Persistence of Volatility in Futures Markets

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This article examines the characteristics of key measures of volatility for different types of futures contracts to provide a better foundation for modeling volatility behavior and derivative values. Particular attention is focused on analyzing how different measures of volatility affect volatility persistence relationships. Intraday realized measures of volatility are found to be more persistent than daily measures, the type of GARCH procedure used for conditional volatility analysis is critical, and realized volatility persistence is not coherent with conditional volatility persistence. Specifically, although there is a good fit between the realized and conditional volatilities, no coherence exists between their degrees of persistence, a counterintuitive finding that shows realized and conditional volatility measures are not a substitute for one another. © 2006 Wiley Periodicals, Inc. Jrl Fut Mark 26:571–594, 2006

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INTRODUCTION

Volatility is the focus of many issues in asset price behavior and risk management. Forecasting volatility, hedging performance, derivative modeling, and the volume–volatility relation are four important examples of how price volatility is a key topic for current research. Poon and Granger (2003) provide a review of research issues concerning volatility, emphasizing various aspects of forecasting volatility, including the persistence (long memory) of volatility through time. In particular, the degree of volatility persistence affects how efficiently one can estimate and predict volatility, because it relates to the stability of volatility over time.

This article examines volatility persistence for various futures contracts, emphasizing a key factor generally ignored by prior research relating to volatility persistence, namely, the method used to measure volatility. Andersen and Bollerslev (1998) and Andersen, Bollerslev, Diebold, and Labys (2003) introduce and examine the realized 5-minute measure of volatility as a more efficient and unbiased estimator of volatility than the popular close-to-close measure. Such a measure could reduce the amount of noise in the measurement of volatility, because noise adversely affects the accurate determination of the persistence effects related to volatility. In fact, Martens and Zein (2004) provide evidence that realized volatility can provide better forecasts than implied volatility. The performances of classical, range-based, and high-frequency realized and conditional volatility estimators are compared to examine both persistence and the relative characteristics of volatility measures for different types of futures contracts. Volatility and persistence impact forecasting accuracy, hedging performance, modeling and evaluation, derivative valuation, and volume–volatility information modeling issues mentioned earlier.

Most financial time series exhibit long-memory (persistence) characteristics for volatility.[1] In fact, recent research provides evidence that long memory exists in both realized *and* conditional volatility.[2] However,

[1]Baillie (1996) states: "The presence of long memory can be defined. . . in terms of the *persistence* of observed autocorrelations. The extent of the persistence is consistent with an essentially *stationary* process, but where the autocorrelation takes far longer to decay than the exponential rate associated with the ARMA class." See Baillie for an excellent survey of the theoretical framework and application of long-memory processes.

[2]In particular, Andersen, Bollerslev, Diebold, and Labys (2001) demonstrate long-memory dynamics and a log-normal distribution for exchange-rate volatility, and Andersen, Bollerslev, Diebold, and Ebens (2001) find the same characteristics for realized stock return volatility. Baillie, Bollerslev, and Mikkelsen (1996) introduce fractionally integrated GARCH (i.e. FIGARCH) to model persistent conditional volatility (applied to exchange rates), while Bollerslev and Mikkelsen (1996) find evidence that dependence in U.S. stock markets' conditional volatility can be characterized by a mean-reverting fractionally integrated process.

only a few studies examine the characteristics of futures market volatility measures. Areal and Taylor (2002) employ daily realized volatility as calculated from 5-minute FTSE-100 index futures, finding that this measure of realized volatility has persistent positive autocorrelation that displays long-memory effects.[3] Thomakos and Wang (2003) study the statistical characteristics of realized volatility (only) for the S&P 500, deutsche mark, T-bond, and eurodollar futures, whereas Luu and Martens (2003) use daily realized volatility and volume to test the relationship of persistence to the mixture of distribution hypothesis (MDH). But none of these studies compare the characteristics of differing volatility measures or examine persistence over different models and types of futures contracts.

The purpose of this article is to examine volatility persistence across different volatility estimators for different types of futures contracts, with a key objective of finding the best measure for identifying volatility persistence. This work differs from previous research, especially for futures markets, in the following respects. First, this article analyzes volatility persistence with the use of different volatility measures: the classical close-to-close measures, the range-based Garman and Klass (1980) method, the high-frequency 5-minute volatility, and the conditional GARCH volatility process. Second, two types of GARCH processes are compared to determine whether the type of GARCH model used is important for examining the volatility process. Third, this research investigates the relationship between the goodness-of-fit and the coherence of fractional integration for the main three volatility estimators.

The results in this article show that the intraday measures of volatility are substantially more persistent than the classical close-to-close measures, the type of GARCH process employed is a critical choice in modeling conditional volatility, and the realized and conditional measures of volatility identify different degrees of persistence. More specifically, the results show that the intraday realized volatilities and the majority of the contracts for the interday conditional volatilities exhibit fractional integration (persistence), but the degree of fractional integration and pattern of persistence differ in terms of the volatility estimator used. Surprisingly, although both the 5-minute and Garman-Klass realized

[3]Fang, Lai, and Lai (1994), Corazza, Malliaris, and Nardelli (1997), and Crato and Ray (2000) investigate the fractional order of futures *prices* and returns (not volatility). Crato and Ray also examine the persistence of volatility, but for noisy squared returns. Lien and Tse (1999) and Booth and Tse (1995) examine fractional co-integration between the spot and futures prices.

volatility estimators have a reasonable goodness-of-fit measure relative to the conditional volatility estimator, they have a very weak coherence of fractional integration between these volatility measures, showing that the realized and conditional volatility measures are *not* substitutes for one another. It is also found that the amount of persistence differs across the type of futures contract, with stock index futures possessing more persistence than agricultural and currency futures. Overall, based on the present results, the measure of volatility used is a critical factor for examining volatility persistence, and hence is an important factor for improving volatility forecasting and providing a stable volatility measure for valuation purposes.

The remaining parts of this article are organized as follows: The next section describes the data and scope of the volatility estimators. The third section shows the preliminary statistics for return and volatility. The persistence of the volatility measures for the eight futures contracts are then examined. The summary and conclusions are in the final section.

DATA AND THE SCOPE OF THE VOLATILITY MEASURES

Data and Volatility Estimators

This research employs eight futures contracts that possess differing characteristics for their underlying cash markets: the S&P 500 stock index, NASDAQ 100 stock index, Japanese yen, British pound, Australian dollar, lean hogs, feeder cattle, and pork bellies.[4] The daily open, high, low, and close prices are obtained from the Commodity Research Bureau (CRB) database to calculate the interday returns and most volatility measures. Intraday trade-by-trade prices obtained from the CMEX are used to construct the 5-minute volatility measure. The

[4]The stocks in the S&P 500 index are almost exclusively traded on the New York Stock Exchange, which is a specialist market, with these stocks dominated by institutional trading. Conversely, the NASDAQ stocks are traded in a dealer market, where most of the stocks are considered speculative and the trading activity is dominated by individuals for all but the largest companies. The yen and pound contracts represent major institutional currency trading in different parts of the world in the 24-hour telephone market, whereas the Australian dollar is a relatively minor currency with limited liquidity. Lean hogs, feeder cattle, and pork bellies have limited-access cash agricultural markets. The S&P 500 and NASDAQ futures trade from 8:30 CST to 15:15 CST, a total of 81 5-minute intervals. Yen, pound, and Australian dollar futures are traded from 7:20 CST to 14:00 CST, a total of 80 time intervals. Lean hogs, feeder cattle, and pork bellies trade from 9:10 CST (9:05 CST for feeder cattle) to 13:00 CST, a total of 46 (47) time intervals. The 5-minute volatility measure is adjusted for the number of time intervals.

first deferred contract becomes the contract analyzed within 1 week of the futures expiration date.[5] All intraday and interday data span the period from January 1998 through December 2002.

