Detecting Volatility Changes Across the Oil Sector

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INTRODUCTION

The presence of sudden changes in variance of financial time series has important implications for understanding the price sensitivity and hedging risks involved in derivative securities, such as options and futures contracts. In this article an iterated cumulative sums-of-squares methodology is used to identify points and the magnitude of sudden changes in the unconditional variance. As Lamoreux and Lastrapes (1990) discuss, the pricing of contingent claims depends on the perception of how permanent the shocks are. For example, shocks perceived to be transitory tend to have a smaller impact on the pricing of derivatives. Also, the duration of the change in volatility varies depending on the nature of economic and political events.

Other studies of sudden variance changes in security prices include Poterba and Summers (1986), who show that the existence of time-varying risk premia depends critically on the extent to which volatility

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shocks are persistent, and Lastrapes (1989), who finds evidence that exchange-rate volatility can be affected by U.S. monetary policy regimes. Kim, Oh, and Brooks (1994) find evidence that sudden volatility changes in common stock prices are systematic in nature, that is, nondiversifiable, which can jeopardize the use of a hedging strategy.

Traders who participate in both the cash and futures markets choose a hedging strategy that reflects their risk and return preferences. The risk and return of the portfolio depends on the hedge ratio. An optimal hedge ratio is one that minimizes the variance of the hedged portfolio return. Baillie and Myers (1991) find that a time-varying hedging strategy outperforms a constant hedge ratio for several commodities. The time-varying hedge strategy depends critically on the predictability of future variances, and consequently assumes no sudden changes in the variance of the series. This study clearly shows that sudden changes in variance occur and that knowledge of such can be used to obtain more accurate hedge ratios. A better understanding of the variance process will result in more correctly priced contingent claims and will aid in determining optimal hedging strategies. During periods of increased volatility, there is also a tendency for the spread between the cash and futures market to widen. This leads to increased basis risk and, therefore, adds to the problem of imperfect hedges.

Sudden changes in variance can be a critical feature of time-series data. This article examines the extent to which sudden changes in variance occur. A new methodology, developed in Inclan and Tiao (1994) is applied for detecting sudden variance changes. The procedure is based on an iterated cumulative sums-of-squares (ICSS) algorithm that is used to detect the number of (significant) sudden changes in variance in the time series, as well as to identify the time point and magnitude of each detected sudden change in the unconditional variance.[1] The ICSS approach can be viewed as an alternative to the standard use of autoregressive conditional heteroscedastic (ARCH) and generalized autoregressive conditional heteroscedastic (GARCH) methodology. These models assume constant unconditional variance and model the conditional variance as a continuous function of past innovations to the process. The sudden changes in variance detected by the ICSS algorithm can be readily incorporated into the ARCH/GARCH framework to include both kinds of disturbances to the process variance.

This study investigates sudden changes in variance in three sets of

[1]The details of the algorithm are given in Inclan and Tiao (1994), the program is available by sending an e-mail request to inclan@guvax.georgetown.edu.

financial time series, using daily data from January 1, 1984 to December 31, 1992. The first set of series includes the 1-month, 2-month, . . . , through 6-month oil futures contract, as reported daily in the *Wall Street Journal*. These contracts figured prominently in the debate over the appropriateness of the hedging activities of the German metals firm, Metallgesellschaft, which suffered a $1.3 billion loss when Deutsche Bank, its biggest shareholder and creditor, forced the metals firm to unwind its hedging position in oil futures. Of particular interest to this study is the influence of the Iran-Iraq and Iraq-Kuwait conflicts and the changes in the OPEC oligopoly on the volatility of these series.

Second, this study investigates a daily return series derived from a portfolio of oil-producing companies to test whether volatility changes spill over between the oil futures market and the stocks of oil-producing companies in the equity market. This linkage may be useful in assessing the common investment strategy of investors with specialized information, for example, attempting to profit through a pure play investment in the stock of an oil company and by using this portfolio to cross hedge the price of oil. This strategy is investigated by Miller and Upton (1985a, 1985b), who develop a valuation model that links the value of an oil-extracting company to the spot value of oil. To be successful, volatility changes in the product market (the oil futures series) have to be closely linked to volatility changes in the derivative market (equity value of the oil company portfolio). Finally, this study uses the spot S&P 500 portfolio returns to examine volatility changes in the overall equity market and the potential impact of those changes on the other price series, especially during the market crash period of October, 1987.

Of particular interest to this study is an issue raised by Diebold (1986), Lastrapes (1989), and Lamoreux and Lastrapes (1990). When ARCH/GARCH methodology is applied to data that include sudden changes in regime (e.g., sudden changes in variance), the analysis may wrongly conclude that an integrated GARCH process is present, in turn implying a strong persistence in conditional variance over time. In contrast, the presence of sudden variance changes in the data implies reduced predictability of future variances. The Lamoreux and Lastrapes (1990) analysis of 30 exchange-traded stocks indicates that when deterministic shifts in the variance are incorporated into the analysis the persistence of variance indicated by GARCH decreases dramatically. The advantage of the methodology applied here is that it can pinpoint the time when the shift in variance occurs.

