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Full Length Research Paper

Standard deviation or variance: The better proxy for large hedgers and large speculators risk in U.S. futures markets

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Using CFTC's COT data, both GARCH and PARCH volatility based models found the lagged volatility and news about volatility from the previous month to be significant in explaining large hedgers' and speculators' volatility. The greater reliance on the ARCH term for speculators' suggested their greater reliance on past information to extrapolate for their current decisions. Furthermore, hedgers' volatility in Treasury bonds and coffee, and speculators' volatility in gold and S&P500 futures have experienced increasing volatility persistence to shocks over the 1990s. In all remaining markets, hedgers' and speculators' volatility has shown a tendency to decay over time in response to shocks, supporting that both players are informed and react well to news volatility. The PARCH model explains volatility of both players better by exhibiting more negative components of volatility than the GARCH model. Both models, under normal and t distribution, supported that most futures returns in the 29 US markets were leptokurtic.

Key words: CFTC, Cot, Garch, Parch, volatility

JEL classification: G13, G14, G15, G18

INTRODUCTION

Besides the benefits associated with risk reductions as important factors in motivating decisions to engage in futures trading, potential users are heavily influenced by their subjective assessment of the performance and reliability of a futures market (Ennew et al., 1992). The subjective assessment of the performance is essentially influenced by the information users have been exposed to about the hedging and speculation services of the futures contract. This is due to the relative complexity of the financial service provided by the futures contract, which is backed by regulation and events. Investors' perceptions about risk have also changed with time, due to events such as the ones shown below[1] in Figure 1.1.

As defined by the Basel Committee, the control of risk by management[2] is the fourth and final most important part of the risk management process. While the benefits of risk dispersion are accomplished without holding massive positions in the underlying financial instruments, too often in financially checkered past, the access to such leverage has induced speculative excesses that have led to financial grief. Moreover, while we are scarcely likely to reform the underlying human traits that lead to excess, we do need to buttress our risk-management capabilities as best as we can to delimit such detours from the path of balanced growth. Alternatively stated, in line with DeBondt and Thaler (1995) and Daniel et al. (1998), it is believed that a good finance theory is to be grounded on evidence about how people actually behave and perform. That is why the understanding of risk and return becomes

[1] Interestingly, the bond market turmoil during 1994 and the Asian crisis in mid-1997 interrupted extended periods of a relaxed market attitude towards risk. Moreover, the market strains following the Russian default and the near-collapse of LTCM took place against a background of a prolonged period characterized by a cautious investor attitude.

[2] Management can be generalized to investors, firms and government bodies, where each of these are concerned about the policy implications of this study.

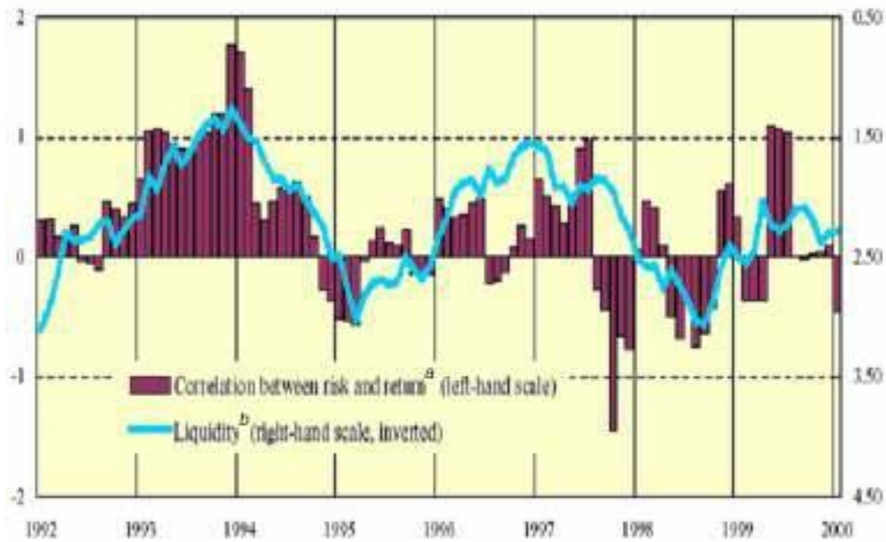

Figure 1: Risk and Return relationship.
[a]Slope coefficient of a cross-sectional regression of realised returns on historical volatility for a number of asset classes.
[b]GDP-weighted average of overnight real rates in the Eurocurrency market for the US dollar, yen, Euro and sterling. A rise in the coefficient indicates greater tolerance for risk; a decline indicates more risk aversion. Sources: Datastream; national data; BIS estimates.

highly critical in understanding the behaviour and performance of any rational player. The aim of this study is to bring contributions in a better understanding of the risk and return relationship, with particular emphasis on the measurement of risk.

Volatility models of GARCH/PARCH help not only in ascertaining the existing usage of these conditional variance models, but also whether standard deviation or variance provides a better proxy of risk for each player. For instance, Davidian and Carroll (1987) argue that standard deviation specifications are more robust than variance specifications. A survey indicated that corporate managers are mostly concerned with one-sided risk, namely, the ”downside risk” (Adams and Montesi, 1995). Also, evidence is rare with models containing information variables, sentiment index, hedging pressures, and net positions. Besides, this is the first study including the hedging pressure variable in performance (mean equation). More important, this study is the first to assess the different impact of different error distribution assumptions on the volatility models. This paper is organised as follows: A literature review is provided before the data section; empirical findings follow before reaching a conclusion.