This study compares the results from three conceptually different types of volatility estimators: the classical daily volatilities (close-to-close squared and daily absolute changes), realized intraday volatilities (the Garman-Klass range-based and 5-minute measures), and conditional volatility (GARCH volatility from interday close-to-close returns). The foundation of these estimators vary in terms of how volatility is measured. The realized intraday volatilities are ex-post measures based on within-day values, the daily volatilities are restricted to closing prices, and the conditional volatility is the expected volatility conditional on past information. Realized volatility is model-free, whereas conditional volatility is estimated from a parametric model. The methodologies of constructing the estimators are detailed in the following sections.

Intraday Realized Volatility

Intraday realized volatility is the ex-post daily variability calculated from within-day data. Two intraday realized volatility estimators are employed, namely, the Garman-Klass (1980) range-based and the 5-minute volatility measures. Because these measures sample the price information in different ways, they possess different robustness to market microstructure biases, such as the bid–ask bounce and the uneven time spacing of transactions.

Garman and Klass show that their popular range-based volatility measure given below (based on open–high–low–close prices) is eight times more efficient than the daily squared return.[6] Andersen and Bollerslev (1998) state that the efficiency of the range-based Garman-Klass volatility estimator is similar to the efficiency of volatility measured with trade

[5]The Samuelson effect states that nearby futures contracts are more volatile than deferred contracts. Here the nearby contracts are used to determine volatility. Deferred contracts for the financial futures typically are inactive. Moreover, the Samuelson effect is small relative to the volatilities encountered in these data and therefore do not affect the conclusions.

[6]A simple high–low range-based volatility is the difference between the highest and lowest log prices over a fixed sample interval, typically 1 day. The advantages of using a range-based volatility measure are associated with Parkinson (1980), who proposes and rigorously analyzes the use of high and low prices for estimating volatility. Since then, Parkinson's estimation has been improved in several ways, including introducing open and closing prices, e.g., Garman and Klass (1980); Rogers, Satchell, and Yoon (1994); Yang and Zhang (2000); Alizadeh, Brandt, and Diebold (2002). The associated realized Garman-Klass standard deviation is referred to as the Garman-Klass realized volatility, and the logarithmic realized standard deviation is labeled the logarithmic Garman-Klass realized volatility.

observations selected every 2–3 hours. The Garman-Klass estimator for the daily realized variance is calculated as:

$$GK(v_t) = (u - d)^2 - [2 \text{ LOG } 2 - 1]c^2 \tag{1}$$

where u = the difference in the natural logarithms of the high and opening prices,
d = the difference in the natural logarithms of the low and opening prices,
c = the difference in the natural logarithms of the closing and opening prices, and
LOG = the natural logarithm.

The Garman-Klass estimator is biased when the number of transactions per day is less than 1000. Hence, the Garman-Klass volatility measure is adjusted for low liquidity, based on Garman and Klass (undated, Table I).

Following Andersen, Bollerslev, Diebold, and Labys (2003), the 5-minute realized variance series is constructed by accumulating the squared intraday 5-minute returns, which are the logarithmic differences between the prices recorded at or immediately before the corresponding 5-minute time stamps.[7,8]

Interday Conditional Volatilities

Interday returns and volatilities are constructed in the typical manner. For example, the daily return is given by $r_t = 100^*(\log p_t - \log p_{t-1})$, where p_t is the daily closing price. The FIGARCH (fractionally integrated GARCH) model by Bollerslev and Mikkelsen (1996) is employed to model the interday conditional return volatility. The FIGARCH(p, d, q) model for the residual process ε_t is defined by

$$r_t = u + \varepsilon_t, \text{ where } \varepsilon_t \sim N(0, \sigma_t^2) \tag{2}$$

$$\beta(L)\, \sigma_t^2 = a + [\beta(L) - \phi(L)(1 - L)^d]\varepsilon_t^2 \tag{3}$$

[7]The 5-minute realized volatility refers to the square root of the 5-minute realized variance, and similarly for the logarithmic realized 5-minute volatility.

[8]The selection of the sampling interval is a trade-off between the cost of market microstructure biases and the desirability of approximate continuous-time models. Ait-Sahalia, Mykland, and Zhang (2005) show that the optimal sampling frequency changes in the presence of market microstructure noise. Following Andersen, Bollerslev, Diebold, and Ebens (2001), an MA (1) model is used to remove the negative serial correlation induced by the uneven spacing of the observed prices and the inherent bid–ask spread. The result is that the realized volatility measures constructed by the unfiltered and filtered return are very similar, which is consistent with the Thomakos and Wang (2003) conclusion in their footnote 10. The possible reason for the similarity between these results is that the bid–ask spread, one of the most pervasive noise components for equities, is small for futures contracts relative to other instruments.

TABLE I
Statistical Characteristics of Daily Close-to-Close Returns and Realized Volatilities

		Mean	*Standard Deviation*	*Skewness*	*Kurtosis*	Q_{20} (*p value*)
Panel A. Daily close-to-close returns						
S&P 500	r_t	−0.020	1.420	0.010	4.928	19.98 (0.459)
	$\|r_t\|$	1.063	0.941	1.806	8.044	335.14 (0.000)
	r_t^2	2.015	3.987	5.721	56.773	294.26 (0.000)
NASDAQ	r_t	−0.020	2.862	0.065	4.667	34.49 (0.023)
	$\|r_t\|$	2.169	1.866	1.724	7.820	354.53 (0.000)
	r_t^2	8.183	15.647	5.690	56.852	287.80 (0.000)
Japanese	r_t	0.002	0.839	1.109	13.044	20.37 (0.435)
yen	$\|r_t\|$	0.596	0.590	3.512	31.880	187.44 (0.000)
	r_t^2	0.704	2.439	19.376	508.234	75.81 (0.000)
Australian	r_t	−0.016	0.745	0.220	6.208	28.17 (0.105)
dollar	$\|r_t\|$	0.560	0.492	2.204	13.109	44.60 (0.001)
	r_t^2	0.555	1.261	10.272	176.120	13.81 (0.840)
British	r_t	−0.002	0.487	0.082	3.841	28.21 (0.105)
pound	$\|r_t\|$	0.368	0.319	1.348	4.873	42.31 (0.003)
	r_t^2	0.237	0.399	3.268	17.062	37.62 (0.010)
Lean	r_t	−0.003	2.800	0.760	35.580	11.07 (0.944)
hogs	$\|r_t\|$	1.560	2.325	6.096	55.541	54.41 (0.000)
	r_t^2	7.834	45.992	13.056	200.858	1.89 (1.000)
Feeder	r_t	0.013	0.725	0.371	8.781	16.25 (0.701)
cattle	$\|r_t\|$	0.501	0.524	2.678	15.621	240.65 (0.000)
	r_t^2	0.526	1.466	9.912	147.749	55.81 (0.000)
Pork	r_t	0.035	2.873	−1.454	15.935	37.87 (0.009)
bellies	$\|r_t\|$	2.078	1.983	4.074	44.920	227.18 (0.000)
	r_t^2	8.246	31.740	21.883	585.242	29.19 (0.084)
Panel B. Realized Garman-Klass volatilities						
S&P 500	v_t	1.206	0.606	2.043	10.468	2576.4 (0.000)
	lv_t	0.083	0.450	0.192	3.182	2679.5 (0.000)
NASDAQ	v_t	2.378	1.161	2.010	12.054	3489.5 (0.000)
	lv_t	0.765	0.445	0.124	3.214	4360.5 (0.000)
Japanese	v_t	0.738	0.397	3.444	27.348	1526.1 (0.000)
yen	lv_t	−0.407	0.435	0.489	3.811	1618.1 (0.000)
Australian	v_t	0.855	0.393	2.201	12.723	1192.3 (0.000)
dollar	lv_t	−0.246	0.420	−0.102	4.879	1594.7 (0.000)
British	v_t	0.522	0.193	1.359	7.387	624.1 (0.000)
pound	lv_t	−0.714	0.356	−0.005	3.094	692.1 (0.000)
Lean	v_t	1.343	0.763	2.347	16.681	3523.2 (0.000)
hogs	lv_t	0.156	0.534	−0.232	3.703	2505.2 (0.000)
Feeder	v_t	0.554	0.312	1.499	7.342	2552.9 (0.000)
cattle	lv_t	−0.745	0.574	−0.379	3.307	2210.5 (0.000)
Pork	v_t	2.140	1.012	1.273	5.376	2345.3 (0.000)
bellies	lv_t	0.654	0.474	−0.414	4.434	1999.3 (0.000)

