6. PRICE VOLATILITY FORECAST FOR AGRICULTURAL COMMODITY FUTURES: THE ROLE OF HIGH FREQUENCY DATA

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Abstract

Realized measures of volatility based on high frequency data contain valuable information about the unobserved conditional volatility. In this paper, we use the Realized GARCH model developed by Hansen, Huang and Shek (2012) to estimate and forecast price volatility for four agricultural commodity futures. Empirical evidences, both in-sample and out-of-sample, show that the Realized GARCH model and its variants outperform the conventional volatility models that only use daily price data, such as GARCH and EGARCH. We also consider skewed student's t-distribution to account for the skewness and fat-tail in the agricultural futures prices. The empirical performances are relatively close for models using three different realized measures, as the measurement equation in the Realized GARCH model can adjust to the different realized measures to some extent.

Keywords: High Frequency Data; Fat-tail; Skewness; Realized Volatility; Agricultural Futures

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Introduction

1.1 Volatility is important for agriculture futures

Price volatility for agricultural futures plays a critical role in the agricultural production and financial future market. The measurement and forecasting of volatility is the foundation of agricultural resource allocation, risk management and product pricing. The prices and volumes of agricultural commodities vary significantly, fact which incurs a high degree of risk and uncertainty. Traditionally, the factors underlying the volatility in agricultural prices were known to be as demand boost in emerging economies, exchange rate movements or global financial crises. More recent studies also found a strong correlation between higher volatility and decreased stocks, also documented a link of causality between agricultural commodity prices and oil prices. Despite a reduction in the prices of agricultural products, the persistence of volatility indicates that significant uncertainty exists in the context of markets' development and market information related design of agricultural policies at regional and global levels.

The causes of variability may be observed over long, medium and short run. As such, over the long run, variability stems out from natural disasters, policy interventions and their transmission which affects market structure including large purchases by the public authorities, and other long-term structural changes. The effect is a sudden, abrupt variation which sometimes occurs irregularly, while shocks either persist or reoccur, causing various successive shifting points. Medium term causes may be of political or cataclysmic nature, but in general they are related to the macroeconomic or political standing (developments outside the agricultural sector), or to the market developments (such as cycles in key markets). As such, the short and long term interest rates practiced by the financial institutions, the access to loans, the exchange rate policy, the anticipations of the economic agents as regards the inflation, and the propensity to consumption are factors that influence the investments and consumption, and ultimately the aggregated demand in the field. In the meantime, the production in the agriculture depends on the production capacities, labor supply and the technological level. Fluctuations in weather conditions or changes in weather patterns also affect the agricultural supply and as such induce price volatility of agricultural commodities. Short run factors are related to financial speculation or hedging with commodity derivatives.

Worth to mention is that volatility of agricultural products varies from one market to another, conditional to the market specific factors such as stability or elasticity of supply and demand or to the elasticity of demand and supply. Agricultural prices are seasonal dependent and also sensitive to speculations made on future prices.

Such multitude of factors affecting agriculture prices made modeling and forecasting of risk associated to such commodities an important and in the same time difficult endeavor. In this perspective, volatility modeling offers the necessary tools to estimate a possible variation in future, based on either from observed realizations of one stochastically moving variable over a historical period, or from deducing implicit volatility from Black-Scholes formula. As such, a thorough understanding of agricultural price variations and of the underlying factors of triggering their patterns would improve policy makers' and risk managers' available tools in managing price risks and providing a safe policy environment. Persistent volatility signals high and persistent uncertainty as regards market fundamentals, and induces higher costs to managing risks, like higher margins at futures contracts, and higher payments at crop insurance contracts. It is natural to consider that higher costs at agricultural prices lead to higher consumer prices, with effects on inflation level and other macroeconomic indicators, fact which reflects the necessity of correct and thorough investigation of this issue.

Agriculture prices behave significantly different from the financial series due to the fact that levels of production and levels of stocks are an important factor that triggers price level and volatility. As well, agriculture prices respond quickly to fluctuations of demand and supply. Basically, three characteristics place agriculture commodities in a different category than the one of high volatile non-farm goods and services. The first one is the seasonality as this determines the type of a particular crop, and expectations on future input and output prices, yields and governmental subsidies form according to this factor. Another characteristic is the derived nature of the agricultural product prices as the agricultural commodities are often used as inputs in the production of other agricultural or industry goods. Finally, the price-inelastic demand and supply which characterizes most of the agricultural products, fact which incurs that unexpected market news induce large fluctuations in prices.

1.2 Historical studies in this field

Behavior of agricultural commodity prices was studied by Deaton and Laroque (1992) and Cashin and McDermott (2002). Hudson, Leuthold and Sarassoro (1987) and Hall, Brorsen and Irwin (1989) identified leptokurtic returns in agricultural commodity futures prices, and that such prices regularly display abrupt, unexpected and discontinuous movements. Samuelson (1965) documented an increase in the volatility of agricultural futures price returns along a simultaneous decrease of time to maturity. Abbott and Borot de Battisti (2011), Gilbert (2010), Gilbert and Morgan (2010) investigated the factors that triggered recent developments in food prices, highlighting that supply/demand factors prevailed. Gilbert and Morgan (2010) provided evidence on a general downwards tendency of food prices, and found little support that global warming, oil price volatility and index investment in futures markets have led to a permanent increase in volatility in grains prices. De Schutter (2010) provided evidence on the role on volatility of speculation in futures and options trading on food commodity markets, while Irwin and Sanders (2010) question the contribution of commodity futures markets to the commodity market performance and the role of speculation in such markets. According to the latter ones, index funds did not cause a bubble in the commodity futures prices, as no statistically significant relationship could be documented to link the changes in index and swap fund positions and an increase in the market volatility, evidence which was found to be the most compelling for the agriculture futures markets. As well, Irwin and Sanders (2010) found a negative relationship between indexes and swap fund positions and market volatility. In turn, Robles, Torero and von Braun (2009) only asserts that speculative activities might have been influential, as some speculation indicators affect current commodity prices of wheat, rice, maize, and soybeans. In thinly traded markets it was found that speculative trades may generate false trends with the effect on a higher price over the consumer side.