Additional studies that investigate stock-market volatility include French, Schwert, and Stambaugh (1987), Schwert (1989a, 1989b, 1990).

Schwert (1990) analyzes the period surrounding the market crash of October, 1987, which includes the largest 1-day percentage change (20.4%) in market value on October 19, 1987. He finds that stock-market volatility rose dramatically during and after the 1987 crash, but it returned to normal levels quite quickly.

Finally, there are reasons to expect that the oil futures series might display greater volatility, and sensitivity to volatility changes, compared to the other two series. Edwards (1988) and Schwert (1990) discuss the following possible contributing factors:

1. The lower transactions costs in the futures market might make investors who have macroeconomic information more likely to trade in the futures market.
2. Speculation may also induce extra volatility in futures contracts.
3. Nonsynchronous trading (e.g., S&P index stocks do not all trade at the end of the day) may smooth the volatility of an index series relative to that of the futures contract.

FINANCIAL TIME SERIES ANALYZED AND RELATED ISSUES

The time period covered by this analysis is the period from January, 1984 to December, 1992, with the use of daily data from the three series: oil futures, oil-producing companies, and the S&P 500 index. This period is selected because it includes major episodes that might influence the volatility of the three series investigated. These include: the events surrounding the changes in the OPEC oligopoly, the Iran-Iraq conflict, the Prince William Sound oil disaster, and the Persian Gulf conflict in 1990 and 1991. This period also includes the October, 1987 stock market crash and a minicrash in the equities markets in October, 1989, which previous studies have shown to have affected the volatility in the overall equities market.

The set of series of particular interest to this study is the daily series of returns on the 1-month, 2-month, . . . and 6-month petroleum futures contracts, whose prices are published daily in the *Wall Street Journal* and are obtained for the study from Data Resources International (DRI). Because these contracts can be used to hedge price risk and to speculate in the oil commodity market, the issue of sudden changes in volatility takes on particular importance. Results are reported only for the 1-month petroleum futures contract, because series with different maturities all show similar patterns in volatility. The near contract represents the most liquid of the petroleum futures contracts available. The series consists of 2192 observations.

The study also examines sudden changes in variance in the overall equities market. In this case, sudden variance changes might be linked to periods of significant changes in valuation, as occurred during the October, 1987 market crash. As well, events that affect sudden changes in variance in the petroleum futures market, such as the January, 1991 U.S. military operations in Kuwait, might be expected to impact volatility in the equities market. To examine the volatility of the overall equities market, the NASDAQ value-weighted and equally weighted CRSP returns, NYSE/AMEX value-weighted and equally weighted CRSP returns, and the S&P 500 returns are examined. The volatility patterns are quite similar for all the market proxies. Therefore, only results for the S&P 500 series (2276 observations) are presented in the article.

Also examined is a series consisting of daily returns on a portfolio of oil and gas companies shares. The volatility of this portfolio should be sensitive to factors affecting the volatility of the other two series examined. First, it is expected that changes in valuation in the overall equities market, as reflected in the S&P 500 index, might impact the valuation of these exchange-traded companies. Second, because these companies specialize in oil production, events affecting oil futures prices might be reflected in the valuation of these companies. Miller and Upton (1985a, 1985b) provide theoretical and empirical results that appear to establish a link between oil prices and oil company valuation.

The oil companies included in the portfolio are oil-extracting companies as described in *Oil Industry Comparative Appraisals,* published by John S. Herold, Inc. The Herold valuation reports are a standard source of industry information and are compiled with the use of information filed with the Securities and Exchange Commission and other regulatory agencies. Only domestic companies whose principal income derives from oil and gas production are included in the sample. International producers (i.e., the majors) and those with significant other product lines, including refining, are not included.

Company returns are obtained from the CRSP tapes, and an equally weighted portfolio is constructed. The portfolio consists of 2276 observations. The final sample that makes up the portfolio consists of 160 companies. One hundred four of the companies trade on the NYSE and AMEX, and 56 trade on NASDAQ. There are 33 limited partnerships and 11 royalty trusts included in the sample.

METHODOLOGY

The methodology used in this study for detecting discrete changes in the variance of an observed time series is based on an algorithm that uses an iterative cumulative sum-of-squares approach [Inclan and Tiao (1994)]. The analysis assumes that the time series of interest displays a stationary variance over some initial period of time, and then there is a sudden change in variance, perhaps driven by a change in the qualitative nature of the news impacting the financial market. The variance is then stationary over the next time interval, until the next sudden change in variance occurs. This process is repeated through time, yielding a time series of observations with an unknown number of changes in the variance. Accordingly, let $\{\varepsilon_t\}$ denote a series of independent observations from a normal distribution with zero mean and with variance σ_t^2, given as follows:

$$\begin{aligned} \sigma_t &= \tau_0, & 1 < t < \kappa_1 \\ &= \tau_1, & \kappa_1 < t < \kappa_2 \\ &\;\;\cdots & \\ &= \tau_{N_\tau} & \kappa_{N_\tau} < t < T \end{aligned} \tag{1}$$

where $1 < \kappa_1 < \kappa_2 < \cdots < \kappa_{N_T} < T$ are the set of time points where a change in variance occurs and N_T is the total number of variance changes in T observations. The variance within each interval is denoted by τ_j^2, $j = 0, 1, \ldots, N_T$.