Literature review

The GARCH model

Autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models help explain conditional variance movements and capture part of the excess kurtosis in commodity prices (Bollerslev, 1986; Engle, 1982). Yang and Brorsen (1992) examined daily cash prices of seven agricultural commodities, and their results support the non-normality of daily returns. Beck (1998) derived that Muth’s (1961) rational-expectations model of commodity markets implies an ARCH process in spot prices of storable commodities. Her analysis of 19 different commodity prices at annual frequency found significant ARCH processes for most storable commodity price series. Bollerslev (1986) extended ARCH by allowing the model to include past variances as well as past forecast errors. Due to these past variances, this model is referred to as generalized ARCH (GARCH). A GARCH (1,1)[3] model is employed and expressed as:

$$\sigma_t^2 = \varphi_0 + \varphi_1 \xi_{t-1}^2 + \varphi_2 \sigma_{t-1}^2 + \varepsilon_t \quad (2.1)$$

Where the restrictions $\varphi_0 > 0$ and φ_1 & $\varphi_2 \geq 0$ are imposed to insure a positive variance. The GARCH process is analogous to an ARMA representation[4]. Both ARCH and GARCH

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[3] The (1, 1) in GARCH (1, 1) refers to the presence of a first order auto regressive GARCH term (the first term in parentheses) and a first- order moving average ARCH term (the second term in parentheses).

[4] ARMA model specification means that only enough AR and MA terms should be used to fit the properties of the residuals. The Akaike information criterion and Schwarz criterion provided with each set of estimates may also be used as a guide for the appropriate lag order selection. If the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations were zero after one lag, then a first-order autoregressive model is appropriate. Alternatively, if

impose restrictions on coefficients to ensure a positive variance. An additional restriction is that both ARCH and GARCH models assume a symmetric distribution of asset returns.

GARCH models have the advantage of incorporating heteroscedasticity into the estimation procedure. All GARCH models are martingale differences, implying that all expectations are unbiased. GARCH models are capable of capturing the tendency for volatility clustering in financial data. Volatility clustering in stock returns implies that large (small) price changes follow large (small) price changes of either sign. Moreover, conclusions regarding the predictability of returns based on the significance of autocorrelation coefficients are valid only after controlling for the ARCH effects. Errunza et al. (1994) show that the persistence of shocks to volatility depends on the sum of the ($\varphi_1 + \varphi_2$) parameters. Values of the sum lower than unity imply a tendency for the volatility response to decay over time. In contrast, values of the sum equal (or greater) than unity imply indefinite (or increasing) volatility persis-tence to shocks over time. However, a significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time (Poterba and Summers, 1986).

Hardouvelis and Kim (1996) studied the volatility of copper futures contracts as it relates to margin requirements. Bracker and Smith (1999) examined the volatility of copper futures prices and concluded that this volatility was more properly modeled as a GARCH process of time-varying volatility. Urich (2000) presents hedging models in which spot and futures prices are cointegrated in their logs and return disturbances are GARCH. Yang and Brorsen (1993) found GARCH effects in 13 of the 15 futures markets studied.

Symmetry: an important assumption

The assumption of symmetry, that is, that all traders have the same initial variance of information, the same cross covariance between signals, and the same covariance between signals and true values, is critical for the analysis (Foster and Viswanathan, 1996). Karpoff (1988) suggests that in equity markets the observed positive correlation between volume and return can be explained by the presence of differential costs in acquiring short- and long-term positions. Accordingly, it should not be observed any asymmetry in futures markets, since the costs of taking short- and long-term positions in such markets are symmetric. This can be verified by calculating the contemporaneous correlation coefficients between the two variables (Karpoff, 1988). Furthermore, Kocagil and Shachmurove's (1998) volume-return correlations support Karpoff's (1988) hypothesis that the absence of trading cost asymmetry assures symmetric trading volumes in futures markets like copper, corn, crude oil, gasoline, gold, heating oil, live cattle, orange juice, palladium, platinum, silver, soybeans, sugar (world), wheat, S&P 500 index, and Treasury bond. Merton (1995) has argued that the introduction of futures trading and derivative markets, in general, can improve efficiency by reducing asymmetric responses to informa-tion. Dadalt et al. (2002) argued that hedging reduces noise related to exogenous factors and hence decreases the level of asymmetric information. Finally, large players are likely to have less asymmetric information, due to higher institutional ownership and greater analysis (Atiase, 1985).

Error distribution

Analyses of probability distributions often use changes in the logarithms of prices. The evidence is mixed on whether price changes are well approximated by the log normal distribution. For example, Hudson et al. (1987) found that the log normal distribution was a good approximation for wheat, soybeans, and live cattle for daily prices for the years 1976 through 1982, although it was not when earlier years were included. Hilliard and Reis (1999) examined a set of intra-day prices—observations on every price change—for soybeans for the period July 1990-June 1992, and they concluded that the logarithmic changes were not distributed normally. It is not uncommon that agricultural futures prices, like many other financial series, are distributed non-normally with the fat tails (Taylor, 1986). Mann and Heifner (1976) suggested that the distribution of commodity price changes is not normal but leptokurtic. For 6 agricultural futures, Corazza et al. (1997), found that returns are not log-normally distributed, primarily because of reasons such as fatter tails and instability in the variance level (accounting for the relatively many outliers). Manfredo et al. (1999) proposed a t distribution after the normal distribution being left with excess kurtosis. Similarly, Bailey and Myers (1991) used a conditional t distribution and found strong evidence of shocks to the volatility being very persistent.

An understanding of the probability distributions of futures prices is important to decision makers. First, optimal hedges in futures depend on the parameters of the underlying probability distributions, and the estimates of these parameters depend, in turn, on the analyst's assumed model of the distribution (McNew and Fackler, 1994). Second, models of options prices make assumptions about the nature of the probability distribution of the underlying asset, and, in the case of traded agricultural options, the underlying asset is a position in a futures

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the autocorrelations were zero after one lag and the partial autocorrelations declined geometrically, a first-order moving average process would seem appropriate. If the autocorrelations appear to have a seasonal pattern, this would suggest the presence of a seasonal ARMA structure.

contract. In addition, changes in volatility can influence the margin level for futures contracts and hence influence the cost of hedging. Moreover, one might expect that with normally distributed data the symmetric GARCH model would exhibit the lowest RMSE. Bracker and Smith (1999) showed that the GARCH model ranked first compared to the asymmetric EGARCH, AGARCH, and GJR for some futures market.