Balcombe (2009) finds strong evidences in favor that persistent volatility exists in agricultural prices and a strong connection to the oil price volatility. Sumner (2009) found, on contrary, that only few periods found to have excessive volatility out of a general trend, 2006-2008 period being the one of the largest in the 1866-2008 period, suggesting also that relatively minor demand-side adjustments to biofuels policy may temper the increase in grain prices.

Milonas (1986) documented the maturity effect when controlling for the seasonality. A similar finding belongs to Galloway and Kolb (1996) who found that maturity effect exists in markets with seasonal patterns of demand and supply, but it is not present in markets in which the cost-of-carry model works well. Anderson (1985) found also support for a secondary to seasonality maturity effect. Labys (2003) documented a direct relationship between price behavior and financial shocks incurred by interest rates or exchange rates. Schnepf (2005) found out that agricultural commodity prices differ from other volatile non-farm goods and services due to production seasonality, the derived demand nature and price-inelastic demand and supply functions.

1.3 Benefits of using realized volatility and Realized GARCH model

Empirical evidences indicate that agricultural commodity futures price processes always have fat-tailed distribution and other properties, which suggests that the normal assumptions may not suit (for instance, Hall, Brorsen and Irwin,1989; Hudson, Leuthold and Sarassoro, 1987;Andersen, Bollerslev, Diebold and Enbens, 2001). Analyzing and forecasting agricultural commodity futures price movements need accurate estimation and forecast of volatility. A number of studies documented agricultural commodity futures volatility (see, Wang and Roberts, 2005; Koekebakker and Lien, 2004; Giot, 2003).

Due to its unobservable nature, analyzing and forecasting volatility is difficult and relies on volatility extraction methods. The classic approach is model based volatility estimation with leading models such as ARCH/GARCH model family introduced by Engle (1982) with various variants documented in Bollerslev (2010), and the stochastic volatility family including Melino and Turnbull (1990) and Harvey, Ruiz and Shephard (1994). Recently, various nonparametric realized measures using high frequency financial data as accurate estimators of volatility are also studied by econometricians. Such measures are applied to many fields including the option pricing and risk management.

Realized volatility introduced by Andersen and Bollerslev (1998) is a commonly used measure due to its intuitive definition and easy to calculate nature. Realized volatility uses the sum of squared intraday returns as an unbiased estimator for the latent volatility. Andersen, Bollerslev, Diebold and Ebens (2001) shows that realized volatility is an approximation of the underlying integrated volatility. Since it is a model-free estimator, realized volatility overcomes some drawbacks of model based volatility and widely applied in empirical works. The usage of high frequency data allow us to treat volatility as an observed variable rather than a latent one, as the measures of intraday volatility proved to be a consistent estimator of the underlying day volatility.

However, there are three disadvantages when using the realized volatility. Firstly, accuracy of realized volatility depends on the dynamic structure and distribution of return series. The market microstructure noise such as bid-ask spread and non-synchronized trading may lead to a highly inaccurate measure (Campbell, Lo and Mackinlay, 1997). Secondly, there are non-trading hours in non-24-hour market and the accuracy of realized volatility is queried when the squares of overnight returns are added. Thirdly, there exists a trade-off between accurate estimation of latent volatility, optimized when sampling is undertaken at high frequencies, and the microstructure noise resulted from price discreteness, asynchronous trading, etc.

Hansen, Huang and Shek (2012) proposed a novel framework to integrate the return and realized measure of volatility, which was called the Realized GARCH model. A measurement equation which joined the realized measure to the conditional variance of returns was added to the normal GARCH model. The measurement equation also included a leverage function which characterized the leverage effect. Realized GARCH is essentially a stochastic volatility model and it has several merits. Firstly, the model mends the drawbacks of realized volatility which are caused by microstructure noise and non-trading hours. Secondly, the model is complete since it can estimate all the parameters at one time by maximizing the likelihood function. By contrast, estimation of stochastic volatility model is time-consuming, when MCMC or other simulation methods are used.

This paper applies Realized GARCH model of Hansen, Huang and Shek (2012) to forecast the price volatility for agricultural commodity futures. As compared to Hansen, Huang and Shek's (2012) paper which only considers Gaussian distribution to study stock volatility, this paper extends the Realized GARCH model by including a standard student t and a skewed-t distribution to account for the skewness and the fat tail effects in agricultural futures returns. Due to their simplicity and popularization, GARCH and EGARCH models are used as benchmark. Moreover, we compare the empirical performance of the Realized GARCH model by using alternative realized measures, such as 1-minute Realized Variance, 5-minute Realized Variance and the Realized Kernel, while Hansen, Huang and Shek (2012) only considered the Realized Kernel. Also, in sample and out-of-sample of partial likelihoods will be used to compare various models in sample fitting and forecasting.

The remainder of this paper is organized as follows. Section 2 specifies the different setting of volatility models. Section 3 describes the agricultural futures data. Empirical results are analyzed in the Section 4. Section 5 accesses the forecasting performance of various volatility models, and Section 6 compares different realized measures of volatility. Conclusions are offered in Section 7.

2. Model Specification

Since agricultural futures prices always exhibit volatility clustering, simple GARCH Model is a starting point.

$$r_t = \sqrt{h_t} z_t \qquad (1)$$

$$\log h_t = \omega + \beta \log h_{t-1} + \gamma \log r_{t-1}^2 \qquad (2)$$

Here $z_t \sim N(0,1)$, r_t is the return, h_t is the volatility.