To estimate the number of changes in variance and the point in time of each variance shift, a cumulative sum of squares approach is used. Let

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \qquad k = 1, \ldots, T,$$

give the cumulative sum of the squared (mean centered) observations from the start of the series to the kth point in time. Then define the statistic D_k as follows:

$$D_k = (C_k/C_T) - k/T, \qquad k = 1, \cdots, T, \qquad \text{with } D_0 = D_T = 0$$

If there are no changes in variance over the sample period, then the D_k statistic will oscillate around zero (a horizontal line, when the D_k values are plotted against k). In contrast, if there are one or more sudden variance changes in the series, then the D_k values will drift either upward or downward away from zero. Critical values based on the distribution of D_k under the null hypothesis of homogeneous variance provide upper and lower boundaries to detect a significant change in variance with a known level of probability. When the maximum of the absolute value of D_k is greater than the critical value, the null hypothesis is rejected. Let k^* be the value of k at which $\max_k |D_k|$ is attained. If $\max_k \sqrt{(T/2)}\, |D_k|$ exceeds the predetermined boundary, then k^* is taken as an estimate of the change point. The factor $\sqrt{(T/2)}$ is needed to standardize the distribution.

Under the null hypothesis that the variance is homogeneous over the entire series, asymptotically D_k behaves as a Brownian bridge. The critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)} \mid D_k \mid$. Therefore, upper and lower boundaries can be set at ± 1.358 in the D_k plot. Exceeding these boundaries brings about a significant change in variance in the series analyzed.

EMPIRICAL RESULTS: ANALYSIS OF SUDDEN VOLATILITY CHANGES

The results of the analysis are given in Tables I–III, respectively, for the oil futures series, the S&P 500 series, and the oil-producing portfolio series. Each table reports, for each period of constant volatility, the starting and ending date, the number of trading days, the daily standard deviation, the percentage change in the standard deviation, and the value of the test statistic $\max_k \mid D_k \mid$. Figure 1 gives a graphical representation of the results in each table, respectively.

Volatility Changes in the Oil Futures Contract

As illustrated in Figure 1, the 1-month oil futures series appears, overall, to show greater volatility and a larger number of significant volatility changes compared to the other two financial time series. The resulting volatility estimates and dates of volatility changes are listed in Table I. For the 1-month oil futures series, 15 significant volatility changes are detected, with 5 of these volatility changes exceeding 100% in absolute value. The baseline (daily) standard deviation of the oil futures series is given as 0.85%, and lasted from 1/3/1984 to 11/18/1985. The unconditional standard deviation of the series is 2.55% disregarding the detected changes in volatility. At least three periods of heightened volatility are apparent from the results presented in Figure 1 and Table I for the oil futures series.

The first period of dramatic increase in volatility spans the period from 11/19/1985 through 12/24/1986. The volatility increased from 0.85% to 2.88% on 11/19/1985 (a 238.82% increase) and then to 5.37% on 2/03/1986 (an 86.46% increase). During this period OPEC imposed no production limits, leading to a large decline in oil prices, and then tried to re-establish production limits during the course of several major OPEC meetings. Also, during this period, the Iran-Iraq conflict and several winters of below-normal temperatures contributed to uncertainty

TABLE I
Magnitude and Timing of Changes in Standard Deviation of 1-Month Oil Futures January, 1984–December, 1992

Start Date	*End Date*	*Number of Trading Days*	*Standard Deviation (%)*	*% Change in Standard Deviation*	*Max* $\mid D_k \mid$
01-03-84	11-18-85	461	0.85	–	7.51
11-19-85	01-31-86	46	2.88	+238.82	1.52
02-03-86	08-05-86	123	5.37	+86.46	3.23
08-06-86	12-24-86	95	2.32	−56.80	3.07
12-30-86	12-04-87	229	1.39	−40.09	2.61
12-07-87	12-22-87	12	3.90	+180.58	1.78
12-23-87	09-13-88	176	1.76	−54.87	3.11
09-14-88	06-20-89	187	2.92	+65.91	3.65
06-21-89	12-14-89	120	1.19	−59.25	3.31
12-15-89	07-31-90	151	2.46	+106.72	3.83
08-01-90	01-11-91	109	5.07	+106.10	2.46
01-14-91	01-23-91	8	15.87	+213.02	3.98
01-24-91	04-23-91	60	2.74	−82.73	3.94
04-24-91	11-15-91	142	1.19	−56.57	1.85
11-18-91	02-19-92	60	1.75	+47.06	2.84
02-20-92	12-31-92	214	1.00	−42.86	–

TABLE II
Magnitude and Timing of Changes in Standard Deviation of the S&P 500 January, 1984–December, 1992