Data

COT (Commitments of Traders)

Essentially, COT reports provide a breakdown of each Tuesday's open interest for market traders who hold positions equal to or above the reporting level established by the CFTC. The weekly reports for Futures-Only Commitments of Traders and for Futures-and-Options-Combined Commitments of Traders are released every Friday at 3:30 p.m. Eastern time. Reports are available in both short and long format. For reportable positions, additional data are provided for commercial and non-commercial holdings, such as spreadings, changes from the previous report, percentage of open interest by category and number of traders. There are roughly 41 scholarly works that have used the COT data up to now (Haigh et al., 2005). In this study, monthly data from Pinnacle Data Corp., Webster, New York-that was extracted from CFTC magnetic tapes-was used. Since 10/16/1992, the CFTC has compiled the data weekly (as per market close on Tuesday) and released two weekly reports every second Friday. Although COT is still based only on weekly data, its quality more than makes up for its quantity - it is the sole source of the actual holding of these three key-groups to have inside information on the trading activities of the "savvy Commercials", the "too shrewd Non-Commercials", and the "unsuspecting Small Traders".[5] A detailed specification list of the 29 futures markets used in this study can be found in the Appendix.

Use of COT

The NGFA (National Grain and Feed Association) provided to CFTC 2006 Review[6] Commission the most comprehensive list of traders who use the COT reports: “farm marketing advisors/brokers; commercial hedging advisors/brokers; FCMs, IBs, and CTAs; cash merchant-diser/hedgers or similar decision makers, including end-users, exporters, processors, merchants; [and] OTC dealers or other trading desks.” For instance, there may be situations when speculators are more likely to have an indication of the hedging imbalances. First, extraordinary surges in the level of hedging imbalances will likely draw the attention of speculators. For instance, sudden surges in the needs of short hedgers in agricultural futures may be caught early when there are harvest revisions, or later, in the trading pits. Second, several commodities follow certain obvious patterns of hedging imbalances. For instance, coffee has historically had an excess of short hedgers over long hedgers, with some exceptions in 1984, and oats has had an excess of short hedgers since 1987 (Chatrath et al., 1997).

Sentiment index

The Sentiment data applied through the empirical models is Consensus bullish sentiment index provided by Investors Co-op and Consensus Inc.[7] the exclusive Consensus Sentiment Index is the premium gauge of positions and attitudes of major professional brokerage firms and advisors as interpreted and recorded by Consensus, Inc. Regarding its reliability, in compiling the Index, Consensus draws from an extensive mix of both brokerage house analysts and independent advisory services, from both contributors and non-contributors, in order to provide the strongest possible data base. The data covers a broad spectrum of approaches to the market, including the fundamental, technical, and cyclical: Consensus makes no attempt to discern to which of these approaches traders may be responsive most. Consensus considers only opinions which have been committed to publications and have therefore an influence on the trading public, and does not consider opinions which brokers or advisors may hold but do not disclose publicly. The data have been published since May 1983 and are available through Consensus Research as early as 8:00 p.m. Central Time on Tuesdays. In this study data are matched with net positions and return series.

Return series and information variables

Continuous monthly series of futures returns are created for each market. The return is measured as the percenttage change in settlement prices of the contract with the nearest delivery date using a rollover strategy (Chatrath et al., 1999). For example, a position is taken in the nearest-to-maturity contract until the delivery month in which the position switches to the second-nearest contract. To match COT data, a monthly (the holding period) return series is constructed, (Tuesday–Tuesday).[8] Data on futures prices and information variables are sourced

[5] http://pinnacledata.com/cot.html (accessed on April 17, 2007)

[6] See http://cftc.gov/files/cftc/cftcnoticeonsupplementalcotreport.pdf (Accessed on:18 April 2007)

[7] http://www.consensus-inc.com/hotline.htm (Accessed on: 20 April 2007)

[8] In the same line as Wang (2003), return is measured as the percentage change in settlement prices of afutures contract over 1-week interval (see also: Urich, 2000; Lauterbach and Smoller, 1996; Sorensen, 2002; Koontz et al., 1998).

from Datastream[9]. The analysis is set on monthly rather than weekly data because it is less likely for traders' perception of risk to be changed over a short interval. Moreover, the choice of this time interval makes the results comparable to the previous studies on backwardation and hedging pressure theories (Wang, 2004; Bessembinder, 1992; Chang, 1985).

Empirical findings

Mean equation

There is huge support for the use of mean equations coming from Grundy and Martin (2001) and Wang (2001, 2003). Its usage extends from understanding relationships between returns and other variables, to volatility and forecasting models. In line with Wang (2001, 2003), this study makes use of the following model:

$$R_t = \phi_0 + \phi_1 SI_t + \phi_2 NP_t + \phi_3 HP_{t-1} + \phi_4 \sum \theta_t + \xi_t \quad (4.10.1)$$

Where R_t is the monthly return at time t, Si_t is the sentiment index, the net positions, HP_{t-1} the own hedging pressure lagged variable, and are the three information variables. A one month lagged own hedging pressure variable is added to the mean equation for the first time in literature to account for the existence of risk premium in futures markets.[10]

GARCH volatility model

In line with Bollerslev (1986), a GARCH (1, 1) model is employed and expressed as:

$$\sigma_t^2 = \phi_0 + \phi_1 \xi_{t-1}^2 + \phi_2 \sigma_{t-1}^2 + \varepsilon_t \quad (4.13)$$

The GARCH process is analogous to an ARMA representation. Both ARCH and GARCH impose restrictions on coefficients to ensure a positive variance. An additional restriction is that both ARCH and GARCH models assume symmetry in the distribution of asset returns. Correlograms of squared residuals and an ARCH LM test are carried out to diagnose that the GARCH model is white noise and efficient. Full results for GARCH volatility models are reported in Table 1.

News about volatility from the previous period, measured as the lag of the squared residual from the mean equation, is significant in 13 markets for hedgers, where 9 out of the 13 markets are from the agricultural group. In 10 markets, news about volatility from the previous month is positive, suggesting that the GARCH term σ^2_{t-1} is quite important in determining current volatility levels for hedgers, particularly for agricultural futures markets. Only in Canadian dollars, live cattle, and pork bellies has previous news about volatility reduced current volatility

levels. On the other hand, the GARCH term σ^2_{t-1} is significant in 24 markets, where 14 markets are from the agricultural group. As expected, $\varphi_2 \geq 0$, except for soybean oil. This is consistent with Yang and Brorsen (1993) who found GARCH effects in 13 out of the 15 futures markets studied.