EGARCH model disposes asymmetric effect of return. Nelson (1991) suggests the following model:

$$r_t = \sqrt{h_t} z_t \tag{3}$$

$$\log h_t = \omega + \beta \log h_{t-1} + d_1 z_{t-1} + d_2 \left(|z_{t-1}| - \sqrt{2/\pi} \right) \tag{4}$$

Here $z_t \sim N(0,1)$, and $d_1 z_{t-1} + d_2 \left(|z_{t-1}| - \sqrt{2/\pi} \right)$ is the leverage effect. The past return affects volatility in terms of quantity, as well as direction. Positive and negative returns have different effects on volatility. Parameters d_1 and d_2 show the leverage effect which is supposed to have different signs.

Realized GARCH model is given as follows:

$$r_t = \sqrt{h_t} z_t \tag{5}$$

$$\log h_t = \omega + \beta \log h_{t-1} + \gamma \log x_{t-1} \tag{6}$$

$$\log x_t = \xi + \phi \log h_t + \tau(z_t) + u_t \tag{7}$$

$$\tau(z_t) = d_1 z_t + d_2 (z_t^2 - 1) \tag{8}$$

Here $z_t \sim N(0,1)$, $u_t \sim N(0, \ \sigma_u^2)$, r_t is the return, h_t is the volatility and x_t is the realized measure of volatility. Combing equations (5) and (6), we get the standard GARCHX model. Equation (7) is called the measurement equation, which relates the realized measure of volatility to the implying volatility. To measure the asymmetric effect of return, Hansen, Huang and Shek (2012) used equation (8) as the leverage function. For two distributions having different tails, the distribution having fatter tail is affected more in response to the same return impulse. EGARCH model doesn't take the distribution into consideration.

Agricultural futures prices always have fat tail and leptokurtosis. Except for the normal distribution, we also consider the Student t distribution and the skewed t distribution of return errors. The Student t distribution was proposed by Bollerslev (1986):

$$f(z) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{(\nu-2)\pi}\,\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{z^2}{\nu-2}\right)^{-\frac{\nu+1}{2}} \tag{9}$$

Hansen (1994) suggested the skewed t distribution which documented the skewness when covering the fat tail.

$$g\left(z|\nu,\zeta\right)=\begin{cases} bc\left[1+\frac{1}{\nu-2}\left(\frac{bz+a}{1-\zeta}\right)^2\right]^{-\frac{\nu+1}{2}}, & z<-\frac{a}{b} \\ bc\left[1+\frac{1}{\nu-2}\left(\frac{bz+a}{1+\zeta}\right)^2\right]^{-\frac{\nu+1}{2}}, & z\geq-\frac{a}{b} \end{cases} \qquad (10)$$

$$a=\frac{4c\zeta\left(\nu-2\right)}{\nu-1} \qquad b=\sqrt{1+3\zeta^2-a^2} \qquad c=\frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\left(\nu-2\right)\pi}\Gamma\left(\frac{\nu}{2}\right)}$$

Here ν is degree of freedom and ζ controls for the degree of skewness. When $\zeta>0$, the distribution is skewed to the right. When $\zeta<0$, the distribution is skewed to the left. When $\zeta=0$, the distribution reduces to standard t distribution.

3. Data

This study uses high frequency, intraday futures returns of four agricultural futures traded in the United States. Corn, oats, soybean, and sugar are typical agricultural products traded at the commodity exchange. All such futures have open trading from 9:30 A.M. until 13:15 P.M. The data set begins on April 04, 2006, and ends on March 31, 2009. The full sample consists of 742 collections of corn futures, 730 collections of oats futures, 750 collections of soybean futures and 720 collections of sugar futures.

The 1-min raw futures data are used to calculate the daily returns and the realized measures of volatility. To contain the information of non-trading hours, daily return uses the close-to-close return. To balance the microstructure frictions and the measurement error, the realized volatilities are calculated at 1-min and 5-min frequencies. The realized volatility is defined as $RV_t^m=\sum_{j=1}^{m} r_{t,j}^2$, where m is the number of one-minute (or five-minute) returns during trading day t.

Barndorff-Nielsen, Lunde and Shephard (2009) suggests realized kernel as another method often used to modify the microstructure noise. The intraday returns are correlated if there are microstructure noises. Realized volatilities omit these correlations. The realized kernel uses the kernel structure to modify these correlations, calculated as $RK=\sum_{j=1}\sum_{h=-H}^{H} K\left(\frac{h}{H}\right)\left|r_{t,j}\right|\left|r_{t,j-h}\right|$, where $K\left(\cdot\right)$ is the kernel function. Here we use Panzer kernel proposed by Hansen and Lunde (2006). H is the bandwidth of the kernel function.

Table 1 reports summary statistics for the daily returns and realized volatilities for four types of agricultural futures. These statistics imply that four types of agricultural futures have very different distributions. Mean return of corn is 0.00073,but mean return of sugar is -0.000509. Corn and soybean have negatively skewed daily return distributions, but oats and sugar have positively skewed daily return distributions. Kurtosis, which measures the peak of distribution, is 4.05 for corn, 4.56 for oats, 4.81for soybean, but 9.00 for sugar.