Start Date	*End Date*	*Number of Trading Days*	*Standard Deviation (%)*	*% Change in Standard Deviation*	*Max* $\mid D_k \mid$
01-3-84	01-23-85	268	0.81	–	1.81
01-24-85	03-10-86	283	0.65	−20.15	3.32
03-11-86	10-12-87	403	0.98	+50.31	8.45
10-13-87	10-26-87	10	8.06	+724.87	3.29
10-27-87	01-20-88	59	2.09	−74.06	3.39
01-21-88	09-02-88	155	1.05	−50.28	2.83
09-06-8	10-12-89	280	0.71	−32.02	2.95
10-13-89	08-01-90	202	0.92	+29.57	3.01
08-02-90	11-12-90	72	1.39	+51.08	2.33
11-13-90	12-30-91	285	0.88	−36.71	2.88
12-31-91	12-31-92	255	0.61	−30.87	–

TABLE III
Magnitude and Timing of Changes in Standard Deviation of Oil and Gas Companies Portfolio January, 1984–December, 1992

Start Date	*End Date*	*Number of Trading Days*	*Standard Deviation (%)*	*% Change in Standard Deviation*	*Max* $\mid D_k \mid$
01-03-84	02-21-85	288	0.68	–	2.16
02-22-85	08-30-85	133	0.41	−39.71	2.42
09-03-85	01-20-86	96	0.69	+68.29	2.26
01-21-86	04-02-86	50	1.15	66.67	1.91
04-03-86	08-04-86	86	0.76	−33.91	3.74
08-05-86	10-08-87	299	1.02	+34.21	5.92
10-09-87	10-30-87	16	3.94	286.27	3.86
11-02-87	04-14-88	114	1.21	−69.28	4.08
04-15-88	05-08-90	522	0.65	−46.28	2.85
05-09-90	02-06-91	190	0.95	+46.15	2.70
02-07-91	08-20-91	135	0.57	−40.00	1.47
08-21-91	05-22-92	192	0.72	+26.32	2.25
05-26-92	08-28-92	68	1.07	+48.61	1.83
08-31-92	12-31-92	86	0.71	−33.64	–

over future price levels. Oil prices varied from a high of $35 to a low of $10 during this period, indicative of the level of market uncertainty.

A second period of increased oil futures volatility occurs from 12/07/1987 through 6/20/1989. Many December meetings of OPEC appear to have significantly impacted volatility during this period, with increased volatility occurring before and during the meeting of oil ministers, followed by a decline in volatility corresponding to the decrease in uncertainty following the meeting. Also, a North Sea oil blast and the Prince William oil spill added uncertainty during this period as shown in Table V.

A third period of heightened oil volatility occurs between 12/15/1989 and 1/23/1991, which coincides with the Iraqi invasion of Kuwait and the U.S. military action in Kuwait against Iraq in January, 1991. During the 8-day period from 1/14/1991 to 1/23/1991, the volatility jumped by 213.02% in value. The period of increased volatility in the futures contract was accompanied by a wider spread between the cash and futures market. Therefore, the occurrence of sudden changes in variance is accompanied by increased basis risk.

The oil futures series will be further investigated within a GARCH framework to show that these detected sudden changes in variance continue to arise when the possibility of GARCH changes in variance is accounted for. However, the analysis to this point indicates that sudden changes in variance can be a significant aspect for understanding the