(*Continued*)

TABLE I
Statistical Characteristics of Daily Close-to-Close Returns and Realized Volatilities (*Continued*)

		Mean	*Standard Deviation*	*Skewness*	*Kurtosis*	Q_{20} (*p value*)
Panel C. Realized 5-minute volatilities						
S&P 500	v_t	1.538	0.770	2.164	9.962	2603.1 (0.000)
	lv_t	0.334	0.422	0.568	3.428	3793.4 (0.000)
NASDAQ	v_t	2.800	1.299	2.084	12.542	6330.6 (0.000)
	lv_t	0.940	0.418	0.209	3.229	8769.3 (0.000)
Japanese	v_t	0.573	0.246	3.731	34.020	2107.8 (0.000)
yen	lv_t	−0.623	0.343	0.797	4.539	2654.5 (0.000)
Australian	v_t	0.704	0.228	1.857	11.843	2032.3 (0.000)
dollar	lv_t	−0.397	0.301	0.134	3.990	2923.9 (0.000)
British	v_t	0.448	0.129	1.916	11.106	609.9 (0.000)
pound	lv_t	−0.838	0.259	0.527	3.928	794.9 (0.000)
Lean	v_t	3.389	1.562	2.683	21.566	7488.4 (0.000)
hogs	lv_t	1.137	0.395	0.470	3.267	8695.5 (0.000)
Feeder	v_t	1.449	0.618	1.506	6.819	5481.7 (0.000)
cattle	lv_t	0.290	0.400	0.063	3.343	6526.8 (0.000)
Pork	v_t	4.968	1.898	1.155	5.068	5899.7 (0.000)
bellies	lv_t	1.535	0.366	0.098	2.834	6183.3 (0.000)

Note. Panel A of this table summarizes the distributional characteristics of daily close-to-close returns used for the conditional volatility, and Panels B and C summarize the distributional characteristics of realized volatility for the Garman-Klass and 5-minute volatilities. The table also reports the Ljung-Box portmanteau test statistics, Q_{20}, for up to the 20th-order autocorrelation for these measures. The daily return r_t, absolute return) $|r_t|$, and squared return r_t^2 are calculated in the typical manner. The volatilities are examined in terms of the standardized deviation v_t and natural logarithmic volatility lv_t. All the Q_{20} statistics are significant at the 0.01 level for Panels B and C.

where $0 < d < 1$, σ_t^2 denotes the variance, $\phi(L)$ and $\beta(L)$ are polynomials for the lag operators of orders p and q, respectively, and ε_t denotes the residuals with the conditional normal distribution. The roots of $\phi(L)$ and $\beta(L)$ lie outside the unit circle.

However, in order to guarantee that a general FIGARCH model is stationary and the conditional variance σ_t^2 is always positive, complicated restrictions have to be imposed on the model. Moreover, FIGARCH assumes that the conditional volatility symmetrically responds to the magnitude of both positive and negative shocks, which is not a desirable characteristic in reality. To circumvent these shortcomings, Bollerslev and Mikkelsen (1996) propose the following fractionally integrated exponential GARCH model (called FIEGARCH). This model is presented as an ARMA process in terms of the logarithm of the conditional variance, based on the framework of

Nelson (1991), and therefore always guarantees that the conditional variance is positive. The (typical) FIEGARCH(p, d, q) model is

$$\beta(L)(1 - L)^d \ln(\sigma_t^2) = w + \sum_{j=1}^{q} (\gamma_j z_{t-j} + \lambda_j(|z_{t-1}| - E|z_{t-j}|)) \qquad (4)$$

where $0 < d < 1$, $\gamma \neq 0$ allows for the impact of a negative return shock on conditional volatility, and z_t is the standardized residual $z_t = \varepsilon_t/\sigma_t$ and follows the standard conditional normality with i.i.d. Bollerslev and Mikkelsen (1996) show that the FIEGARCH model is stationary for all values of $d < 1$.

Unlike the finite-lag representation for the standard GARCH(p, q) model, fractionally integrated GARCH models theoretically employ an infinite lag series. However, for implementation purposes a truncation of the infinite lags is required. But, because the fractional differencing operator is designed to capture the long memory of the volatility series, truncating at too low a lag may destroy important long-run dependencies. As in Bollerslev and Mikkelsen (1996), the truncation lag is fixed at 500 for all the series estimated. The quasi-maximum-likelihood estimates (QMLE) are used to obtain an asymptotic robust covariance matrix for the parameter estimates, and the Akaike and Schwarz-Bayesian information criteria (respectively, AIC and BIC) are employed as the model-selection criteria. Finally, the Shapiro-Wilks (SW) normality test and the Ljung-Box portmanteau tests are used for the estimated standardized residuals in order to evaluate the validity and adequacy of the selected models.

STATISTICAL CHARACTERISTICS OF RETURN AND VOLATILITY

An examination of the statistical properties of the futures contracts provides initial insights to the characteristics of the data. For example, the kurtosis of the interday return provides preliminary information of the *possible* existence of GARCH processes.

Interday Return and Volatility

All of the return series, r_t, shown in Panel A of Table I, possess means that are statistically insignificant from zero and are leptokurtic. The daily close-to-close absolute returns and squared returns (volatilities) are right skewed and highly leptokurtic.[9] The Ljung-Box Q_{20} statistics (up to 20 lags) for the absolute and squared returns generally reject the null hypothesis of no serial autocorrelation. Combined with the high kurtosis of the volatility series, the large values for the Q_{20} statistics provide further evidence that the heterogeneous variance can be modeled by GARCH class models.

Intraday Volatility

Panel B of Table I presents the statistics for the volatility and (natural) logarithmic volatility of the Garman-Klass estimator. The volatility of the futures contracts are right-skewed and leptokurtic. Currency futures are less volatile than the other contracts. The logarithmic Garman-Klass volatility is normally distributed, based on the density graphs.[10] These results are similar to those found by Thomakos and Wang (2003) for their daily data. All the Ljung-Box Q_{20} statistics for the Garman-Klass volatility and logarithmic volatility estimators reject the hypothesis of no autocorrelation across the four contracts. In particular, the Q_{20} statistics given in Panel B are higher than those in Panel A by several magnitudes, showing that the autocorrelations in the intraday realized volatilities are much higher than for the interday return volatilities. This *suggests* that the intraday realized volatility could be more persistent, although the Q_{20} statistics only test the joint significance of the first 20 autocorrelations and hence do not directly examine volatility persistence.

Similar to the daily Garman-Klass volatilities, the daily 5-minute volatilities in Panel C are right-skewed and leptokurtic, with the logarithmic version generally possessing a normal distribution. However, the kurtosis statistics of the logarithmic 5-minute volatilities are often higher than those for the Garman-Klass volatilities. Moreover, the consistently higher Q_{20} values for the volatility and logarithmic volatility measures in Panel C relative to those in Panel B show that the daily 5-minute volatilities are more autocorrelated than the Garman-Klass volatility. This provides preliminary evidence that the 5-minute volatility is the most autocorrelated series relative to the Garman-Klass and interday volatilities. Currency futures continue to exhibit the least volatility.

[9]Bollerslev (1988) recommends determining the time-series properties of the volatilities by analyzing the autocorrelations of the absolute return.
[10]The plots of the kernel density for the logarithmic Garman-Klass and 5-minute volatilities across the eight contracts visually confirm that they follow a Gaussian-normal distribution. The graphs are available upon request.