Table 1

Summary Statistics of Daily Returns and Realized Volatilities of Agricultural Futures

		Mean	Median	Variance	Skewness	Kurtosis
Corn	r_{cc}	7.30	11.00	56000	-0.23	4.05
	RK	2.72	1.95	5.81	2.90	18.10
	RV_1	3.22	2.53	4.60	2.16	10.07
	RV_5	3.00	2.16	6.84	3.06	19.68
Oats	r_{cc}	1.64	18.42	51000	0.12	4.56
	RK	4.59	3.25	18.70	2.46	11.91
	RV_1	8.14	5.17	86.70	4.64	41.75
	RV_5	6.35	4.17	45.90	3.63	22.82
Soybean	r_{cc}	6.96	16.33	37000	-0.24	4.81
	RK	1.88	1.30	3.25	2.44	11.04
	RV_1	2.12	1.47	3.36	2.60	13.66
	RV_5	2.05	1.36	4.16	3.45	23.93
Sugar	r_{cc}	-5.09	-18.00	63600	0.80	9.00
	RK	2.80	2.03	7.36	2.98	18.18
	RV_1	3.89	3.21	6.26	1.98	8.77
	RV_5	3.16	2.40	7.22	2.94	19.03

Note: Mean is in order of 10^{-4} *, Median is in order of* 10^{-4} *, and variance is in order of* 10^{-8} *.*

Figure 1 and Figure 2 show the daily returns and realized kernels for corn, oats, soybean and sugar for 2006 to 2009period. All four return series exhibit a great deal of volatility, particularly after 2008.

4. Empirical Results

We estimate the GARCH, EGARCH and Realized GARCH models with normal distribution, standard Student t distribution and skewed Student distribution using the full sample. Table 2 summarizes the estimation result of four agricultural futures.

Log-likelihood is closely related to KLIC measure in probability theory which measures the distance between the estimated distribution and the underlying true distribution. Since the log-likelihood from different models cannot be directly compared since the models use different data (GARCH models only use return data and Realized GARCH models use both return and realized measure data. Within the Realized GARCH class, different realized measures are also used.), we compare the partial log-likelihood which is the log-likelihood associated with returns when necessary.

Figure 1

Daily Return for Agricultural Futures for Period 2006-2009

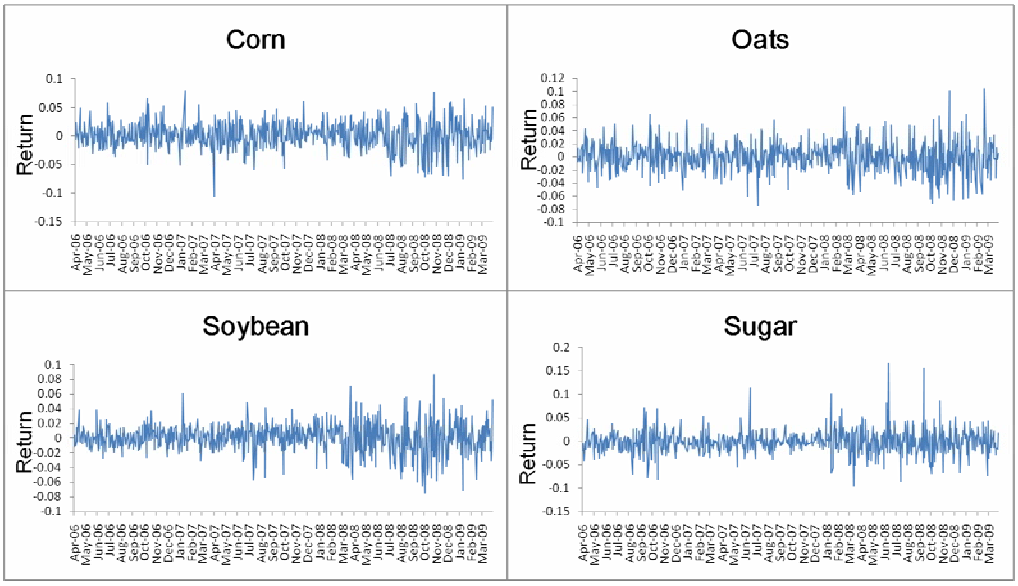


Figure 2

Daily Realized Kernel for Agricultural Futures for Period 2006-2009

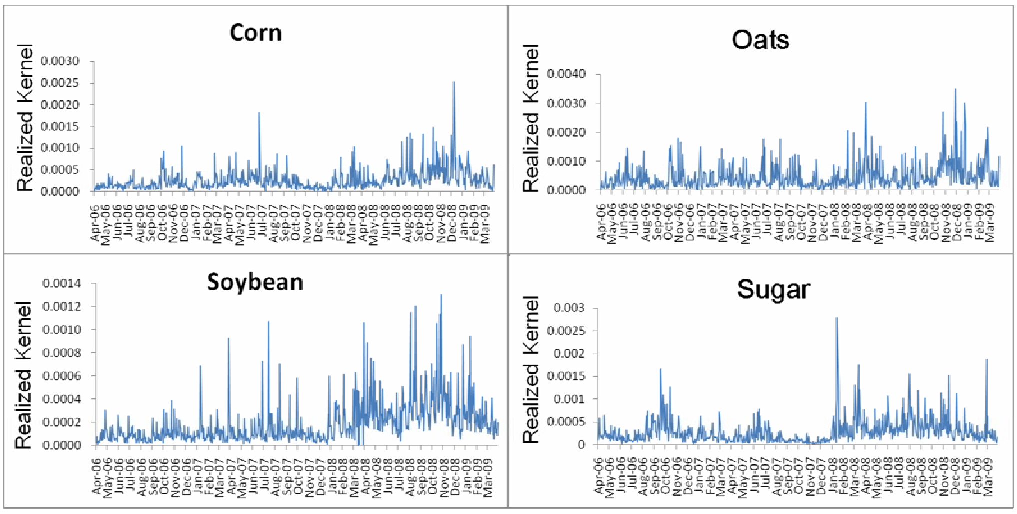


Table 2

Estimation Results of Agricultural Futures

Corn

	ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
GARCH	-0.031	0.976	0.017								1744.06	
	(0.043)	(0.025)	(0.020)									
EGARCH	-0.225	0.970				-0.054	0.049				1749.57	
	(0.028)	(0.001)				(0.030)	(0.008)					
RGARCH	-0.648	0.761	0.135	2.080	1.405	0.018	0.058	0.474			970.07	1744.80
	(0.199)	(0.051)	(0.033)	(1.407)	(0.186)	(0.026)	(0.015)	(0.024)				
RGARCH_T	-0.468	0.754	0.163	0.590	1.207	0.015	0.058	0.474	9.017		978.49	1753.10
	(0.197)	(0.022)	(0.060)	(0.088)	(0.014)	(0.025)	(0.040)	(0.021)	(0.650)			
RGARCH_ST	-0.449	0.754	0.165	0.489	1.194	0.015	0.057	0.474	8.981	0.020	978.55	1753.10
	(0.215)	(0.056)	(0.035)	(0.792)	(0.104)	(0.025)	(0.014)	(0.024)	(2.642)	(0.053)		