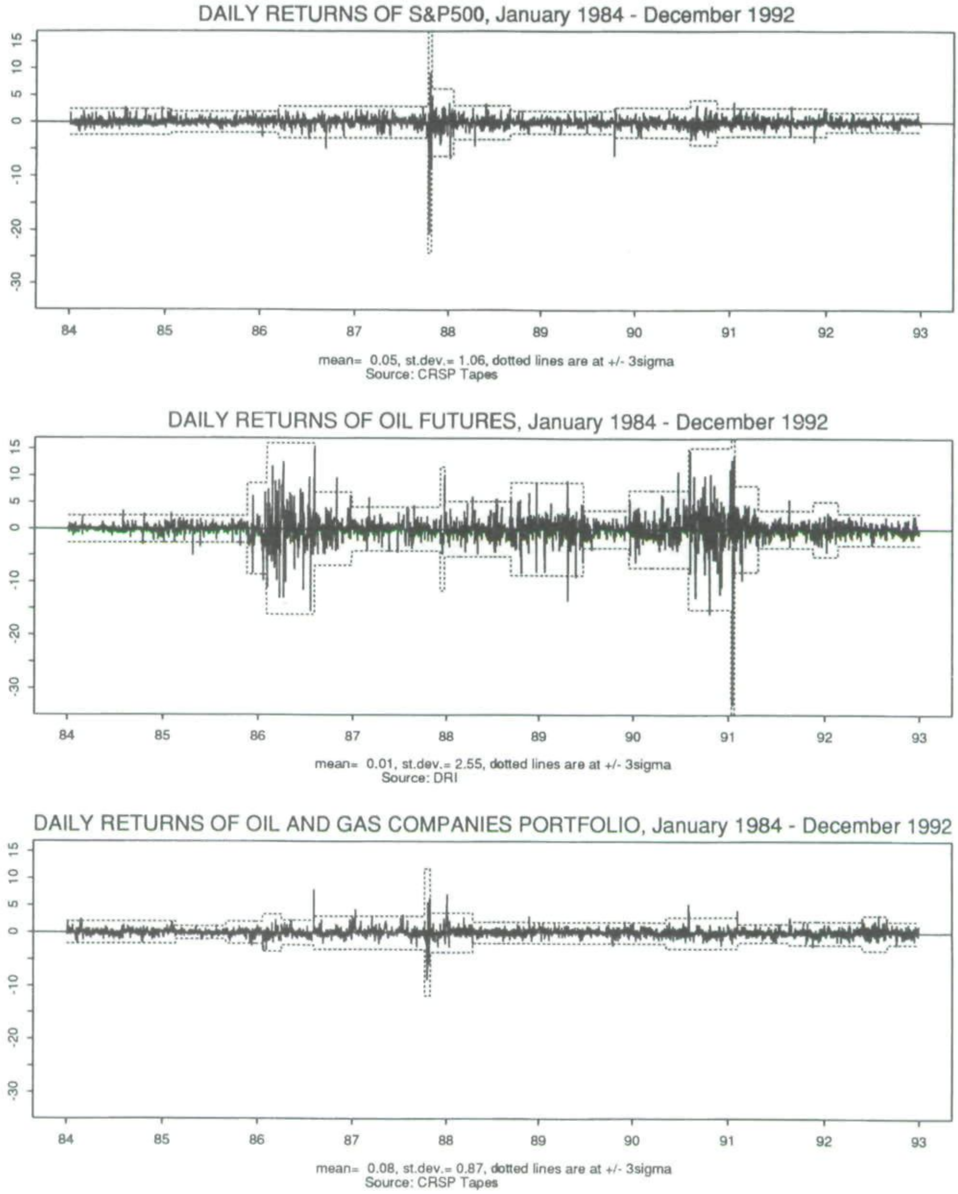

FIGURE 1

Daily returns of S&P 500, January 1984–December 1992.
Daily returns of oil futures, January 1984–December 1992.
Daily returns of oil and gas companies portfolio, January 1984–December 1992.

behavior of a derivative contract, such as 1-month oil futures. It is apparent from the comparison of the oil futures with the S&P 500 series and oil-producing index series in Figure 1, that the oil futures series shows greater overall volatility and seems more sensitive to volatility changes. As argued in Edwards (1988) and Schwert (1990), futures prices, in general, may tend to be more volatile than other price series for several reasons that are related to transactions costs, speculation, and nonsynchronous trading.

Volatility Changes in the S&P 500 Index

Table II and Figure 1 give the results of the analysis of the S&P 500 index. A total of 10 significant volatility change points in the S&P series are uncovered by the ICCS algorithm. For this series, the (unconditional) daily standard deviation for the 2276 observations in the sample is 1.06%. Only one variance change is found in this series that exceeds 100%, in comparison with the oil futures series, where six such volatility changes are found. Also, only one period of striking volatility increase stands out for this series.

The period of dramatic increase in volatility appears around the October, 1987 market crash. First, during the 10-day trading period from October 12, 1987 to October 26, 1987, the standard deviation increased from 0.98% to 8.06%, representing a jump in volatility of 724.87%. The max $|D_k|$ test statistic given in Table II for this period has a value of 8.74, whereas the critical value is 1.358 at the 5% significance level. Volatility for the next 59 days continues to be quite high, with an estimated standard deviation of 2.09% and an associated max $|D_k|$ test statistic that is significant, as shown in Table II. The largest increase in volatility during the 1987 crash period lasted only 10 trading days, but the period of heightened volatility continued for months after the crash. This persistence in volatility following the October, 1987 market crash is also reported by Schwert (1990).

There is no other period of very heightened volatility for this series during the 1984–1992 period. Even during the minicrash of 1989, no significant sudden changes of variance are detected. The graph in Figure 1 illustrates that overall stock market volatility does not seem to have increased during this period.

Volatility Changes in the Oil-Producing Portfolio

Table III and Figure 1 present the results for the oil-producing company portfolio. As discussed previously, this series is interesting, because the equity values of these oil-producing companies derive their value, in part, from the spot oil market [see Miller and Upton (1985a, 1985b)] and, thus, might be used for cross hedging. These are exchange-traded contracts; therefore the volatility of the resulting series is expected to be affected by events that affect volatility changes in the broader equity market, as given in the S&P 500 portfolio returns. Therefore, the sudden changes in variance discussed above for the 1-month oil futures contract and for the S&P 500 portfolio might be expected to spill over to sudden volatility changes in the oil-producing portfolio.

The analysis of the oil-producing portfolio indicates that a total of 13 changes in standard deviation occurred during the study period, as given in Table III and Figure 1. The change in volatility exceeds 100% on only one occasion. This series has an initial standard deviation of 0.68%. The series displays roughly four relatively short periods of heightened volatility.

