Stock Volatility and the Crash of '87

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This article analyzes the behavior of stock return volatility using daily data from 1885 through 1988. The October 1987 stock market crash was unusual in many ways. October 19 was the largest percentage change in market value in over 29,000 days. Stock volatility jumped dramatically during and after the crash. Nevertheless, it returned to lower, more normal levels more quickly than past experience predicted. I use data on implied volatilities from call option prices and estimates of volatility from futures contracts on stock indexes to confirm this result.

On October 19, 1987, the Standard & Poors composite portfolio fell from 282.70 to 224.84, or 20.4 percent. This is the largest one-day drop in the history of major stock market indexes from February 1885 through the end of 1988. Following this drop, daily stock prices rose and fell by large amounts during the next several weeks. Thus, the fall in stock prices was followed by a large increase in *stock volatility.*

This article documents the behavior of daily stock returns before, during, and after the October 1987 crash. It compares and contrasts the 1987 crash with previous crashes. Stock volatility rose dramatically during and after the 1987 crash, but it returned to lower, more normal levels unusually quickly. This

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article also analyzes the behavior of prices for options on stock market portfolios and for futures contracts on the S&P 500. These contingent claims contracts reinforce the conclusion that stock market volatility returned to lower, more normal levels quickly following the 1987 crash. This is unusual relative to the evidence from previous crashes.

Section 1 summarizes some of the literature on time-varying stock volatility. Section 2 contains estimates of the conditional standard deviations of daily stock returns from 1885–1988. It shows that stock volatility was unusually high during the 1929–1934 and 1937–1938 depressions, and during the 1973–1974 OPEC recession. Section 3 compares the estimates of daily stock volatility from the stock, options, and futures markets during 1987–1988. Section 4 summarizes the empirical results and relates these findings to the October 1987 stock market crash.

1. Review of Previous Research

Officer (1973) shows that aggregate stock volatility increased during the Great Depression, as did the volatility of money growth and industrial production. He also shows that stock volatility was at similar levels before and after the depression. It is difficult to credit the creation of the Securities and Exchange Commission (SEC) in 1934 with the reduction in stock volatility that did not occur until after 1939. Benston (1973) shows that the volatility of individual stocks, and particularly the part of volatility that is unrelated to general market movements, did not decrease until well after the SEC began its operations in October 1934. Like Officer, Benston concludes that the reduction in stock volatility cannot be attributed to activities of the SEC. Schwert (1989b) analyzes the relation of stock volatility to real and nominal macroeconomic volatility, financial leverage, stock trading activity, default risk, and firm profitability using monthly data from 1857–1987. Schwert (1989a) shows that monthly stock volatility was higher during recessions and following the major banking crises from 1834–1986 [see also Wilson, Sylla, and Jones (1988)]. Moreover, he shows that the Federal Reserve Board has raised margin requirements *following* decreases in stock volatility during the period from 1934–1986. There is no reliable evidence that increases in margin requirements have been followed by reductions in volatility. French, Schwert, and Stambaugh (1987) show that stock volatility is highly persistent and that, on average, unexpected increases in volatility are associated with negative stock returns. They also show there is weak evidence that expected risk premiums are positively related to expected stock volatility.

2. Estimates of Conditional Stock Volatility

2.1 Extreme changes in stock prices

Panel A of Table 1 shows the 25 largest increases and decreases in *daily* percent stock returns from February 16, 1885 through 1988. This sample includes 29,137 daily returns. From 1885 through 1927, I use a composite of the Dow Jones Industrial and Railroad Averages, weighted by the number of stocks in each index [Farrell (1972)]. From January 1928 to the present, I use the Standard & Poors composite portfolio [90 stocks until March 1957, and 500 since that time—see Standard & Poors (1986)]. The Dow Jones portfolios are price-weighted, while the S&P portfolio is value-weighted; neither includes dividends in the returns. See Schwert (1990) for further information on these data.[1]