PERSISTENCE OF VOLATILITY

Volatility typically decays at a slow hyperbolic rate, as opposed to the geometric decay rate associated with the conventional *stationary* and invertible $I(0)$ process, or alternatively compared to an infinite persistence pattern resulting from a non-stationary unit root $I(1)$ process. In fact, the hyperbolic decay process is a fractionally integrated process with a fractional order ranging from 0 to 1. When the fractional order is between 0 and 0.5, then the process is mean-reverting stationary.

This section starts with a visual inspection for long memory of the classical and intraday realized volatility processes, and then statistically tests the futures series persistence. The visual and statistical analysis of the classical interday absolute and squared return volatilities justifies the modeling of the GARCH volatility process.

Long-Memory Correlograms

A visual inspection of volatility persistence provides insights to the long-memory characteristics of these volatility measures. Figure 1 plots the correlograms of the absolute-return, squared-return, Garman-Klass, and 5-minute measures of volatility. Bollerslev (1988) recommends determining the time-series properties of volatility by analyzing the autocorrelations of the absolute return. The correlograms for the absolute returns start to decline with a hyperbolic rate at lag 1, with statistically significant clustering occurring up to about lag 50 for all but the Australian dollar, British pound, and lean hogs. There is little consistent clustering for the squared returns, except for stock index futures. In general, these two volatility measures have similar correlograms, although there are fewer significant autocorrelations for the yen, feeder cattle, and pork-belly squared return series. More importantly, the patterns in Figure 1 show that the absolute and squared returns are far less autocorrelated than the other two measures of realized volatilities. The correlograms of the Garman-Klass and 5-minute volatilities in Figure 1 show similar patterns of a hyperbolic decay in their correlograms, with persistence often reaching the 150 lag limit shown in the figures. The similarities in these two measures are somewhat surprising, given that they are determined by using different timing intervals. The 5-minute measure has somewhat higher autocorrelations relative to the Garman-Klass measure for the agricultural contracts.

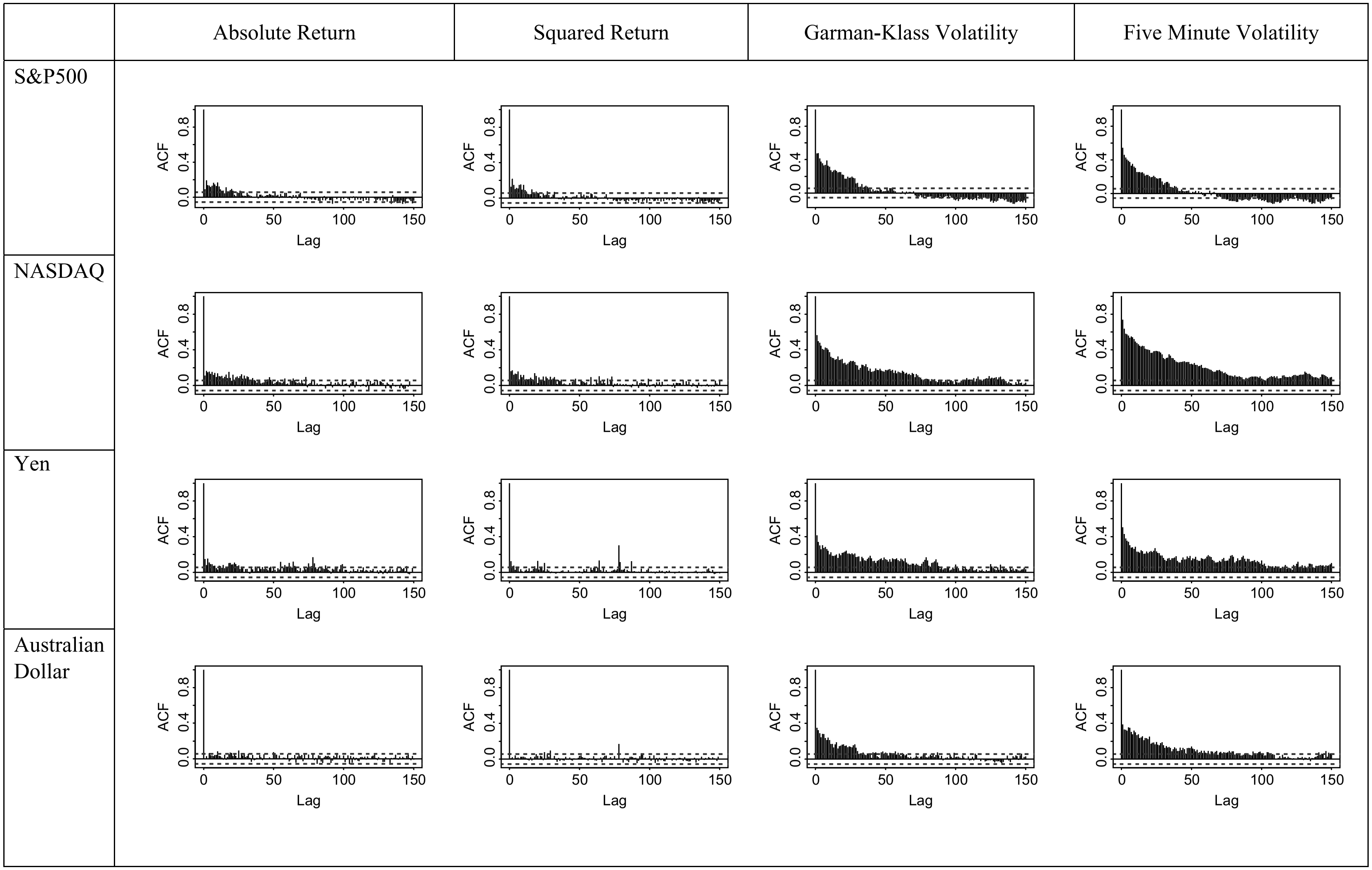

FIGURE 1
Correlograms for Volatility

The figure graphs the Autocorrelation Function (ACF) up to 150 lags (days) for the absolute return, squared return, Garman-Klass, and five-minute volatilities for the S&P 500 listed futures contracts.