Oats

	ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
GARCH	-0.132	0.943	0.033								1750.67	
	(0.187)	(0.020)	(0.012)									
EGARCH	-0.269	0.964				-0.022	0.094				1753.27	
	(0.109)	(0.016)				(0.056)	(0.028)					
RGARCH	-0.381	0.865	0.080	1.013	1.190	-0.085	0.154	0.572			911.80	1743.50
	(2.209)	(2.986)	(1.208)	(1.014)	(6.240)	(16.610)	(5.114)	(0.309)				
RGARCH_T	-0.450	0.841	0.094	0.899	1.179	-0.086	0.157	0.570	5.690		926.85	1757.70
	(1.767)	(0.742)	(0.275)	(1.596)	(0.122)	(0.690)	(0.826)	(0.463)	(1.283)			
RGARCH_ST	-0.464	0.840	0.093	1.010	1.194	-0.086	0.158	0.570	5.581	-0.026	927.00	1757.90
	(0.069)	(0.019)	(0.015)	(0.157)	(0.029)	(0.050)	(0.026)	(0.030)	(1.095)	(0.066)		

Soybean

	ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
GARCH	0.014	0.965	0.031								1961.40	
	(0.007)	(0.013)	(0.012)									
EGARCH	-0.098	0.987				-0.027	0.103				1967.40	
	(0.054)	(0.007)				(0.016)	(0.032)					
RGARCH	0.081	0.884	0.113	-1.363	0.941	-0.001	0.116	0.414			1223.40	1957.30
	(0.078)	(0.024)	(0.022)	(0.578)	(0.071)	(0.0243)	(0.014)	(0.023)				
RGARCH_T	0.186	0.876	0.132	-1.948	0.870	-0.003	0.116	0.413	6.581		1239.00	1971.80
	(0.025)	(0.033)	(0.042)	(0.388)	(0.047)	(0.025)	(0.014)	(0.027)	(0.739)			
RGARCH_ST	0.167	0.875	0.130	-1.850	0.883	-0.004	0.118	0.413	6.293	-0.083	1240.40	1973.33
	(0.240)	(0.028)	(0.063)	(0.747)	(0.142)	(0.047)	(0.115)	(0.066)	(1.212)	(0.050)		

Sugar

	ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
GARCH	-0.118	0.919	0.054								1668.67	
	(0.251)	(0.020)	(0.016)									
EGARCH	-0.229	0.967				0.008	0.192				1667.55	
	(0.067)	(0.004)				(0.056)	(0.050)					
RGARCH	0.281	0.811	0.200	-2.122	0.856	-0.090	0.106	0.403			988.43	1683.20
	(0.052)	(0.026)	(0.026)	(0.133)	(0.008)	(0.028)	(0.039)	(0.040)				

From Table 2, the fact that almost all partial log-likelihood functions from Realized GARCH models are larger than the log-likelihood from GARCH and EGARCH models suggests that Realized GARCH models are better in terms of return in-sample fit. Also, the Realized GARCH model with skewed student t distribution outperforms those with normal and standard t distributions. This suggests that the Realized GARCH model with skewed student's t distribution does better in modeling financial data not only with respect to the volatility clustering but also with respect to the fat-tail (leptokurtosis) and skewed-tail. Such advantage is gained by explicitly introducing leptokurtosis and skewness into return distribution.

The estimated conditional volatility of GARCH and Realized GARCH models are showed in Figure 3.The conditional volatility of Realized GARCH has the same trend with that of GARCH. However, conditional volatility of Realized GARCH fluctuates more than that of Realized GARCH, except for the oats. The dynamics of the conditional volatility of the four agricultural futures has different patterns. Sugar has the most drastic fluctuations and oat has the least drastic ones. Before 2008, the price of oats and soybean moved smoothly, while price of sugar and corn moved drastically. After 2008, they all suffered severe fluctuations.