In contrast, speculators volatility tends to be affected by news about volatility from the previous month. In fact, is significant for 18 of the markets, where all 3 financials, 3 currencies, 3 minerals, and 9 agriculturals volatility are affected by the previous month news on volatility. 15 out of these 18 markets exhibit a significant positive effect on current volatility, where only Canadian dollar, Swiss franc and live cattle exhibit a negative effect on current volatility. This supports the fact that large speculators are more geared towards herding behaviour and volatile trading, with news from the previous period affecting current volatility level significantly. Furthermore, the

GARCH term is significant for speculators in 20 markets, where only wheat (Chicago) exhibited a negative effect on current volatility.

Furthermore, in line with Bollerslev et al. (1992), who showed that the persistence of shocks to volatility depends on the sum of and, the findings in table 1 support hedgers' volatility in Treasury bonds and coffee. Moreover, speculators volatility in gold and S&P500 futures has experienced increasing volatility persistence to shocks over the 1990s. In contrast, in all the remaining markets, hedgers and speculators volatility has shown a tendency to decay over time in response to shocks over the 1990s.[12] This supports that both players are informed and react well to news volatility.

Power ARCH (PARCH) volatility model

In line with Davidian and Carroll (1987), who argue that, standard deviation specifications are more robust than variance specifications, a Taylor (1986) and Schwert (1989) standard deviation volatility model is constructed as follows:

$$\sigma_t^{\delta} = \phi_0 + \sum_{i=1}^{p} \phi_i \left(|\xi_{t-i}| - \gamma_i \xi_{t-i} \right)^{\delta} + \sum_{j=1}^{q} \phi_j \sigma_{t-j}^{\delta} + \varepsilon_t \quad (4.14.1)$$

[9] Corporate bond yields are those from Lehman Brothers (see: Athanassakos and Carayannopoulos, 2001; Kliger and Sarig, 2000).

[10] Full results available on request to the author.

[12] However, a significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time (Poterba and Summers, 1986).

Table 1. This table shows the results of using a Garch (1,1) volatility model to estimate the conditional variance and mean equation for both hedgers and speculators. Only the intercept, ARCH and GARCH term of the volatility equation are provided below. The numbers are t-statistics relevant to the hypothesis that the relevant parameter is zero. Estimated symmetric GARCH volatility equation is 4.13.

GARCH volatility equation		Hedger			Speculator	
		ξ_{t-1}^2	σ_{t-1}^2		ξ_{t-1}^2	σ_{t-1}^2
	Intercept			Intercept		
Minerals						
GC	6.310	0.084	-0.088	0.356	0.533	0.605
						4.936
SI	2.910	0.190	0.645	9.942	0.455	0.013
		1.648	3.630	3.125	3.515	
HG	32.322	0.048	0.005	8.659	-0.001	0.744
					-0.012	
PL	2.163	0.334	0.516	2.225	0.332	0.507
			3.530		1.712	3.842
CL	6.420	0.046	0.766	6.656	0.070	0.745
			5.192			5.645
HO	4.330	0.013	0.835	5.512	0.067	0.780
			6.688			5.365
Financials						
SP	2.031	0.308	0.530	0.157	0.159	0.848
	1.689	1.740	3.051		2.008	11.147
ED	0.008	0.090	0.819	0.007	0.088	0.821
		1.740	10.227		1.764	9.814
US	0.020	-0.035	1.040	4.231	0.610	-0.043
			10.086	5.006	1.726	
Currencies						
BP	0.005	-0.026	1.018	-0.006	-0.015	1.006
			8.585			12.209
SF	1.132	-0.044	0.947	2.826	-0.070	0.827
			20.392	2.017	-3.193	5.950
CD	0.074	-0.087	1.040	0.064	-0.083	1.046
	2.863	-2.754	26.838	2.341	-2.586	24.536
JY	4.302	0.312	-0.097	4.874	0.351	-0.002
	2.950			2.950	1.862	
Agriculturals						
W	6.650	0.092	0.590	41.534	0.062	-1.066
			2.026	6.703	1.773	-9.246
KW	2.149	0.126	0.781	2.957	0.129	0.749
			8.446		1.781	5.847
MW	2.192	0.070	0.818	2.673	0.138	0.742
			4.894			4.471
C	3.144	0.008	0.813	6.215	0.030	0.657
			2.702			
S	6.471	0.297	0.115	9.084	0.228	0.147

Table 1. Contd

	2.976	2.109		2.381		
BO	11.847	0.343	-0.442	7.123	0.346	-0.082
	4.643	3.308	-3.257	2.833	2.706	
SM	3.193	0.175	0.585	3.159	0.113	0.700
		2.185	3.364			4.129
PB	8.402	-0.071	1.031	102.558	0.421	0.015
	3.346	-1.840	20.220	3.748	1.997	
LH	1.342	0.116	0.876	1.637	0.117	0.867
		1.645	13.652			13.903
LC	5.724	-0.072	0.544	5.817	-0.074	0.552
	1.792	-5.385	1.706	1.865	-5.703	1.850
FC	0.527	0.044	0.853	0.406	0.055	0.876
			6.362			7.414
SB	6.349	0.429	0.454	4.452	0.206	0.696
	2.129	3.228	3.551		2.038	3.870
CC	2.867	0.097	0.778	3.544	0.066	0.798
			2.954			4.329
KC	15.789	1.104	0.015	30.952	0.871	-0.045
	4.428	3.269		4.090	2.847	
CT	2.312	0.176	0.730	2.537	0.206	0.706
			5.283		1.758	4.470
LB	5.228	0.370	0.571	3.975	0.221	0.712
		1.923	3.352		2.817	6.879

where $\delta>0$, $|\gamma_i| \le 1$ for i = 1,… , r, and $\gamma_i = 0$ for all i > r, $r \le p$.