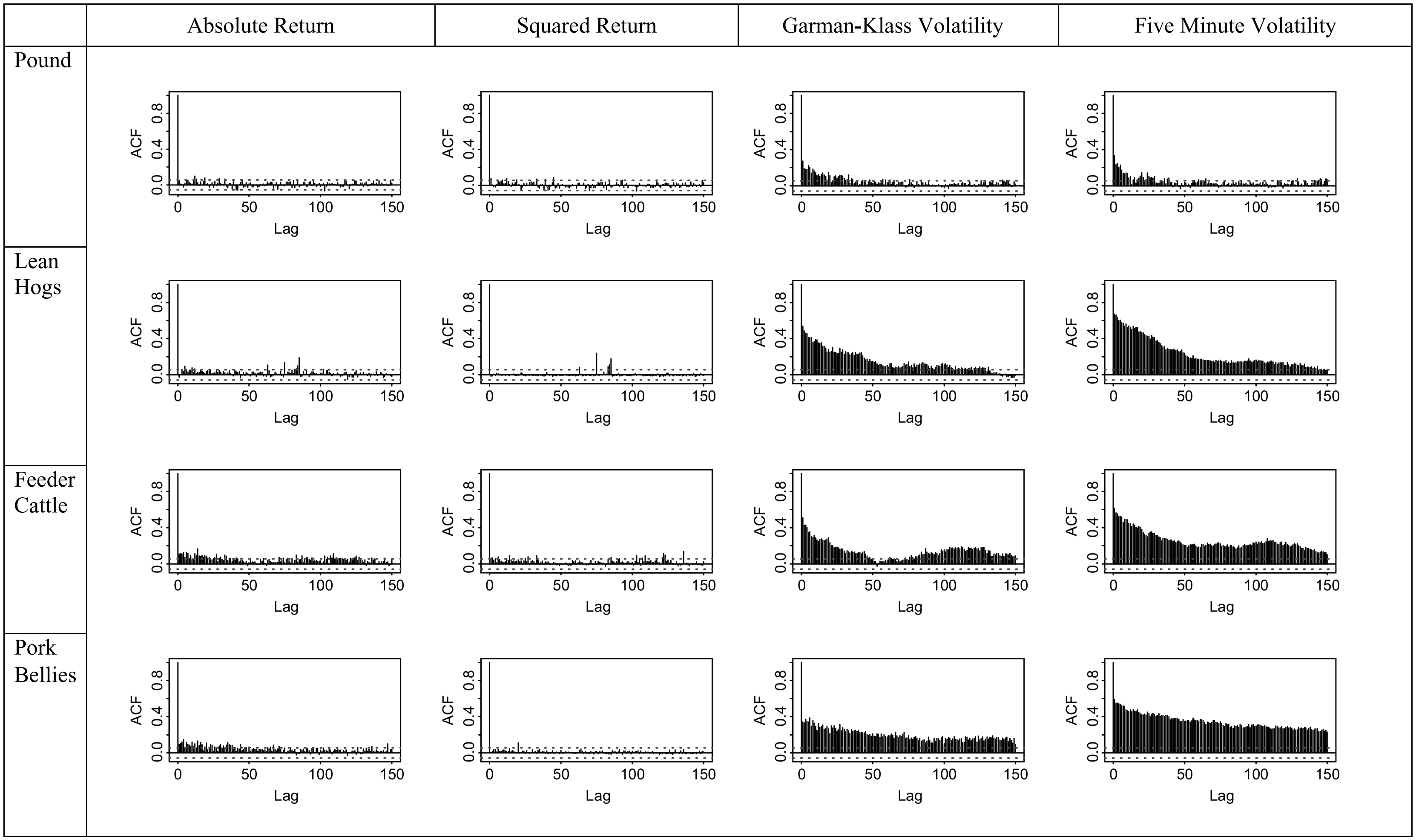

FIGURE 1 (*Continued*)
Correlograms for Volatility

Persistence of Realized Volatility

This subsection presents the stationarity and persistence properties of futures markets volatility. Table II reports the results of the unit root tests, stationary test, and the estimated fractional order (persistence) for the absolute return, squared return, Garman-Klass, and 5-minute volatility series. The results are consistent with previous studies of other types of financial series.[11] By examining the number of augmented autoregressive lags from the augmented Dickey-Fuller (ADF) test, long-run persistence and a very slow autocorrelation decay are found, especially for the Garman-Klass and 5-minute volatility measures.[12] This finding, combined with the results of the rejection of the null hypotheses of both a unit root (via ADF and Phillip-Perron [PP] tests) and conventional stationarity (via Kwiatrowski, Phillips, Schmidt, and Shin, 1992 [KPSS]), provides initial statistical evidence of long-memory across all of the series, with a resultant hyperbolic decay of the autocorrelation function.

Based on the evidence of a slow hyperbolic decay from the above visual and statistical results, the fractional integration estimate, d_r, is calculated with the method proposed by Robinson (1995).[13] The estimates of the d_r values for fractional integration appear in the last column of Table II. The estimated d_r values for the eight contracts and four volatility measures have $0 < d < 0.5$, showing that the volatility processes are fractionally integrated and stationary.[14] Although the d_r values for all four volatility measures show persistence with fractional integration, the absolute-return and squared-return measures possess fewer significant and noticeably lower d_r values than the Garman-Klass and 5-minute volatilities. Comparing across futures, the currency contracts generally possess a lower estimated degree of fractional integration values for the

[11]The unit root tests are conducted by using the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods. These test statistics overwhelmingly reject the null hypothesis that a unit root exists for all of the futures contracts. Conventional stationarity also is examined with the Kwiatrowski, Phillips, Schmidt, and Shin (1992) (KPSS) method, with the KPSS statistics rejecting the null hypothesis of a conventional stationary $I(0)$ process for the vast majority of situations.

[12]The number of lags for the daily squared return is zero or one for four of the eight contracts, indicating less persistence for this volatility measure for these contracts. The d values are not significant for three of the daily absolute series and four of the daily squared return series.

[13]The Robinson method estimates d_r by regressing the logarithm of the periodogram estimate of the spectral density on $\ln(w)$ over the jth Fourier frequency, $w_j = 2\, t_j/T$, $j = 1, 2, \ldots, m$, where T is the number of observations in the sample. The estimate of d_r in this test depends on the specific selection of m. Following the procedure of Taqqu and Teverovsky (1996), $m = T^{4/5}$, is used, consistent with the asymptotic rate of $O(T^{4/5})$ established by Hurvich, Deo, and Brodsky (1998).

[14]There are two marginal exceptions to this general conclusion: one insignificant negative value for the lean hog daily squared return and a d value of 0.516 (which is insignificantly different from the stationary value of 0.499) for the 5-minute volatility measure of the lean hog contract.

TABLE II

Stationarity and Fractional Order Tests

	AR	*ADF*	*PP*	*KPSS*	d_r (*t values*)
Panel A. Daily absolute return					
S&P 500	11	−5.954 (0.000)	−33.382	0.862	0.226 (5.657)
NASDAQ	10	−6.825 (0.000)	−32.689	1.951	0.208 (5.213)
Japanese yen	6	−10.636 (0.000)	−30.938	2.927	0.188 (4.709)
Australian dollar	10	−8.521 (0.000)	−34.704	0.522	0.036 (0.900)
British pound	1	−32.871 (0.000)	−32.909	0.301*	0.053 (1.333)
Lean hogs	10	−8.065 (0.000)	−35.728	0.501	0.066 (1.641)
Feeder cattle	14	−5.621 (0.000)	−32.234	1.228	0.126 (3.144)
Pork bellies	18	−5.091 (0.000)	−32.539	2.813	0.167 (4.160)
Panel B. Daily squared return					
S&P 500	10	−6.916 (0.000)	−32.275	0.504	0.265 (6.654)
NASDAQ	10	−7.375 (0.000)	−31.035	1.211	0.206 (5.157)
Japanese yen	3	−17.252 (0.000)	−31.043	1.554	0.133 (3.328)
Australian dollar	0	−34.293 (0.000)	−34.340	0.371*	0.041 (1.035)
British pound	1	−32.021 (0.000)	−32.024	0.240*	0.062 (1.561)
Lean hogs	0	−35.288 (0.000)	−35.286	0.152*	−0.033 (−0.834)
Feeder cattle	6	−12.015 (0.000)	−32.875	0.625	0.127 (3.175)
Pork bellies	0	−34.27 (0.000)	−34.358	1.055	0.044 (1.099)
Panel C. Daily Garman-Klass volatility					
S&P 500	8	−5.543 (0.000)	−23.211	1.098	0.376 (9.427)
NASDAQ	9	−4.931 (0.000)	−19.974	2.865	0.401 (10.034)
Japanese yen	22	−3.433 (0.000)	−24.421	3.368	0.307 (7.697)
Australian dollar	9	−6.675 (0.000)	−26.524	0.698	0.274 (6.872)
British pound	9	−6.977 (0.000)	−28.006	0.729	0.250 (6.263)
Lean hogs	30	−3.148 (0.023)	−21.098	1.243	0.418 (10.474)
Feeder cattle	9	−5.907 (0.000)	−21.745	1.775	0.376 (9.418)
Pork bellies	23	−2.763 (0.064)	−27.416	5.902	0.263 (6.555)
Panel D. Daily 5-minute volatility					
S&P 500	8	−6.037 (0.000)	−20.598	0.919	0.401 (10.047)
NASDAQ	8	−4.626 (0.000)	−13.383	3.567	0.458 (11.477)
Japanese yen	10	−5.819 (0.000)	−21.703	4.251	0.396 (9.906)
Australian dollar	10	−4.895 (0.000)	−25.737	0.693	0.288 (7.217)
British pound	24	−4.492 (0.000)	−26.475	0.473	0.250 (6.249)
Lean hogs	30	−2.927 (0.042)	−16.403	1.400	0.516 (12.933)
Feeder cattle	27	−3.047 (0.031)	−18.408	2.953	0.400 (10.015)
Pork bellies	17	−2.595 (0.094)	−19.374	7.399	0.386 (9.628)

Note. The table summarizes the statistics of stationarity and estimated fractional orders for the return and volatility for the listed futures contracts. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods test the null hypothesis of a unit root, with the AR lags determined by the Akaike Information Criterion (AIC). The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test examines the null hypothesis of conventional stationarity $I(0)$ against a unit root and long memory. The numbers in parentheses for the ADF statistics are the probability levels for significance; all PP and KPSS values are significant at the .001 level or better. The d_r value is the fractional order, estimated with the Robinson (1995) method, with the t values in parentheses.