Figure 3

Conditional Volatility of GARCH and Realized GARCH Models

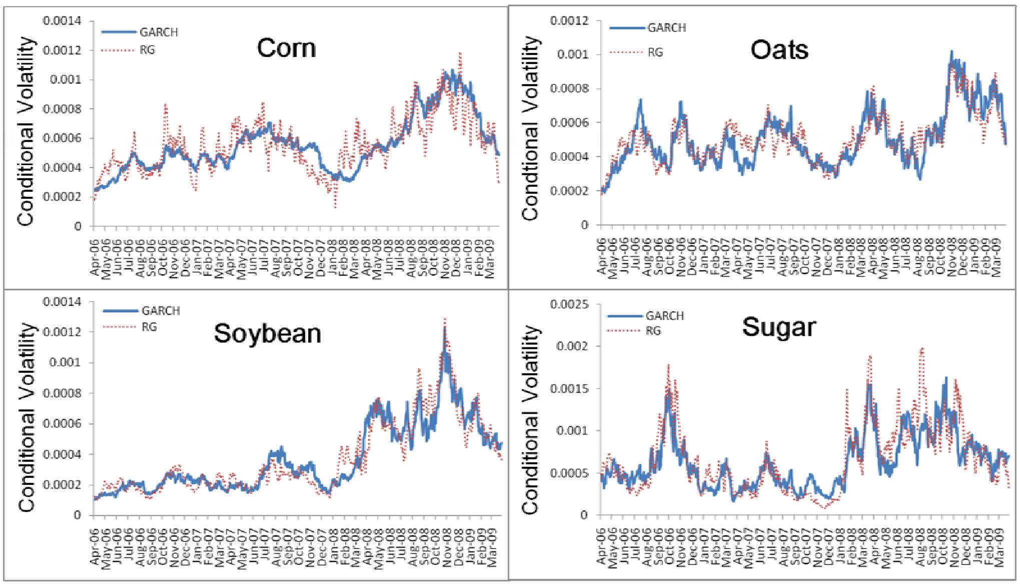
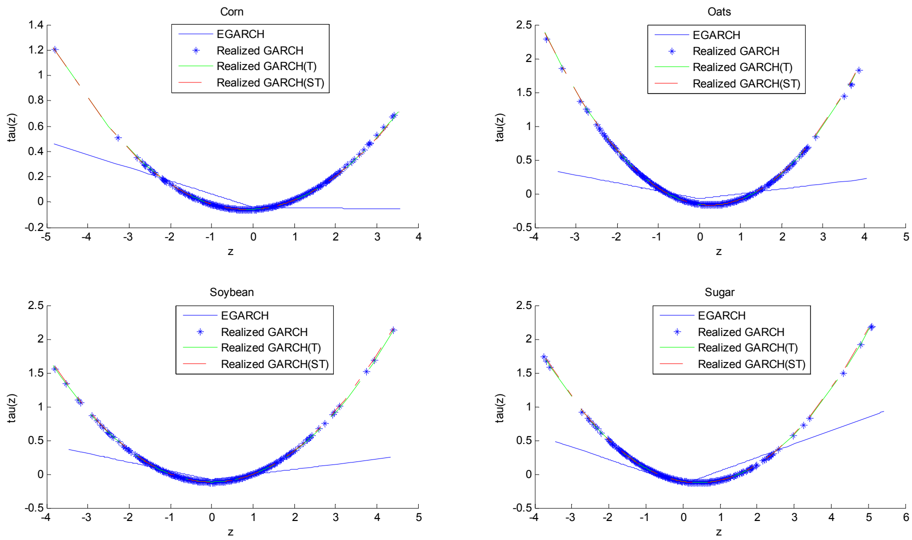


Figure 4 plots each futures various kinds of leverage functions. Since the Realized GARCH models include the quadratic component of return impulse, they response strongly in extreme case. Leverage functions of Realized GARCH models exhibit the U shape, while leverage functions of EGARCH model reveal the broken line. The distributions of return error don't influence the leverage function; therefore, the leverage functions of Realized GARCH with Gaussian distribution, student t distribution and skewed t distribution have almost the same pattern.

Figure 4

Leverage Functions for Agricultural Futures



Accessing Forecasting Performance

To compare the forecasting ability of various models, we split the full sample into two subsamples and calculate the log-likelihood of the GARCH model as well as the partial log-likelihood of the Realized GARCH models. One subsample of corn futures is from April 04, 2006 to December 31, 2007 and the other subsample of corn futures is from January 2, 2008 to March 31, 2009.The division was made on whether the hypotheses that the volatility model forecasts the financial volatility. Conditional to the parameters estimated in first sample, each volatility model forecasted the out-sample volatility. The in sample and out-of-sample fit were estimated in order to evaluate the forecasting ability of each volatility model. As previously stated, we used the partial likelihood values in order to estimate the forecasting performance. Results are presented in Table 3.

Table 3

Forecast Performances of Agricultural Futures

		In Sample	Out of Sample
Corn	GARCH	1058.40	664.60
	EGARCH	1059.30	676.81
	RGARCH	1061.10	681.30
	RGARCH_T	1069.90	681.90
	RGARCH_ST	1070.80	678.66

		In Sample	Out of Sample
Oats	GARCH	1072.70	639.98
	EGARCH	1072.90	633.40
	RGARCH	1067.40	656.69
	RGARCH_T	1076.20	670.13
	RGARCH_ST	1076.30	671.87
Soybean	GARCH	1254.60	496.71
	EGARCH	1252.90	683.36
	RGARCH	1249.10	657.53
	RGARCH_T	1262.50	673.48
	RGARCH_ST	1263.40	675.72
Sugar	GARCH	1054.90	614.97
	EGARCH	1054.90	602.91
	RGARCH	1058.00	624.82
	RGARCH_T	1073.00	647.71
	RGARCH_ST	1074.80	647.20

Note: 'In Sample' means the (partial) log-likelihood function values calculated in the sample. 'Out-of-Sample' means the (partial) log-likelihood function values calculated out of the sample. RGARCH is Realized GARCH with normal distribution which using realized kernel as realized measure. RGARCH_T is Realized GARCH with standard student's t distribution. RGARCH_ST is Realized GARCH with standard skewed student's t distribution.

In Table 3 it can be seen that the partial log-likelihood of the Realized GARCH models is slightly higher than the log-likelihood of GARCH and EGARCH models, with no regard to the agriculture futures we used. This indicates that the Realized GARCH models perform well in the in-sample fit, and they are also efficient forecasters. The Realized GARCH model with skewed student t distribution has higher partial log-likelihood than that of the similar model with normal and standard t distributions, result which appears to be robust to different subsamples. This suggests that the Realized GARCH model with skewed student t distribution is also a better forecasting model. Given the error term distribution, using different realized measures only brings very small difference in terms of partial log-likelihoods, both in the-sample and out-of-sample. This suggests that the Realized GARCH model can adjust certain amounts of noise measurement error in the realized volatility.

5. Accessing Realized Measure of Volatility

We also use the realized volatility estimated from 1-min and 5-min returns in order to check whether Realized GARCH models adjust the micro-structure noise bias in the realized volatility. Table 4 shows the estimation results for the full sample. Table 5 summarizes the forecasting performance of the realized volatility.