Substituting $\delta=1$, i=j=1 and $\gamma_i = 0$ in equation 4.14.1, results in a symmetrical PARCH model as follows:

$$\sigma_t = \phi_0 + \phi_1 \xi_{t-1} + \phi_2 \sigma_{t-1} + \varepsilon_t \quad (4.14.2)$$

Note that if $\delta=2$ and $\gamma_i = 0$ for all i, the PARCH model is simply a standard GARCH specification. Correlograms of squared residuals and an ARCH LM test are carried out to diagnose that the model is white noise and efficient. Output for the Taylor-Schwert volatility model can be found in Table 2.

Volatility or the proxy measure of risk- is measured as the standard deviation σ_t under the PARCH model. As expected, findings from Table 2 show that the effect of ξ_{t-i} on current volatility is much more mixed and significant than its counterpart ξ_{t-1}^2 in table 1. News 19 markets. In 7 markets, namely Treasury bonds, Canadian dollar, Japanese yen, wheat (Minnesota), corn, live cattle, and cotton, news about volatility from the previous month has a significant negative effect on current volatility. On the other hand, in silver, platinum, heating oil, S&P500, Eurodollar, British pound, wheat (Kansas), soybean, soybean oil, pork bellies, coffee, and lumber markets, news about volatility from the previous month has a significant positive effect on current volatility. Moreover, lagged volatility is significant in 17 markets, where in heating oil, wheat (Chicago), soybean meal, live hogs, and cocoa, lagged volatility has a significant negative impact on current volatility. This is in line with the 24 markets that were significantly affected by from the GARCH model.

Speculators also bear the significant effect of on current volatility in 15 markets. In 10 out of these 15 markets, news about volatility from the previous month tends to add to the current volatility level. This result is interestingly in line with the 18 markets that were significantly affected by from the GARCH model. Furthermore, lagged volatility of large speculators' trading activity is significant and positive for 10 out of 14 markets. Only in about volatility from the previous month is significant for wheat did lagged volatility have a significant negative impact on current volatility. Hedgers and speculators' current volatility (under GARCH) has been significantly increased (decreased) by the last month's volatility in 23 (1) and 19 (1) markets respectively. More important, while speculators' current volatility (under GARCH) has significantly increased (decreased) in 14 (5) markets after accounting for news about volatility (under GARCH) from

Table 2. This table shows the results of using a PARCH volatility model to estimate the conditional variance and mean for both hedgers and speculators. Only the intercept, lagged absolute error residual and lagged volatility term of the volatility equation are provided below. The numbers in italics are t-statistics relevant to the hypothesis that the relevant parameter is zero. Estimated symmetric PARCH volatility equation is 4.14.2.

PARCH volatility equation						
		Hedger			Speculator	
		$\lvert\xi_{t-i}\rvert$	σ_{t-1}		$\lvert\xi_{t-i}\rvert$	σ_{t-1}
	Intercept			Intercept		
Minerals						
GC	3.083	-0.235	0.471	4.468	0.165	-1.055
				8.067		-11.637
SI	1.020	0.189	0.599	2.535	0.498	-0.011
		1.833	2.632	3.883	5.766	
HG	5.248	0.037	0.073	1.924	-0.020	0.685
PL	0.774	0.317	0.520	5.982	-0.087	-0.739
		2.190	2.037	3.303	-2.069	-1.946
CL	0.835	0.095	0.789	14.636	0.056	-1.026
			6.082	4.600		-11.369
HO	5.585	0.674	-0.276	0.662	0.095	0.818
	5.966	4.010	-2.943		1.969	8.629
Financials						
SP	0.557	0.274	0.615	1.490	0.571	0.113
		2.258	4.002	2.700	4.454	
ED	0.027	0.080	0.844	0.027	0.074	0.849
		1.824	9.364			8.098
US	2.068	-0.373	0.549	1.732	-0.441	0.716
	2.556	-3.360		4.083	-3.782	3.414
Currencies						
BP	0.152	0.187	0.796	0.030	0.063	0.936
		3.141	10.266			24.347
SF	1.628	0.190	0.373	1.428	0.246	0.391
	1.660			1.805	1.842	
CD	0.048	-0.084	1.031	0.051	-0.092	1.037
	2.256	-2.164	24.531	1.989	-2.363	23.230
JY	0.069	-0.082	1.034	2.294	0.420	-0.176
		-1.662	45.221	3.047	3.326	
Agriculturals						
W	8.404	0.084	-0.907	2.717	0.061	0.390
	4.279		-3.164			
KW	0.326	0.145	0.819	6.411	-0.355	-0.089
		2.085	8.696	4.328	-10.839	
MW	4.769	-0.280	0.047	0.671	0.183	0.715
	4.652	-7.322			2.216	4.174
C	4.260	-0.255	0.157	1.505	0.017	0.649
	2.363	-8.276				
S	1.802	0.261	0.237	2.134	0.213	0.265
	2.270	2.802		1.540	1.662	
BO	3.228	0.334	-0.286	2.523	0.363	-0.123

Table 2. Contd.

	3.390	3.566		2.741	3.449	
SM	6.515	-0.044	-0.693	6.801	-0.022	-0.597
	5.837		-2.749	2.084		
PB	7.101	0.319	0.198	0.641	-0.105	1.031
	3.095	2.229		2.995		15.116
LH	15.145	0.032	-1.061	15.137	0.093	-1.056
	6.617		-5.787	9.787		-14.720
LC	0.218	-0.114	1.025	3.078	-0.231	0.239
	2.007	-2.531	34.308	2.851	-4.148	
FC	0.032	-0.058	1.027	1.055	-0.031	0.607
			28.534			
SB	-9.967	-0.044	0.731	0.897	0.171	0.722
	-2.188				1.901	3.760
CC	9.909	-0.033	-0.924	2.060	0.064	0.551
	11.556		-6.828			
KC	3.455	0.773	-0.037	0.199	-0.060	1.028
	4.393	4.596		1.782		25.818
CT	7.900	-0.301	-0.417	6.578	-0.009	-0.359
	3.460	-16.830				
LB	1.117	0.401	0.527	1.478	0.588	0.349
		3.306	3.231	2.210	4.879	2.522

the previous month, hedgers' current volatility (under PARCH) has significantly increased (decreased) in 12 (7) markets after accounting for similar news about volatility from the previous month. In sum, as expected, while the PARCH model exhibited more significant negative variables; the GARCH model produced more significant positive variables. Furthermore, it can be observed that the significance of over is much higher for both hedgers and speculators. However, while is more significant than for large speculators, that is not the case for hedgers, where appears to have more impact than. Although is more significant than for large speculators, it is also important to understand that the PARCH model has resulted in a more significant negative impact of news about lagged volatility than in the GARCH model for speculators. In that line of thought, findings suggest that the PARCH model, by capturing more significant negative impact of variables, is a more informative model than its counterpart GARCH model for speculators. On the other hand, while the PARCH model for hedgers also captures more significant negative impact of variables like lagged volatility and news about volatility from the previous month, the PARCH model also captures more significant positive impact of the news about volatility from the previous month than its GARCH counterpart.

