2009

	GARCH	FIGARCH	S-FIGARCH	SA-FIGARCH
1 day	94.1*	94.5**	**93.1†**	93.3
10 days	93.1	93.7	**91.5**	91.6
25 days	95.8	96.2	**92.2**	92.4
40 days	99.9**	99.9*	93.6††	**93.5††**

Notes: 1). Lowest MSE in bold fonts for each period and horizon
       2). †††,††,† significance at 1, 5 and 10% relative to GARCH for each period and horizon
       3). ***,**,* significance at 1, 5 and 10% relative to the best forecast for each period and horizon

23

Figure 1 Average Monthly Corn Futures Volatility
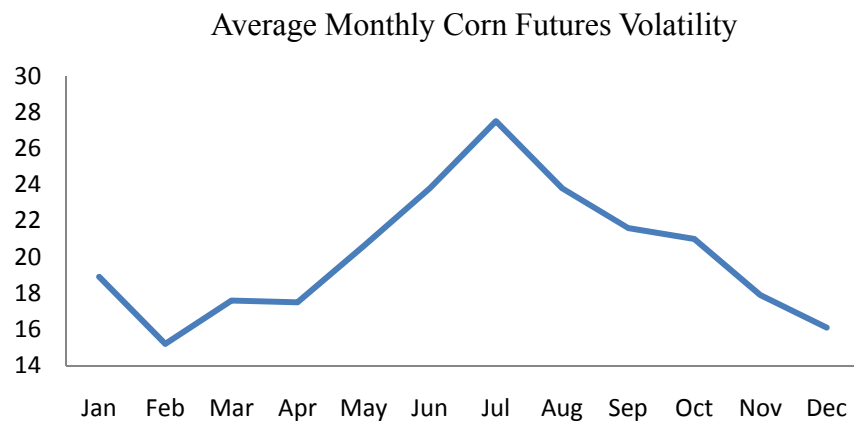

Average Monthly Corn Futures Volatility

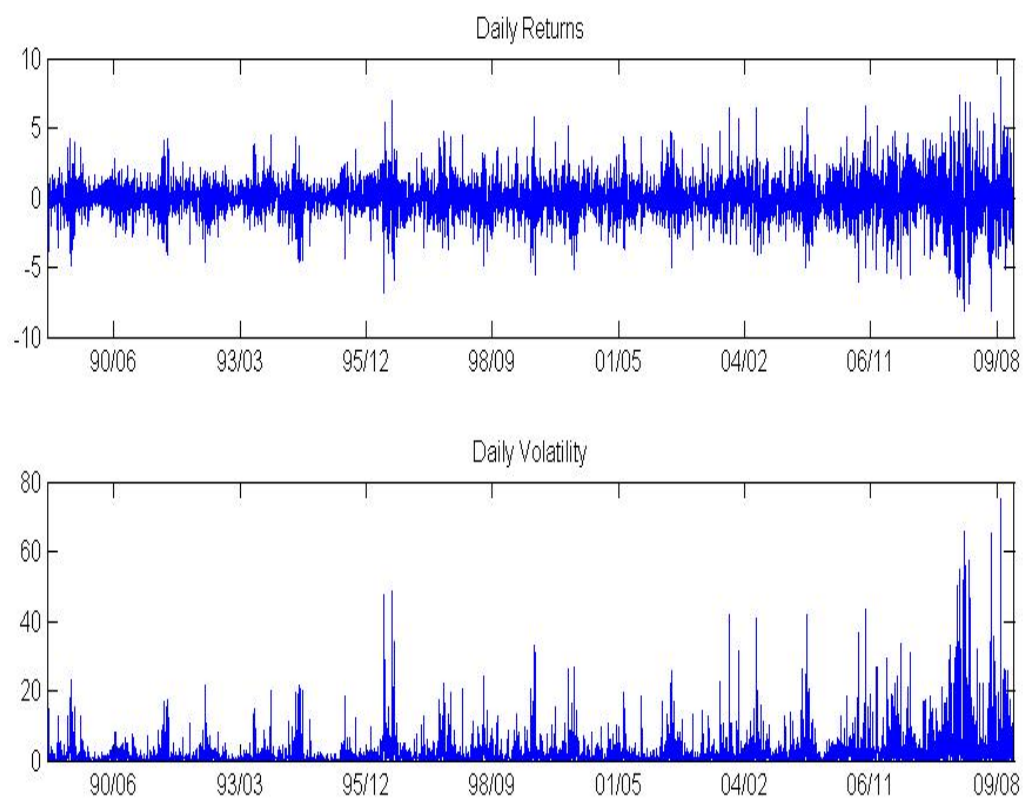Figure 2 Daily Corn Futures Return and Volatility, 1989-2009