The highest standard deviation is 3.94% during the 16 days from October 9, 1987 to October 30, 1987, corresponding to the market crash, as found with the S&P index series above. The magnitude of this increase in volatility post-1987 market crash is roughly one-third compared to that reported for the overall S&P 500 market portfolio in Table II. This period of increased relative volatility continues into a second volatile period, lasting from 11/02/1987 to 4/14/1988. Interestingly, the stock market minicrash of October, 1989 is also not evident in the results of Table III. The sudden changes in volatility found in the 1-month oil futures series and associated with changes in the structure of OPEC, the Iran-Iraq conflict and the Persian Gulf crisis are not evident with the oil-producing company portfolio. Therefore, sudden changes in oil futures volatility appear to have little spill-over impact on the volatility of the oil-producing company portfolio. The basis risk is therefore more severe in this case.

EMPIRICAL RESULTS: SUDDEN VARIANCE CHANGES AND ARCH/GARCH

As demonstrated by the Lamoreux and Lastrapes (1990) analysis of 30 exchange-traded stocks, when sudden changes in the variance are incorporated directly into a ARCH/GARCH analysis, the persistence of variance indicated by the analysis may decrease dramatically. For lack of a methodology, such as the ICSS algorithm, to detect time points of sudden variance change, their analysis divided the study period into 14 equal nonoverlapping time intervals, within which the variance might show sudden change. By including these shift dummies into the GARCH analysis,

TABLE IV

Arch Model with Sudden Changes in Variance

Persistence in Variance with Shift Dummies									
ARCH only					*ARCH plus sudden changes*				
μ	σ^2	a_1	a_2	a_3	μ	σ^2	a_1	a_2	a_3
One-Month Oil Futures—Daily Return Series									
0.033	0.686	0.527	0.448	0.342	0.014	0.480	0.143	0.047	0.089
(0.025)	(0.032)	(0.038)	(0.032)	(0.026)	(0.026)	(0.032)	(0.020)	(0.020)	(0.020)
S&P 500 Market Index—Daily Return Series									
0.055	0.755	0.226	NS	NS	0.062	0.645	.0122	NS	NS
(0.020)	(0.012)	(0.008)			(0.017)	(0.049)	(0.010)		
Oil-Producing Company Portfolio—Daily Return Series									
0.035	0.499	0.321	NS	NS	0.033	0.354	0.088	NS	NS
(0.017)	(0.008)	(0.016)			(0.015)	(0.035)	(0.023)		

they test the impact of sudden changes of variance on the resulting analysis.

With the present analysis, the sudden changes in variance detected by the ICSS algorithm (see Tables I–III) can be incorporated directly into an ARCH/GARCH analysis to (1) test the relative strengths of each type of change in variance (sudden changes vs. GARCH) and (2) to analyze the impact of the sudden change dummies on the persistence of variance indicated by a GARCH analysis alone. The first question is of importance because the sudden changes in variance analysis using the ICSS algorithm may not capture all of the variance effects; that is, there may be residual GARCH effects to that analysis. Therefore, a more complete analysis would allow for both kinds of effects. The second question relates to the issues of persistence of variance and the existence of time-varying risk premium, as raised by Poterba and Summers (1986).

Table IV presents the results of the combined analysis. In the left panel of the table, the results from fitting an ARCH model alone (no sudden changes) to each of the three series is presented.[2] The right panel of Table IV presents the results of fitting an ARCH model that incorporates shift dummies that correspond to the time points of sudden variance

[2]An attempt was made to fit the more general GARCH model to each series first. However, in several instances the fitted GARCH parameter proved to be negative, indicating model instability. Therefore, an ARCH approach is adopted for each of the three series, to allow results to be compared across series.

TABLE V
Oil Futures Volatility and *Wall Street Journal* Chronology

Date of Change	*Std. Dev. Before (%)*	*Std. Dev. After (%)*	*Events*
	0.85		OPEC abandons price supports.
11-18-85	0.99	2.88	Futures surge on frigid weather.
			Oil drops below $10 per barrel.
01-31-86	2.88	5.37	Oil increases to $15 on Iran-Iraq war.
			New Saudi oil minister.
08-05-86	5.37	2.32	OPEC meets—reaches an accord.
			OPEC meets in Geneva.
12-04-87	1.39	3.90	IRAQ drops out of OPEC.
			OPEC production surges.
			Prince William Sound oil spill.
09-13-88	1.76	2.92	Price soars on North Sea blast.
			Iraq invades Kuwait.
			Saudis increase oil production.
07-31-90	2.46	5.07	Oil futures exceed $40 per barrel.
01-11-91	5.07	15.87	U.S. attacks Iraqi troops in Kuwait.

changes, given in Tables I–III. In each panel, the mean of the series, (μ), its unconditional variance, (σ^2), and ARCH parameters, a_1, a_2, and a_3, are presented, along with their standard errors, noted in parentheses.