Error distribution

In line with Baillie and Myers (1991) and McNew and Fackler (1994) who underlined the importance of probability distributions, and backed by Bera and Garcia (2002) and Manfredo et al. (1999) who showed the relevance t distribution over normal distribution, the GARCH and PARCH models used in this study are tested for normality in their probability distributions. Skewness, Kurtosis, and the Jarque-Bera statistics for both the GARCH and PARCH models (under normal and t distribution) are provided in Table 3.

Findings from Table 3 show that the skewness for hedgers returns (GARCH model) under normal distribution is positive for 20 markets, and negative for Eurodollar, Treasury bonds, British pound, corn feeder cattle, sugar, cotton, live cattle, and silver. The fact that 20 markets have a probability distribution with a long tail to the right is also reflected in the upward trend of the S&P500 returns in the 1990s, where many hedgers have had positive returns in their respective markets. The skewness values under t distribution can be positive or negative as under the normal distribution. However, under t distribution, the probability distributions are as skewed as or more skewed to the right if the skewness is positive;

Table 3. This table shows the values for skewness, kurtosis and Jarque-Bera statistics for the GARCH and PARCH volatility models. Panel A reports the results of hedges under normal and t distributions, while Panel B reports the results for speculators. If the skewness value is positive (negative) that would indicate that error distribution is skewed to the right (left). A kurtosis value less than 3 indicates the distribution is flat (platykurtic) and peaked (leptokurtic) relative to the normal if it's greater than 3. The probability of the Jarque-Bera test is the probability that a Jarque –Bera statistic exceeds (absolute value) the observed value under the null hypothesis of a normal distribution. A small probabiliuty rejects the null hypothesis. S denotes skewness and K denotes Kurtosis.

		GARCH							PARCH			
		Normal dist.			t dist.		Normal dist.				t dist.	
	S	K	Prob.	S	K	Prob.	S	K	Prob.	S	K	Prob.
			(J-Bera)			(J-Bera)			(J-Bera)			(J-Bera)
Panel A: Hedger												
Minerals												
GC	4.076	36.339	0.000	5.551	52.863	0.000	-0.254	3.094	0.463	3.312	30.844	0.000
SI	-0.225	3.171	0.515	-0.225	3.203	0.496	-0.460	3.491	0.044	-0.460	3.491	0.044
HG	0.010	3.138	0.946	1.003	0.013	0.938	-0.009	3.152	0.935	0.106	3.187	0.795
PL	1.027	6.081	0.000	2.232	14.846	0.000	1.166	6.985	0.000	2.090	14.127	0.000
CL	0.831	5.495	0.000	1.083	2.238	0.000	0.829	5.528	0.000	1.344	8.405	0.000
HO	0.792	5.575	0.000	1.018	1.390	0.000	0.954	5.577	0.000	1.285	10.661	0.000
Financials												
SP	0.749	4.782	0.000	0.950	5.496	0.000	0.706	4.628	0.000	0.864	5.452	0.000
ED	-0.563	3.872	0.003	-0.630	4.515	0.000	-0.560	3.939	0.002	-0.656	4.589	0.000
US	-0.390	3.353	0.122	-0.870	5.509	0.000	-0.742	5.611	0.000	-1.149	7.608	0.000
Currencies												
BP	-0.095	3.987	0.055	-1.151	10.942	0.000	-0.341	4.700	0.000	-0.676	5.929	0.000
SF	0.165	3.960	0.052	0.298	4.438	0.001	0.310	3.712	0.077	0.273	4.510	0.001
CD	0.021	2.633	0.675	0.020	2.614	0.649	0.029	2.642	0.685	0.025	2.648	0.695
JY	0.381	5.516	0.000	0.544	6.526	0.000	-0.184	4.214	0.010	-5.422	51.136	0.000
Agriculturals												
W	0.493	4.517	0.000	0.571	4.794	0.000	0.268	4.184	0.008	0.259	4.399	0.002
KW	0.732	5.259	0.000	0.873	6.911	0.000	0.593	4.532	0.000	0.143	5.351	0.000
MW	0.888	6.557	0.000	0.888	6.557	0.000	0.498	6.040	0.000	0.638	7.016	0.000
C	-0.640	5.997	0.000	-0.662	5.890	0.000	-0.451	4.977	0.000	-0.593	5.838	0.000
S	0.218	3.772	0.105	0.216	4.114	0.016	0.268	3.586	0.164	0.253	3.941	0.038
BO	0.125	2.813	0.756	0.136	2.825	0.742	0.028	2.856	0.934	-0.116	3.136	0.812
SM	0.300	3.582	0.134	0.466	5.062	0.000	0.200	3.241	0.534	0.380	4.457	0.000
PB	0.860	4.164	0.000	1.062	5.436	0.000	0.816	4.311	0.000	0.748	3.921	0.000
LH	1.080	5.217	0.000	1.263	7.005	0.000	1.251	6.623	0.000	0.477	5.084	0.000
LC	-0.736	4.105	0.000	-0.743	4.153	0.000	-0.568	3.373	0.016	-0.821	4.449	0.000
FC	-0.394	4.256	0.002	-0.475	5.073	0.000	-0.304	3.451	0.193	-0.109	4.288	0.007
SB	-0.269	2.784	0.380	-0.269	2.785	0.380	-0.058	2.698	0.740	-0.023	2.805	0.891

Table 3. contd.