Table 4

Estimation Results of Agricultural Futures Based on Realized Volatility

Corn

		ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
RV1	RGARCH	-0.47	0.63	0.28	-0.11	1.07	0.01	0.02	0.19			1311.71	1748.40
		(0.14)	(0.05)	(0.04)	(0.47)	(0.06)	(0.02)	(0.01)	(0.01)				
	RGARCH_T	-0.15	0.64	0.31	-1.03	0.95	0.01	0.02	0.19	10.03		1319.22	1756.00
		(1.70)	(0.04)	(1.50)	(0.58)	(0.80)	(0.19)	(0.79)	(0.09)	(8.98)			
	RGARCH_ST	-0.14	0.64	0.32	-1.04	0.95	0.01	0.02	0.19	10.02	0.00	1319.23	1756.00
		(0.32)	(0.05)	(0.05)	(0.87)	(0.12)	(0.02)	(0.01)	(0.01)	(3.09)	(0.06)		
RV5	RGARCH	-0.68	0.72	0.17	1.72	1.34	0.02	0.05	0.35			1084.89	1745.60
		(0.21)	(0.06)	(0.04)	(1.27)	(0.13)	(0.13)	(0.21)	0.02				
	RGARCH_T	-0.47	0.73	0.19	0.56	1.19	0.02	0.05	0.35	9.60		1093.24	1754.20
		(0.25)	(0.06)	(0.05)	(1.32)	(0.17)	(0.03)	(0.03)	0.02	(2.08)			
	RGARCH_ST	-0.46	0.73	0.19	0.52	1.18	0.02	0.05	0.35	9.58	0.01	1093.25	1754.30
		(0.71)	(0.31)	(0.20)	(1.58)	(0.49)	(0.03)	(0.07)	0.02	(2.34)	(0.14)		

Oats

		ω	β	Γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
RV1	RGARCH	-0.47	0.87	0.07	3.54	1.45	-0.09	0.15	0.52			946.05	1746.60
		(0.14)	(0.03)	(0.02)	(1.67)	(0.22)	(0.03)	(0.02)	(0.03)				
	RGARCH_T	-0.51	0.86	0.08	3.49	1.45	-0.09	0.16	0.52	6.11		958.80	1759.10
		(0.09)	(0.03)	(0.02)	(0.69)	(0.09)	(0.03)	(0.02)	(0.03)	(1.25)			
	RGARCH_ST	-0.52	0.86	0.08	3.59	1.46	-0.09	0.16	0.52	5.95	-0.03	959.00	1759.30
		(0.18)	(0.03)	(0.02)	(1.93)	(0.25)	(0.03)	(0.03)	(0.03)	(0.89)	(0.04)		
RV5	RGARCH	-0.37	0.87	0.08	1.60	1.23	-0.09	0.15	0.55			926.55	1745.90
		(0.12)	(0.03)	(0.02)	(0.46)	(0.06)	(0.03)	(0.02)	(0.03)				
	RGARCH_T	-0.42	0.85	0.09	1.39	1.20	-0.09	0.15	0.55	5.97		940.30	1759.10
		(0.21)	(0.04)	(0.02)	(1.50)	(0.20)	(0.03)	(0.02)	(0.03)	(1.42)			
	RGARCH_ST	-0.43	0.85	0.09	1.47	1.21	-0.09	0.16	0.55	5.87	-0.02	940.41	1759.20
		(0.08)	(0.03)	(0.02)	(0.58)	(0.08)	(0.03)	(0.02)	(0.03)	(1.25)	(0.05)		

Soybean

		ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
RV1	RGARCH	0.25	0.82	0.19	-1.79	0.86	-0.01	0.08	0.24			1435.40	1957.50
		(0.14)	(0.03)	(0.03)	(0.54)	(0.07)	(0.02)	(0.01)	(0.01)				
	RGARCH_T	0.49	0.81	0.23	-2.54	0.77	-0.01	0.08	0.23	6.43		1452.40	1971.90
		(0.09)	(0.03)	(0.03)	(0.69)	(0.08)	(0.03)	(0.02)	(0.01)	(1.61)			
	RGARCH_ST	0.46	0.81	0.22	-2.46	0.78	-0.01	0.08	0.23	6.21	-0.08	1453.60	1973.50
		(0.14)	(0.03)	(0.03)	(0.46)	(0.06)	(0.02)	(0.01)	(0.01)	(1.33)	(0.05)		
RV5	RGARCH	0.15	0.87	0.14	-1.65	0.89	-0.01	0.11	0.36			1278.30	1959.20
		(0.09)	(0.02)	(0.02)	(0.54)	(0.07)	(0.02)	(0.01)	(0.02)				
	RGARCH_T	0.27	0.86	0.15	-2.21	0.82	-0.01	0.11	0.36	6.84		1293.30	1972.90
		(0.03)	(0.02)	(0.02)	(0.19)	(0.02)	(0.02)	(0.01)	(0.02)	(0.58)			
	RGARCH_ST	0.25	0.86	0.15	-2.13	0.83	-0.01	0.11	0.36	6.54	-0.08	1294.50	1974.30
		(0.07)	(0.02)	(0.02)	(0.45)	(0.06)	(0.02)	(0.01)	(0.02)	(1.39)	(0.05)		