*Not significant at the 95% confidence interval.

Garman-Klass and 5-minute realized volatilities than do the stock index and agricultural futures contracts. Interestingly, stock index futures are more persistent than the other contracts for the daily absolute and squared return volatility measures, whereas the commodity contracts have longer lags for three of the volatility measures.

Persistence of Conditional Volatility: FIGARCH Results

This section employs GARCH class models to examine volatility persistence, proxied by the degree of fractional integration in the models. The estimation and specification of the FIGARCH results for the eight futures contracts are presented in Table III. All the models are selected according to their lowest AIC and BIC statistics.[15]

Table III shows that the fractional orders d are less than 0.5, indicating fractionally integrated stationarity. All d values are statistically significant. The stock index futures typically possess higher d values (representing a high degree of persistence) than the currency futures values, whereas currency futures generally have somewhat higher d values than agricultural futures. However, the sums of the β (GARCH) and λ (ARCH) coefficients are greater than 1.0 for the yen, Australian dollar, pound, and lean hogs, suggesting nonstationarity. Moreover, the estimated negative coefficients λ for the S&P500, NASDAQ, and pork-belly futures imply a negative conditional variance. These two problems are overcome by implementing the FIEGARCH model, as shown below.

Persistence of Conditional Volatilities: FIEGARCH Results

In order to overcome the problems of nonstationarity and nonnegativity constraints noted above, and to investigate the effects of negative return shocks on conditional volatility, FIEGARCH is used to model conditional volatility, with the results given in Table IV.[16] As expected, the sum of the β (GARCH) and λ (ARCH) coefficients are all < 1.0 (four contracts had β plus λ coefficients greater than 1.0 for the FIGARCH model). Combined

[15]The Shapiro-Wilks (SW) statistics for the normality tests show that the estimated standardized residuals for most of the futures contracts follow a normal distribution (those for the yen and agricultural contracts are nearly normally distributed). All of the serial autocorrelation test statistics for Q_{20} and Q_{20}^2 indicate no serial autocorrelation structures are left in the standardized and squared standardized residuals. Therefore, both the SW and Q statistics show that the models selected are adequate. FIGARCH(2, d, 1) and FIGARCH(1, d, 2) models are also used; the AIC and BIC both suggest the FIGARCH(1, d, 1) model is appropriate.

[16]Similar to Table III, the SW and Q statistics show the adequacy and validity on the selected models.

TABLE III

FIGARCH(1, d, 1) for Daily Close-to-Close Returns

	S&P 500	*NASDAQ*	*Japanese yen*	*Australian dollar*	*British pound*	*Lean hogs*	*Feeder cattle*	*Pork bellies*
u	0.020	0.108	−0.019	−0.005	−0.001	0.029	0.032	0.014
	(0.578)	(1.437)	(−0.871)	(−0.245)	(−0.049)	(0.362)	(1.831)	(0.169)
w	0.353	0.408	0.028	0.024	0.015	2.455	0.054	1.987
	(1.929)	(1.772)	(1.503)	(0.834)	(1.351)	(47.324)	(1.274)	(4.180)
β_1	−0.116	0.424	0.821	0.723	0.756	0.610	0.552	NA
(GARCH)	(−0.363)	(2.113)	(9.534)	(5.416)	(12.954)	(107.185)	(2.74)	NA
λ_1	−0.394	−0.007	0.728	0.330	0.515	0.544	0.286	−0.267
(ARCH)	(−1.483)	(−0.062)	(6.217)	(3.447)	(5.762)	(44.346)	(1.883)	(−3.814)
d	0.300	0.480	0.251	0.393	0.291	0.056	0.279	0.259
	(4.934)	(3.295)	(2.184)	(1.848)	(2.415)	(8.025)	(2.772)	(3.721)
AIC	4126.6	5781.5	2839.5	2684.4	1670.3	5897.1	2557.9	5834.8
BIC	4152.1	5806.9	2865.0	2709.8	1695.8	5922.6	2583.4	5855.1
SW	0.987	0.991	0.977	0.987	0.984	0.759	0.952	0.940
	(0.503)	(0.979)	(0.000)	(0.517)	(0.072)	(0.000)	(0.000)	(0.000)
Q_{20}	22.020	17.072	24.115	29.267	24.873	13.008	12.189	33.171
	(0.339)	(0.648)	(0.237)	(0.083)	(0.206)	(0.877)	(0.909)	(0.032)
Q^2_{20}	17.534	19.150	7.626	9.077	14.871	1.595	7.539	7.427
	(0.618)	(0.512)	(0.994)	(0.982)	(0.784)	(1.000)	(0.995)	(0.995)

Note. The table reports the FIGARCH model estimated by quasi-maximum likelihood (QMLE) with the use of the daily close-to-close returns for the listed futures contracts. The t statistics are included in parentheses. AIC and BIC refer to the Akaike and Schwarz-Bayesian information criteria, respectively. SW refers to the Shapiro-Wilks test for the null hypothesis of a normal distribution for the residuals. Q_{20} and Q^2_{20} stand for the Ljung-Box portmanteau tests for up to the 20th-order serial autocorrelation in the standardized residuals and the squared standardized residuals, respectively. The significance levels of SW, Q_{20}, and Q^2_{20} are in parentheses.

$$Y_t = 100\log(P_t/P_{t-1}) = u + \varepsilon_t,\ \varepsilon_t/\sigma_t \sim \text{i.i.d. } N(0,1)$$
$$\sigma^2_t = w + \beta_1\sigma^2_{t-1} + [1 - \beta_1 L - (1 - \lambda_1 L)(1 - L)^d]\varepsilon^2_t$$