CC	0.448	4.980	0.000	0.589	6.509	0.000	0.517	4.801	0.000	0.830	5.317	0.000
KC	0.304	3.666	0.096	0.469	4.113	0.002	0.414	3.700	0.034	0.585	4.990	0.000
CT	-0.658	6.658	0.000	-1.439	11.948	0.000	-0.720	7.323	0.000	-1.069	10.198	0.000
LB	0.463	4.893	0.000	0.549	5.349	0.000	0.360	4.264	0.002	0.327	3.791	0.048
		Normal dist.			T dist.			Normal dist.			T dist.	
	S	K	Prob.	S	K	Prob.	S	K	Prob.	S	K	Prob.
			(J-Bera)			(J-Bera)			(J-Bera)			(J-Bera)
Panel B: Speculator												
Minerals												
GC	1.543	11.677	0.000	3.893	33.207	0.000	1.123	12.157	0.000	2.849	25.705	0.000
SI	-0.375	3.211	0.175	-0.378	3.275	0.156	-0.320	2.957	0.306	-0.225	3.353	0.390
HG	-0.096	3.161	0.835	-0.091	3.171	0.836	-0.109	3.144	0.821	0.175	2.760	0.594
PL	0.739	4.755	0.000	1.698	11.363	0.000	1.281	8.296	0.000	1.683	10.864	0.000
CL	0.743	5.442	0.000	1.154	2.543	0.000	1.390	8.236	0.000	1.957	14.205	0.000
HO	0.770	5.546	0.000	1.057	7.227	0.000	0.728	5.298	0.000	0.803	8.902	0.000
Financials												
SP	0.477	4.242	0.000	0.638	4.680	0.000	0.510	4.196	0.001	1.040	5.392	0.000
ED	-0.644	4.009	0.000	-0.701	4.555	0.000	-0.660	4.282	0.000	-0.726	4.718	0.000
US	-0.594	3.845	0.000	-0.995	6.222	0.000	-0.632	4.963	0.000	-1.242	8.123	0.000
Currencies												
BP	-0.292	4.061	0.015	-0.941	8.451	0.000	-0.339	4.475	0.001	-0.837	6.154	0.000
SF	0.238	4.019	0.026	0.398	4.390	0.001	0.359	3.500	0.111	0.338	4.467	0.001
CD	0.044	2.509	0.488	0.046	2.511	0.490	0.054	2.567	0.564	0.071	2.581	0.569
JY	0.375	4.648	0.000	1.088	7.386	0.000	0.352	4.613	0.000	0.614	4.999	0.000
Agriculturals												
W	0.255	3.335	0.342	0.689	5.010	0.000	0.600	4.708	0.000	0.196	3.710	0.151
KW	0.743	5.098	0.000	0.877	6.232	0.000	-0.056	4.502	0.001	0.476	5.842	0.000
MW	0.635	4.569	0.000	0.373	6.566	0.000	0.558	4.519	0.000	0.343	5.803	0.000
C	-0.651	5.736	0.000	-0.639	5.886	0.000	-0.664	5.694	0.000	-0.507	5.168	0.000
S	-0.136	2.984	0.807	-0.137	2.984	0.806	-0.123	3.077	0.825	-0.165	3.533	0.323
BO	0.085	3.107	0.891	0.036	3.295	0.767	0.117	3.016	0.854	-0.224	3.244	0.474
SM	0.191	3.225	0.569	0.197	3.400	0.404	-0.010	3.188	0.903	0.041	3.530	0.437
PB	0.787	4.265	0.000	1.049	5.431	0.000	0.911	4.424	0.000	0.690	3.679	0.001
LH	1.050	4.946	0.000	1.294	7.504	0.000	0.942	5.175	0.000	0.518	5.353	0.000
LC	-0.722	4.006	0.000	-0.735	4.073	0.000	-0.551	3.850	0.004	-0.791	4.316	0.000
FC	-0.598	4.719	0.000	-0.618	5.777	0.000	-0.384	4.479	0.000	-0.336	4.628	0.000
SB	-0.417	3.462	0.073	-0.506	3.850	0.007	-0.399	3.378	0.107	-0.038	2.552	0.553

Table 3. contd.

CC	0.363	3.551	0.092	0.433	3.930	0.010	0.389	3.475	0.091	0.700	4.252	0.000
KC	0.335	4.292	0.002	0.672	5.474	0.000	0.379	3.555	0.079	0.810	5.050	0.000
CT	-0.568	5.933	0.000	-1.385	11.935	0.000	-1.337	11.221	0.000	-1.337	11.306	0.000
LB	0.520	5.019	0.000	0.594	5.322	0.000	0.328	3.889	0.030	0.332	3.775	0.050

and as skewed as or more skewed to the left if the skewness is negative. The only exception was the Canadian dollar, where the positive skewness value was larger than under t distribution. The skewness for hedgers (under PARCH, normal) is negative for 12 markets, where the 9 markets (under GARCH, normal) are also reflected here in addition to the gold, copper, and Japa-nese yen markets. The skewness under PARCH (normal) had less value than under GARCH (t) for 26 markets, except for Swiss franc, Canadian dollar, and soybean, where skewness under PARCH (normal) had a higher value.The skewness under PARCH (t) for hedgers' probability distribution returns was negative for 11 markets, which is the same as for GARCH (normal) with the exceptions of the Japanese yen and the soybean oil.

The skewness for speculators probability distributions returns under GARCH (normal) was negative in 11 markets, which is the same as under GARCH (normal) for hedgers in addition to soybean and copper. The negative skewness for Eurodollar and Treasury bonds - for both hedgers and speculators - can be attributed to the introduction of the Euro, which affected Eurodollar Treasury bonds (BIS, 1999). The skewness under GARCH t was the same as under GARCH normal. However, under t distribution the probability function is more skewed to the right if the skewness is positive and more skewed to the left if the skewness is negative. This similarity holds for 25 markets except for copper, wheat (Minnesota), corn, and soybean oil. Under PARCH (normal) the skewness for speculators' probability return was negative for 13 markets. In fact, under PARCH normal the skewness has less value than the skewness under GARCH t, except for soybean oil, corn, wheat (Minnesota), Canadian dollar, crude oil, and copper. In contrast, under PARCH (t) the skewness was negative in 11 markets, which was the same as under GARCH (normal), except for copper and soybean oil.