The 1-month oil futures series is listed first in Table IV, and provides the most striking results of the three series. When fitted as a pure ARCH process, the overall mean of the series is given as 0.033. The estimated ARCH parameters are $a_2 = 0.527$, $a_2 = 0.448$, and $a_3 = 0.342$, and indicate a strong persistence of variance in the series. In fact, the sum of the ARCH parameters exceeds unity in value. In contrast, when the shift dummies from the ICSS analysis are added to the ARCH analysis, the mean of the process reduces to 0.014. The estimated ARCH parameters are now given as $a_1 = 0.143$, $a_2 = 0.047$, and $a_3 = 0.089$, where a_2 in particular, is now only marginally significant.[3] The impact of the inclusion

[3]The final ARCH model fitted to the oil futures series, including shift dummies, is as follows, with standard errors noted parenthetically:

$$y_t = \underset{(0.026)}{0.014}$$

$$h_t = \underset{(0.032)}{0.480} + \underset{(0.020)}{0.143}\,\varepsilon_{t-1}^2 + \underset{(0.020)}{0.047}\,\varepsilon_{t-2}^2 + \underset{(0.022)}{0.089}\,\varepsilon_{t-3}^2 + \underset{(0.022)}{6.7}\,D460_t + \underset{(0.022)}{14.9}\,D506_t$$

of the shift dummies is to greatly reduce the magnitude of the ARCH effects, to the extent that their sum now equals 0.279, as opposed to a sum of 1.317 for the pure ARCH analysis, indicating a reduction of the parameter sum by 78.8%. Therefore, the indicated persistence of variance is accordingly greatly reduced.

The S&P 500 and oil-producing company portfolios show similar results.[4,5] In these two cases a single ARCH parameter proves to be significant, with values of a_1 equal to 0.226 and 0.336 for the S&P 500 and oil-producing portfolios, respectively. These parameter estimates reduce

$$\begin{aligned}
&\underset{(0.022)}{-\,18.0\,D629_t} \underset{(0.022)}{-\,2.6\,D724_t} \underset{(0.022)}{+\,12.1\,D953_t} \underset{(0.022)}{-\,11.2\,D965_t} \underset{(0.022)}{+\,3.4\,D1141_t} \underset{(0.022)}{-\,4.8\,D1328_t}\\
&\underset{(0.022)}{+\,3.5\,D1448_t} \underset{(0.022)}{+\,15.3\,D1599_t} \underset{(0.022)}{+\,172\,D1708_t} \underset{(0.022)}{-\,185\,D1716_t} \underset{(0.022)}{-\,5.0\,D1776_t}\\
&\underset{(0.022)}{+\,1.2\,D1918_t} \underset{(0.022)}{-\,1.6\,D1978_t}
\end{aligned}$$

The ICSS shift point dummy variables are given by the symbol, D, followed by a number representing the number in the time series of observations where the variance shift occurs. Note that most estimated dummy coefficients remain highly significant in the presence of the ARCH effects.

[4]The final ARCH model fitted to the S&P 500 series, including shift dummies, is as follows, with standard errors noted parenthetically:

$$\begin{aligned}
y_t &= \underset{(0.017)}{0.062}\\
h_t &= \underset{(0.049)}{0.645} \underset{(0.010)}{+\,0.0122\,\varepsilon_{t-1}^2} \underset{(0.010)}{-\,0.23\,D269_t} \underset{(0.010)}{+\,0.53\,D55_t} \underset{(0.010)}{+\,63.0\,D955_t} \underset{(0.010)}{-\,60.0\,D965_t}\\
&\quad \underset{(0.010)}{-\,3.07\,D1024_t} \underset{(0.010)}{-\,0.59\,D1182_t} \underset{(0.010)}{+\,0.33\,D1462_t} \underset{(0.010)}{+\,1.10\,D1664_t}\\
&\quad \underset{(0.010)}{-\,1.16\,D1736_t} \underset{(0.010)}{-\,0.40\,D2021_t}
\end{aligned}$$

The ICSS shift point dummy variables are given by the symbol, D, followed by a number representing the number in the time series of observations where the variance shift occurs. Note that most estimated dummy coefficients remain highly significant in the presence of the ARCH effects.

[5]The final ARCH model fitted to the oil-producing company series, including shift dummies, is as follows, with standard errors noted in parentheses. Note that with this series it is necessary to fit an autoregressive component of order 5, AR(5), to reduce the series to white noise before using the ICSS algorithm:

$$\begin{aligned}
y_t &= \underset{(0.015)}{0.033} \underset{(0.025)}{+\,0.109\,y_{t-1}} \underset{(0.021)}{+\,0.105\,y_{t-2}} \underset{(0.021)}{+\,0.024\,y_{t-3}} \underset{(0.021)}{+\,0.047\,y_{t-4}} \underset{(0.021)}{+\,0.056\,y_{t-5}}\\
h_t &= \underset{(0.035)}{0.354} \underset{(0.023)}{+\,0.088\,\varepsilon_{t-1}^2} \underset{(0.039)}{-\,0.201\,D289_t} \underset{(0.060)}{+\,0.251\,D422_t} \underset{(0.243)}{+\,0.824\,D518_t}\\
&\quad \underset{(0.250)}{-\,0.770\,D568_t} \underset{(0.084)}{+\,0.418\,D654_t} \underset{(5.043)}{+\,13.099\,D953_t} \underset{(5.043)}{-\,12.688\,D969_t} \underset{(0.099)}{-\,0.887\,D1083_t}\\
&\quad \underset{(0.056)}{+\,0.402\,D1605_t} \underset{(0.063)}{-\,0.501\,D1795_t} \underset{(0.056)}{+\,0.181\,D1930_t} \underset{(0.230)}{+\,0.691\,D2122_t} \underset{(0.238)}{-\,0.68\,D2190_t}
\end{aligned}$$