TABLE IV
FIEGARCH for Daily Close-to-Close Returns

	S&P500	*NASDAQ*	*Japanese yen*	*Australian dollar*	*British pound*	*Lean hogs*	*Feeder cattle*	*Pork bellies*
u	−0.037	0.020	−0.002	−0.021	0.001	0.114	0.053	0.005
	(−1.018)	(0.245)	(−0.111)	(−1.012)	(0.040)	(2.892)	(5.188)	(0.059)
w	−0.100	−0.116	−0.211	−0.001	−0.079	0.074	0.021	−0.086
	(−2.986)	(−1.734)	(−3.38)	(−0.343)	(−0.832)	(6.343)	(9.380)	(−1.387)
β_1	0.505	0.893	0.074	0.663	−0.043	−0.623	0.061	0.500
(GARCH)	(2.501)	(4.684)	(0.200)	(2.147)	(−1.244)	(−4.169)	(0.236)	(1.355)
β_2		−0.206			0.915			
(GARCH)		(−0.852)			(8.666)			
λ_1	0.136	0.182	0.250	0.001	0.045	−0.138	−0.038	0.119
(ARCH)	(3.389)	(4.499)	(2.982)	(0.217)	(1.675)	(−7.418)	(−7.895)	(1.291)
γ_1	−0.192	−0.090	0.182	−0.023	−0.003	−0.197	−0.087	0.011
	(−3.659)	(−2.471)	(2.586)	(−1.295)	(−0.047)	(−6.794)	(−4.996)	(0.494)
d	0.513	0.426	0.457	0.803	0.202	0.740	0.854	0.730
	(4.318)	(1.161)	(3.460)	(8.005)	(0.592)	(38.773)	(17.753)	(2.383)
AIC	4074.4	5773.9	2813.0	2671.7	1686.3	5718.3	2467.4	5802.9
BIC	4105.0	5809.6	2843.6	2702.2	1722.0	5748.9	2498.0	5833.4
SW	0.988	0.990	0.980	0.992	0.983	0.807	0.972	0.944
	(0.738)	(0.907)	(0.000)	(0.992)	(0.022)	(0.000)	(0.000)	(0.000)
Q_{20}	22.795	17.403	23.847	29.063	25.820	10.195	21.230	33.168
	(0.299)	(0.627)	(0.249)	(0.087)	(0.172)	(0.964)	(0.384)	(0.032)
Q^2_{20}	36.247	27.900	6.894	11.508	25.766	2.593	24.785	5.337
	(0.014)	(0.112)	(0.997)	(0.932)	(0.174)	(1.000)	(0.210)	(1.000)

Note. The table reports the FIEGARCH model estimated by quasi-maximum likelihood (QMLE) using the daily close-to-close returns for the listed futures contracts. The t statistics are included in parentheses. AIC and BIC refer to the Akaike and Schwarz-Bayesian information criteria, respectively. SW refers to the Shapiro-Wilks test for the null hypothesis of a normal distribution for the residuals. Q_{20} and Q^2_{20} stand for the Ljung-Box portmanteau tests for up to the 20th-order serial autocorrelation in the standardized residuals and the squared standardized residuals, respectively. The significance levels of SW, Q_{20} and Q^2_{20} are in parentheses. The FIEGARCH(1, d, 1) model, used for most contacts, is:

$$Y_t = 100 \log(P_t/P_{t-1}) = u + \varepsilon_t$$
$$(1-\beta_1 L)(1-L)^d \ln(\sigma_t^2) = w + \gamma_1 z_{t-1} + \lambda_1[|z_{t-1}| - E(|z_{t-1}|)]$$

where z_1 is the standardized residual, $\varepsilon_t/\sigma_t \sim$ i.i.d. conditional $N(0, 1)$.

The NASDAQ and British pound futures need a FIEGARCH(2, d, 1) model to be fit appropriately, with this model represented as:

$$Y_t = 100 \log(P_t/P_{t-1}) = u + \varepsilon_t$$
$$(1-\beta_1 L - \beta_2 L^2)(1-L)^d \ln(\sigma_t^2) = w + \gamma_1 z_{t-1} + \lambda_1[|z_{t-1}| - E(|z_{t-1}|)]$$

with the results that the d values fall between 0 and 1 and that negative estimated coefficients are not an issue for FIEGARCH, these results show that the FIEGARCH model overcomes the stationarity and nonnegativity issues found previously.[17] Consequently, the FIEGARCH model is superior to the FIGARCH model for examining futures time-series data.

The results also show that the fractional orders of persistence generally are high;[18] in fact, the FIEGARCH conditional volatility results show a degree of persistence that is similar to the intraday measures given in Table II. Therefore, the FIEGARCH persistence results could provide similar information as the persistence found in the intraday volatility measures. The next section tests whether the persistence values are similar between the FIEGARCH conditional and the realized methods of examining long memory.

Table IV also shows that six of the eight γ coefficients for the standardized residual return z_t are negative (and four are statistically significant); that is, they show a negative relation between the lagged standardized residual return and the conditional volatility.[19] Similarly, the two positive γ coefficients (one significant) for the yen and pork-belly contracts indicate a positive relation between the lagged standardized residual returns and their conditional volatilities. This significant lagged return to volatility relation is similar to the equity leverage effect. However, equity leverage is not an appropriate explanation for futures contracts. Hence, this association merits additional investigation, but that is beyond the scope of this article.

R^2 and Coherence Relationships Between the Conditional and Realized Volatilities

This section investigates the relationships among the conditional, Garman-Klass, and 5-minute volatility measures. The relationships between these measures are evaluated by investigation of their goodness

[17]Bollerslev and Mikkelsen (1996) show that the FIEGARCH model is stationary if $0 < d < 1$; therefore, the futures contracts are considered to be fractionally integrated and stationary.
[18]An intuitive explanation for the substantially higher d values for FIEGARCH is that the logarithmic transformation for the variance in the FIEGARCH system, as shown in Eq. (4), *reduces* the dispersion of the variance, thereby increasing the d values representing the persistence of the variance. Negative coefficients for FIEGARCH are acceptable in the model because of this transformation process. A complicating factor affecting the interpretation of persistence is the effect of the ARCH and GARCH coefficients, which are factors that also relate to the stability of volatility. However, the clear-cut evidence that FIEGARACH is a more appropriate model compared to FIGARCH, as well as its relative consistency of the persistence values, indicates the usefulness of the results presented here.
[19]Schroeder and Goodwin (1991) show that the long-term basis between futures and cash hog prices is generally nonstationary. There also is a lack of co-integration between the futures and cash prices. These relationships most likely contribute to the results for the FIGARCH and FIEGARCH models for lean hogs.

of fit and estimation of the coherence of the degrees of their fractional integration. The relationship between these two properties is then discussed.

Table V shows the fit between the realized and conditional volatility measures via the adjusted R^2 estimates obtained by regressing the realized Garman-Klass and 5-minute volatilities on the conditional volatility series. The estimated conditional volatility is used as the benchmark series, because it is the expected volatility value, and hence has less noise. As shown in Table V, the adjusted R^2 values range from 0.080 to 0.576, with the realized 5-minute volatility measure typically having the higher R^2 value with the conditional volatility. The stock index futures possess higher R^2 values than the ones for the agricultural contracts, which, in turn, are higher than the R^2 values for currency futures. Also, the R^2 values for the Garman-Klass versus 5-minute regressions show that these two measures of realized volatility are more similar to one another than they are to the conditional volatility, showing that the two intraday volatility measures include similar elements of systematic volatility that are eliminated by the conditional volatility.

Robinson (1995) proposes the log-periodogram regression method for estimating the degree of fractional integration, and his multivariate model provides the justification for testing whether different time series share a common differencing factor. The coherence of fractional integration is examined by testing the null hypothesis that two volatility estimators have the same *degree* of fractional integration. The χ^2 statistics, labeled d_c, and their associated levels of significance (in parentheses) in Table V show that this null hypothesis is *rejected* at the 1% significance level between the realized and conditional volatility estimators for all the contracts except the 5-minute yen comparison. However, the null hypothesis that the Garman-Klass and 5-minute volatilities have the same degree of fractional integration *cannot* be rejected for any contract at the 1% significance level. Therefore, although the conditional and realized volatilities do not have the same fractional order, the two realized volatilities do have the same degree of fractional integration. Consequently, these results show that there is no direct relationship between (a) the goodness of fit that exists for these data, and (b) whether the series have the same degree of fractional integration. For example, NASDAQ has the best goodness of fit between its conditional and realized volatilities among the contracts studied; however, its Robinson d_c statistic shows that its conditional and realized volatilities do not have the same degree of fractional integration. Hence, the intuitive belief that