Having assumed symmetry in the GARCH and PARCH models, it is interesting to know which model (GARCH, PARCH) and under what error distribution (normal, t) do hedgers and speculators' distribution returns appear to exhibit more tendency towards symmetry. Table 3 shows that the PARCH model, under normal distribution, ranks first in converging hedgers' returns towards symmetry.[13] This contrasts with speculators, where the GARCH model, under normal distribution, ranks first in converging speculators' returns towards zero skewness.[14]

Regarding kurtosis, a value less than 3 would suggest that the probability function is flat (platykurtic), and a value greater than 3 would suggest the probability function is peaked (leptokurtic). Hedgers' probability functions would theoretically have a lower (flatter) kurtosis in more futures markets than speculators, due hedgers entering the market to reduce risk and speculators entering the market to bear that risk. Table 3 shows that this is the case under GARCH (normal), GARCH (t), PARCH (normal), but not under PARCH (t).[15] As such, the first three models help to support the fact that hedgers enter the market to reduce the risk and they have managed to do so in copper, crude oil, heating oil, soybean oil, sugar, and Canadian dollar. Speculators, however, also have a kurtosis lower than 3 in silver, copper, crude oil, Canadian dollar, sugar, and soybean. Furthermore, the kurtosis of hedgers is much smaller than speculators in copper, crude oil, and sugar; but bigger than that of speculators in Canadian dollar.

The probability of the Jarque-Bera statistic is also reported under each model in Table 3. It appears that in 4 markets, hedgers' probability distribution returns approach normality due to their high probability in the Jarque-Bera test. In fact, copper and soybean oil have the highest probability under GARCH (normal); Canadian dollar and sugar under PARCH (t). Speculators' probability distribution returns also approach normality in copper, soybean, soybean oil, and soybean meal. Soybean and soybean meal have the highest probability under PARCH (normal); copper under GARCH (t), and soybean oil under GARCH (normal). The high probability of the Jarque-Bera test is supported by low skewness and kurtosis not far from 3. Overall, Table 3 supports the non-normal distribution in 25 markets for both hedgers and speculators probability distribution returns. This is consistent with Hilliard and Reis (1999) and Taylor (1986) who concluded non-normality in most futures markets. This is also supportive of studies by Mann and Heifner (1976), Blattberg and Gonedes (1984), and Houthakker (1961) where the distribution of large hedgers' and speculators' returns appear to be not normal, but rather leptokurtic.

Conclusion

Both lagged volatility and news about the volatility of the previous month are significant in explaining large hedgers' and speculators' current volatility. The greater significance of the news about volatility from the previous month for speculators suggests their greater reliance on noise trading and herding behaviour, where news from the previous period affects current volatility. Furthermore, hedgers' volatility in Treasury bonds and coffee, and speculators' volatility in gold and S&P500 futures have experienced increasing volatility persistence to shocks over the 1990s. In all remaining markets hedgers' and speculators' volatility has shown a tendency to decay over time in response to shocks, supporting that both players are informed and react well to news volatility.

[13] The (GARCH, normal) model ranks 2nd, followed by (PARCH, t) and lastly, (GARCH, t).

[14] The (PARCH, t) model ranks 2nd, followed by (PARCH, normal), and lastly, (GARCH, normal).

[15] In fact, hedgers (speculators) have a kurtosis in 3 (2) markets under (GARCH, normal), in 6 (3) markets under (GARCH, t), in 3 (2) markets under (PARCH, normal), and a kurtosis in 2 (3) in (PARCH, t).

Table Appendix: Data coding and classification.

	Symbol	Market*	Reporting levels (contracts)
Minerals			
Silver	SI	CE	150
Gold	GC	CE	200
Copper	HG	CE	100
Platinum	PL	NYMEX	50
Crude Oil, light sweet	CL	NYMEX	350
Heating Oil #2	HO	NYMEX	250
Financials			
Eurodollars	ED	IMM	1000
T-bonds	US	CBOT	1000
S&P500	SP	IMM	1000
Currencies			
British Pounds	BP	IMM	400
Swiss Francs	SF	IMM	400
Canadian dollar	CD	IMM	400
Japanese Yen	JY	IMM	400
Agriculturals			
Soybean	S	CBOT	500,000 bushels, 100 contracts
Soybean Oil	BO	CBOT	200
Soybean Meal	SM	CBOT	200
Porc Bellies, frozen	PB	CME	25
Hogs	LH	CMM	100
Cattle (live)	LC	CME	100
Feeder cattle	FC	CME	50
Wheat - Chicago	W	CBOT	500,000 bushels, 100 contracts
Wheat - Kansas	KW	KCBOT	500,000 bushels, 100 contracts
Wheat - Minn	MW	MGE	500,000 bushels, 100 contracts
Corn	C	CBOT	750,000 bushels, 150 contracts
Sugar #1	SB	CSCE	400
Cocoa	CC	CSCE	50
Coffee	KC	CSCE	100
Cotton	CT	NYCE	50
Lumber	LB	CME	25
*CE	Commodity Exchange Inc.		
NYMEX	New York Mercantile Exchange		
IMM	International Monetary Market		
CBOT	Chicago Board of Trade		
CME	Chicago Mercantile Exchange		
CMM	Chicago Mercantile Market		
KCBOT	Kansas City Board of Trade		
MGE	Minn. Grain Exchange		
CSCE	Coffee, Sugar and Cocoa Exchange		
NYCE	New York Cotton Exchange		

The PARCH model for speculators, in contrast, exhibited more significant negative variables for both lagged volatility and news about volatility from the previous month. By capturing more significant negative impact of lagged volatility and news of volatility from the previous month, the PARCH is suggested to be more informative than the GARCH model for speculators' and hedgers' current volatility. The (GARCH, normal), (GARCH, t), (PARCH, normal) models supported this claim in copper, crude oil, heating oil, soybean oil, and sugar, where hedgers managed to have a lower risk relative to speculators. Moreover, the distribution of large hedgers' and speculators' returns appear to be not normal, but rather leptokurtic.

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