Figure 3 ACF of Daily Corn Futures Volatility 1989/1/3-2009/12/31
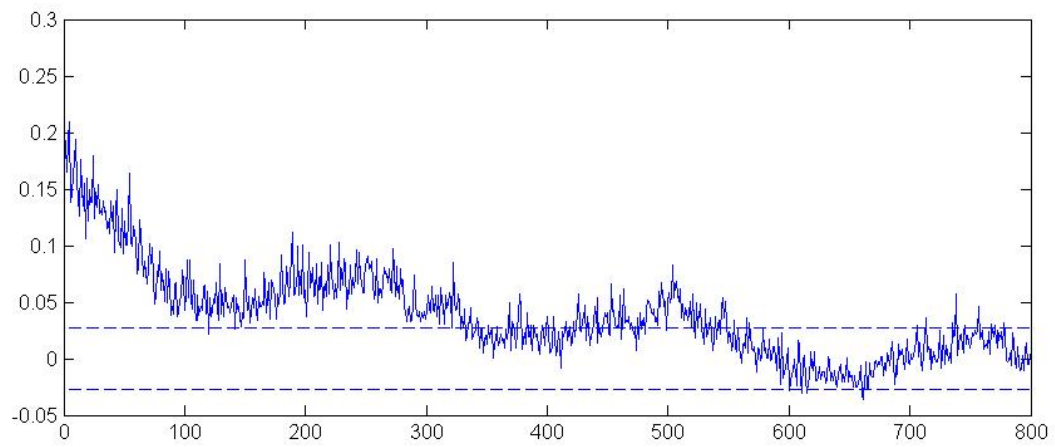
Figure 4 Long-term volatility structure and seasonality in the SA-FIGARCH
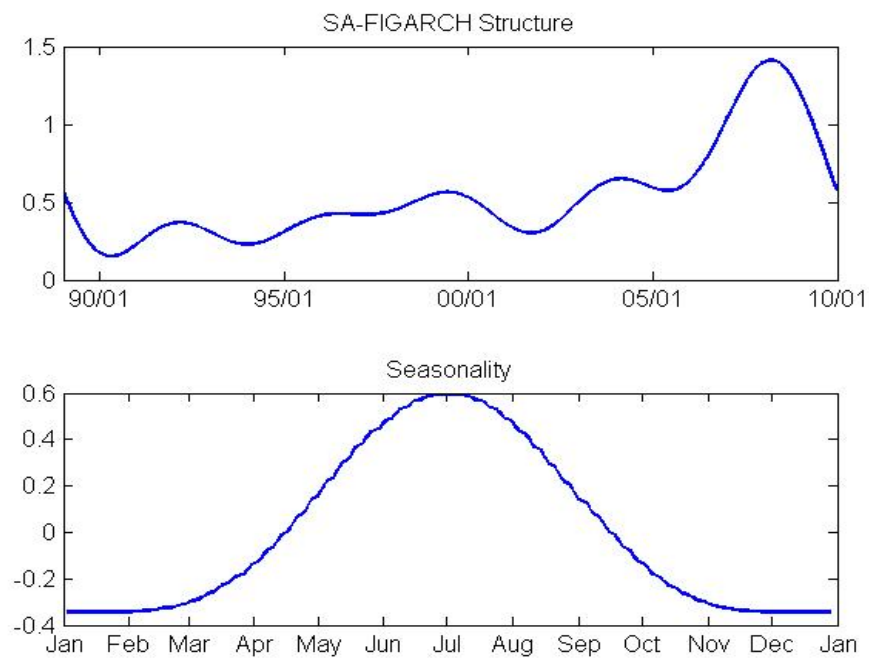
Figure 5 Volatility in forecast period and estimated adaptive structural pairs