The ICSS shift point dummy variables are given by the symbol, D, followed by a number representing the number in the time series of observations where the variance shift occurs. Note that most estimated dummy coefficients remain highly significant in the presence of the ARCH effects.

to values of a_1 equal to 0.0122 and 0.088, or a reduction by 94.6% and 72.6%, respectively, for the S&P 500 and oil-producing portfolios. The ARCH is, in fact, not significant in the S&P 500 series once the variance dummies are included. Therefore, the indicated persistence of variance declines dramatically when sudden changes in variance are accounted for within the ARCH framework.

The results presented in Table IV indicate that the sudden changes in variance identified by the ICSS algorithm reduce the level of persistence in variance implied by the ARCH model, but they do not eliminate the ARCH effects completely in two of the series. Furthermore, the shift dummies continue to be significant in most cases, when incorporated in the presence of the estimated ARCH effects. Therefore, the analysis of the oil futures series and oil-producing companies indicates the presence of both types of effects, that is, both sudden changes in variance as well as the presence of ARCH effects. The implication is that sudden changes in variance need to be incorporated into an ARCH analysis to properly estimate the degree of persistence in variance of the particular series. This will result in pricing contingent claims differently and also provide different optimal hedge ratios than those proposed by Baillie and Myers (1991).

SUMMARY AND CONCLUSIONS

The pricing of contingent claims relies on the estimation of variance and the duration of the changes in variance. A better understanding of the changes in variance is also important in portfolio hedging strategies that use optimal hedge ratios. This article examines the extent of sudden changes in variance with the use of iterative cumulative sum-of-squares methodology in three series: the 1-month oil futures return series, a series constructed from the returns of oil-producing companies, and an S&P 500 return series. The approach is an alternative to other popular approaches to model nonconstant variance in a time series, such as the GARCH approach, because of the essentially nonparametric nature of the ICSS algorithm. The methodology allows for sudden changes in variance that may arise with qualitative changes in the information arrival process affecting the particular series of interest. As well, the results of the ICSS approach can be easily incorporated into a standard GARCH framework for further analysis.

The results indicate that the oil futures series is susceptible to sudden volatility changes during several key time periods during the 1980s and 1990s. These results are particularly striking given the prominent role played by oil futures in the hedging of oil price risk, as recently publicized in the debate over the appropriateness of the hedging activities of the German metals firm, Metallgesellschaft, which suffered a $1.3 billion loss when Deutsche Bank, its biggest shareholder and creditor, forced the metals firm to unwind its hedging position. If the sudden changes in variance are not accounted for, then the portfolio will not be hedged correctly. This will also result in incorrect pricing of contingent claims. Two episodes in particular stand out. First, during 1986 and the first half of 1987, uncertainty over the Iran-Iraq conflict, the breakup of the OPEC pricing oligopoly, and unusually cold winter weather spells appear to be linked to several large volatility increases over this period. The second period, 1990 to March, 1991, coincides with a period of heightened Persian Gulf tensions, including the Iraq invasion of Kuwait and subsequent U.S. military operations in the Persian Gulf. During periods of increased volatility the basis risk also tends to increase, thus heightening the problem of imperfect hedging and pricing of contingent claims.

The article also explores a sample of domestic U.S. crude oil-producing companies to test whether the volatility changes observed in their product market (the oil futures series) are reflected in volatility changes in the market-traded equity of these companies. As a baseline for comparison the S&P 500 return series is also investigated for sudden volatility changes. Two major episodes of volatility changes are observed in the S&P 500 series, corresponding to the stock market crash of October, 1987 and a smaller market correction that occurred in 1989. These same two episodes of increased volatility are observed with the oil-producing company portfolio. In contrast, no spillover of volatility changes is observe from the oil futures series to the oil-producing company portfolio. Therefore, this equity portfolio would represent a poor pure play alternative for an investor with specialized information about future volatility changes in oil prices. The market crashes discussed above are not significant features observed in the oil futures series. The results suggest that the portfolio of oil-producing companies is not very useful in constructing a cross hedge.

As with Lamoreux and Lastrapes (1990), when sudden changes in the variance are incorporated directly into a ARCH/GARCH analysis, the persistence of variance indicated by the analysis decreases dramatically. There are several occurrences of sudden changes in variance in the oil futures portfolio. Once these are accounted for, the indicated persistence of variance in the series is greatly reduced. This study concludes that sudden shifts in variance are a significant feature of the series investigated. These shifts need to be accounted for in the analysis before conclusions concerning the predictability of future variances can be made. The existence of sudden changes in variance also implies there can be inherent risk in hedging strategies.

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