TABLE V

Goodness of Fit and Coherence of Different Volatility Estimators

		S&P 500	*NASDAQ*	*Japanese yen*	*Australian dollar*	*British pound*	*Lean hogs*	*Feeder cattle*	*Pork bellies*
Five-minute vs.	Adj. R^2	0.349	0.576	0.354	0.162	0.080	0.134	0.329	0.373
conditional volatility	d_c	32.990	49.320	0.633	249.845	127.435	23.143	67.898	129.475
		(0.000)	(0.000)	(0.426)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Garman-Klass vs.	Adj. R^2	0.384	0.440	0.310	0.099	0.101	0.094	0.169	0.254
conditional volatility	d_c	44.973	56.367	7.517	261.325	139.037	53.253	75.035	145.327
		(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Garman-Klass vs.	Adj. R^2	0.576	0.684	0.615	0.443	0.385	0.557	0.477	0.520
5-Minute volatility	d_c	0.107	2.104	4.518	0.373	2.135	5.164	2.023	5.494
		(0.744)	(0.147)	(0.034)	(0.541)	(0.144)	(0.023)	(0.155)	(0.019)

Note. The table reports the goodness of fit and the coherence of the degrees of fractional integration among the three different volatility estimators for the listed futures contracts. The numbers reported are the adjusted *R*-squares estimated from ordinary least squares (OLS) regression to measure the goodness-of-fit and Robinson's (1995) χ^2 statistic for testing the null hypothesis that two series have the same degree of fractional integration. The χ^2 statistic has one degree of freedom and its critical value is 6.63. The *p* values included in parentheses are for the χ^2 statistic. Conditional volatility refers to the volatility estimated from FIEGARCH. Adj.R^2 refers to the adjusted R^2, and d_c refers to the χ^2 statistic measuring the degree of coherence of the fractional orders.

a related volatility pattern means an association in the degree of volatility persistence is incorrect.

SUMMARY AND CONCLUSIONS

This article explores the persistence of volatility in relation to different measures of volatility for the S&P500, NASDAQ, yen, pound, Australian dollar, lean hog, feeder cattle, and pork-belly futures contracts. Model-free realized intraday volatilities (the Garman-Klass and 5-minute estimators) and the conditional volatility from the FIEGARCH class of models are constructed, and the classical close-to-close volatility measures are also used. In addition, this article examines the relationship of three classes of volatility estimators in terms of their goodness of fit and coherence of fractional integration. The main results are as follows:

- The two *intraday* realized volatility estimators are significantly more autocorrelated and persistent than the classical close-to-close squared return and absolute return measures. Hence, how volatility is measured is a critical choice for persistence and forecasting studies, as well as valuation models.
- The procedure employed to determine the conditional volatility via GARCH techniques is very important. The more appropriate FIEGARCH model generates substantially higher persistence values (in most cases), and avoids methodological problems and includes asymmetric effects.
- The relationship between the intraday realized volatilities and the conditional volatilities is generally low (with the possible exception of stock index futures), whereas the relationship between the intraday measures is typically near or above an R^2 of 0.50. Their degrees of fractional integration are indistinguishable on a statistical basis. Moreover, although both realized volatility measures and conditional volatilities possess high degrees of persistence, there is no direct relationship between the goodness of fit among the conditional versus realized volatility estimators and the coherence of their fractional integrations. Therefore, realized volatility and conditional volatility measure different aspects of persistence, and one type of volatility measure is *not* a substitute for the other type.
- Although the FIEGARCH results show the benefits of employing GARCH methodologies in studying financial time series, especially when characteristics of the series such as asymmetry are examined, the persistence results of the intraday realized volatility measures show that the intraday measures provide the most promising tools for generating highly persistent series for forecasting and derivatives valuation.

- Differences do exist across types of contracts. In general, currency futures are the least persistent of the contracts studied, and stock index futures are the most persistent. Additional work to determine why such results exist by type of contract is needed.

In conclusion, this study shows that the measure of volatility used critically affects the results for any analysis of volatility or volatility persistence. It is found that the model-free realized intraday volatility estimators provide an effective unbiased measure to estimate the latent volatility. Questions for future research include why different types of contracts (e.g., stock index futures) are more persistent than other contracts, and whether/why negative asymmetric relationships between lagged standardized residual returns and the conditional volatilities exist for futures contracts. Such results will be of interest to financial and agricultural economists studying the behavior of markets.

BIBLIOGRAPHY

Ait-Sahalia, Y., Mykland, P., & Zhang, L. (2005). How often to sample a continuous-time process in the presence of market microstructure noise. Review of Financial Studies, 18, 351–416.

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. Journal of Finance, 57, 1047–1091.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review, 39, 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of stock return volatility. Journal of Financial Economics, 61, 43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of exchange rate volatility. Journal of the American Statistical Association, 96, 42–55.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. Econometrica, 75, 579–626.

Areal, N. M. P. C., & Taylor, J. S. (2002). The realized volatility of FTSE-100 futures prices. Journal of Futures Markets, 22, 627–648.

Baillie, T. R. (1996). Long memory process and fractional integration in econometrics. Journal of Econometrics, 73, 5–59.

Baillie, T. R., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 74, 3–30.

Bollerslev, T. (1988). On the correlation structure for the generalized autoregressive conditional heteroskedasticity process. Journal of Time Series Analysis, 9, 121–131.

Bollerslev, T., & Mikkelsen, H. O. (1996). Modeling and pricing long memory in stock market volatility. Journal of Econometrics, 73, 151–184.

Booth, G. G., & Tse, Y. (1995). Long memory in interest rate futures markets: A fractional cointegration analysis. Journal of Futures Markets, 15, 573–584.

Corazza, M., Malliaris, A. G., & Nardelli, C. (1997). Searching for fractal structure in agricultural futures markets. Journal of Futures Markets, 17, 433–473.

Crato, N., & Ray, B. K. (2000). Memory in returns and volatilities of futures contracts. Journal of Futures Markets, 20, 525–543.

Fang, H., Lai, K. S., & Lai, M. (1994). Fractal structure in currency futures price dynamics. Journal of Futures Markets, 14, 169–181.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatility from historical data. The Journal of Business, 53, 67–78.

Garman, M. B., & Klass, M. J. (n.d.). The estimation of security price volatility from newspaper data (working paper).

Hurvich, C. M., Deo, R., & Brodsky, J. (1998). The mean squared error of Geweke and Porter Hudak's estimator of the memory parameter of a long memory time series. Journal of Time Series Analysis, 19, 19–46.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54, 159–178.

Lien, D., & Tse, Y. K. (1999). Forecasting the Nikkei spot index with fractional cointegration. Journal of Forecasting, 18, 259–273.

Luu, C. J., & Martens, M. (2003). Testing the mixture-of-distributions hypothesis using "realized" volatility. Journal of Futures Markets, 23, 661–679.

Martens, M., & Zein, J. (2004). Predicting financial volatility: High-frequency time-series forecasts vis-á-vis implied volatility. Journal of Futures Markets, 24, 1005–1028.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347–370.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. Journal of Business, 53, 61–66.

Poon, S., & Granger, C.W.J. (2003). Forecasting volatility in financial markets: A review. Journal of Economic Literature, 41, 478–539.

Robinson, P. M. (1995). Log-periodogram regression of time series with long-range dependence. The Annals of Statistics, 23, 1048–1072.

Rogers, L.C.G., Satchell, S. E., & Yoon, Y. (1994). Estimating the volatility of stock prices: A comparison of methods that use high and low prices. Applied Financial Economics, 43, 241–247.

Schroeder, T. C., & Goodwin, B. K. (1991). Price discovery and cointegration for live hogs. Journal of Futures Markets, 11, 685–696.

Taqqu, M. S., & Teverovsky, V. (1996). Semi-parametric graphical estimation technique for long-memory data. In P. M. Robinson & M. Rosenblatt (Eds.), Time series in memory of E. J. Hanna (pp. 420–43). New York: Springer-Verlag.

Thomakos, D., & Wang, T. (2003). Realized volatility in the futures markets. Journal of Empirical Finance, 10, 321–353.

Yang, D., & Zhang, Q. (2000). Drift-independent volatility estimation based on high, low, open and close prices. The Journal of Business, 73, 477–491.