Sugar

		ω	β	γ	ξ	Φ	d1	d2	σ_u	v	ζ	LogL	PLogL
RV1	RGARCH	0.82	0.75	0.33	-2.95	0.68	-0.07	0.07	0.14			1359.69	1674.40
		(0.20)	(0.03)	(0.04)	(0.38)	(0.05)	(0.01)	(0.01)	(0.01)				
	RGARCH_T	0.73	0.76	0.32	-2.83	0.70	-0.07	0.07	0.14	4.42		1397.37	1712.50
		(0.16)	(0.03)	(0.04)	(0.28)	(0.04)	(0.01)	(0.01)	(0.01)	(0.66)			
	RGARCH_ST	0.74	0.76	0.32	-2.83	0.70	-0.07	0.07	0.14	4.42	0.06	1398.36	1713.50
		(0.23)	(0.03)	(0.04)	(0.47)	(0.06)	(0.01)	(0.01)	(0.01)	(0.83)	(0.04)		
RV5	RGARCH	0.44	0.79	0.24	-2.52	0.77	-0.07	0.09	0.28			1121.29	1679.00
		(0.13)	(0.03)	(0.03)	(0.43)	(0.06)	(0.02)	(0.01)	(0.01)				
	RGARCH_T	0.41	0.80	0.23	-2.47	0.78	-0.08	0.09	0.28	4.48		1159.56	1717.40
		(0.03)	(0.03)	(0.03)	(0.23)	(0.03)	(0.02)	(0.01)	(0.01)	(0.45)			
	RGARCH_ST	0.43	0.79	0.24	-2.50	0.78	-0.08	0.09	0.28	4.47	0.08	1161.00	1718.70
		(0.22)	(0.03)	(0.04)	(0.61)	(0.09)	(0.06)	(0.04)	(0.02)	(0.75)	(0.05)		

Note: LogL is the log-likelihood function value. PLogL is the Partial log-likelihood function value. RGARCH is Realized GARCH with normal distribution. RGARCH_T is Realized GARCH with standard student's t distribution. RGARCH_ST is Realized GARCH with standard skewed student's t distribution. Standard deviation is in the parenthesis.

Table 5

Forecast Performances of Agricultural Futures Based on Various Realized Measure of Volatility

		In Sample	Out-of-Sample
Corn	RGARCH(RK)	1061.10	681.30
	RGARCH(RV1)	1062.80	684.02
	RGARCH(RV5)	1060.10	681.09
	RGARCH_T(RK)	1069.90	681.90
	RGARCH_T(RV1)	1071.80	684.05
	RGARCH_T(RV5)	1069.50	682.17
	RGARCH_ST(RK)	1070.80	678.66
	RGARCH_ST(RV1)	1072.40	681.55
	RGARCH_ST(RV5)	1070.20	679.17
Oats	RGARCH(RK)	1067.40	656.69
	RGARCH(RV1)	1067.10	665.82
	RGARCH(RV5)	1066.90	659.32
	RGARCH_T(RK)	1076.20	670.13
	RGARCH_T(RV1)	1075.40	674.63
	RGARCH_T(RV5)	1075.70	671.19
	RGARCH_ST(RK)	1076.30	671.87
	RGARCH_ST(RV1)	1075.30	677.01
	RGARCH_ST(RV5)	1075.80	673.03
Soybean	RGARCH(RK)	1249.10	657.53
	GARCH(RV1)	1248.10	691.86
	RGARCH(RV5)	1249.20	667.64
	RGARCH_T(RK)	1262.50	673.48
	RGARCH_T(RV1)	1262.00	701.39
	RGARCH_T(RV5)	1262.70	680.54
	RGARCH_ST(RK)	1263.40	675.72
	RGARCH_ST(RV1)	1262.90	702.56
	RGARCH_ST(RV5)	1263.70	682.66
Sugar	RGARCH(RK)	1058.00	624.82
	RGARCH(RV1)	1050.30	622.64
	RGARCH(RV5)	1053.40	625.38
	RGARCH_T(RK)	1073.00	647.71
	RGARCH_T(RV1)	1065.50	646.27
	RGARCH_T(RV5)	1069.60	647.39
	RGARCH_ST(RK)	1074.80	647.20
	RGARCH_ST(RV1)	1066.60	646.19
	RGARCH_ST(RV5)	1071.00	647.25

Note: 'In Sample' means the (partial) log-likelihood function values calculated in the sample. 'Out-of-Sample' means the (partial) log-likelihood function values calculated out of the sample. RGARCH(RK) is Realized GARCH with normal distribution which using realized kernel as realized measure. RGARCH(RV1) is Realized GARCH with normal distribution which using *realized volatility calculated on the frequency of 1-min as realized measure. RGARCH(RV5) is Realized GARCH with normal distribution which using realized volatility calculated on the frequency of 5-min as realized measure. RGARCH_T is Realized GARCH with standard student's t distribution. RGARCH_ST is Realized GARCH with standard skewed student's t distribution.*

Comparing the estimation and the forecasting performance, we find that the empirical results for models with various realized measure are similar. Although1-min realized volatility has lower log-likelihood values, and 5-min realized volatility has log-likelihood values close to the realized kernels; these three realized measures have similar results. It implies that the choice of the realized measure does not affect the estimation and forecasting ability of the Realized GARCH models.

6. Conclusion

In the current paper, volatilities corresponding to four kinds of high frequency agricultural futures are analyzed and forecasted. Although such agricultural futures have different distributions, the volatility models provide similar results. Realized GARCH models perform better than GARCH and EGARCH models in both fitting and forecasting endeavors. The Realized GARCH model with Skewed-t distribution outperforms the similar model with student t and Gaussian distributions. This illustrates that agricultural futures prices' tail and other distribution information help us to analyze and forecast volatilities.

That Realized GARCH models outperform GARCH and EGACH models implies that Realized GARCH models have four advantages. Firstly, Realized GARCH models successfully integrate realized measures of volatility in conditional volatility in order to utilize intraday information. Secondly, Realized GARCH models take the skewness and tail information into consideration. Thirdly, Realized GARCH models effectively employ the leverage function to capture the asymmetric effect of past return. Fourthly, the Realized GARCH models adjust the microstructure noise.

The work can be extended by improving forecasting methodology and evaluation criteria. For instance, it could be used the rolling window for forecasting, or there could be employed the loss functions in order to evaluate the forecasting performance (for example, Khalifa, Miao, and Ramchander, 2011).

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