As mentioned at the beginning of this article, October 19, 1987, is the largest one-day percent change in stock prices (−20.4 percent) out of the sample of 29,137 observations.[2] The next largest change in stock prices occurred on March 15, 1933, when stock prices *rose* 16.6 percent following the federal banking holiday. In perusing this list, several patterns emerge. First, there are many reversals, when large drops in stock prices have been followed by large increases in stock prices. For example, the 1929 stock market crash represents the next two largest drops in stock prices, −12.3 and −10.2 percent on October 28 and 29. The market rebounded on October 30 with the second largest one-day gain in the sample, 12.5 percent. This is characteristic of an increase in stock market volatility; that is, an increased chance of large stock returns of indeterminate sign. In fact, 29 of the 50 most negative returns and 36 of the 50 most positive returns occurred in the October 1929–July 1934 period. The September 1937–September 1939 period accounts for seven of the most negative and five of the most positive returns. The week from October 19 to 26, 1987, accounts for two of the most negative and two of the most positive returns. March 1907 accounts for one large and one small return. July

[1] For the purposes of measuring stock volatility dividend payments are unimportant, probably because ex-dividend dates differ across stocks. I have compared the estimates of volatility for the CRSP value-weighted portfolio (which includes dividends) with the S&P portfolio (which does not) over the July 1962–December 1987 period, and there are no important differences in the estimates of stock volatility.

[2] The *Wall Street Journal,* in a story by Cynthia Crossen on October 19, 1987, mistakenly reported that the Dow Jones Industrial Average fell by 24.4 percent at the start of World War I when trading on the New York Stock Exchange was halted from July 31 to December 12, 1914. While it is plausible that a four-month trading halt accompanying the start of a major war could cause stock prices to drop by large amounts, in fact they did not. Dow Jones redefined its industrial portfolio after the trading halt, and the *Wall Street Journal* made the mistake of splicing the two different indexes. Using a consistent definition of the portfolio, the return from July 31 to December 12, 1914, was 2.2 percent.

Table 1
The 25 largest and smallest daily percent returns to market portfolios, 1885–1988, and the 25 largest and smallest monthly percent returns, 1802–1988

	Smallest percent returns		Largest percent returns	
	Panel A: Extreme daily percent returns, 1885–1988			
1	October 19, 1987	−20.39	March 15, 1933	16.61
2	October 28, 1929	−12.34	October 30, 1929	12.53
3	October 29, 1929	−10.16	October 6, 1931	12.36
4	November 6, 1929	−9.92	September 21, 1932	11.81
5	October 18, 1937	−9.27	September 5, 1939	9.63
6	July 20, 1933	−8.88	April 20, 1933	9.52
7	July 21, 1933	−8.70	October 21, 1987	9.10
8	December 20, 1895	−8.52	November 14, 1929	8.95
9	October 26, 1987	−8.28	August 3, 1932	8.86
10	October 5, 1932	−8.20	October 8, 1931	8.59
11	August 12, 1932	−8.02	February 13, 1932	8.37
12	May 31, 1932	−7.84	December 18, 1931	8.29
13	July 26, 1934	−7.83	February 11, 1932	8.27
14	March 14, 1907	−7.59	July 24, 1933	8.14
15	May 14, 1940	−7.47	June 10, 1932	7.66
16	July 26, 1893	−7.39	June 3, 1931	7.54
17	September 24, 1931	−7.29	November 10, 1932	7.51
18	September 12, 1932	−7.18	October 20, 1937	7.48
19	May 9, 1901	−7.02	June 19, 1933	7.23
20	June 15, 1933	−6.97	May 6, 1932	7.22
21	October 16, 1933	−6.78	April 19, 1933	7.21
22	January 8, 1988	−6.76	August 15, 1932	7.20
23	September 3, 1946	−6.73	October 11, 1932	7.17
24	May 28, 1962	−6.68	January 6, 1932	7.02
25	May 21, 1940	−6.64	October 14, 1932	6.90
	Panel B: Extreme monthly percent returns, 1802–1988			
1	September 1931	−28.79	April 1933	37.68
2	October 1857	−24.37	August 1932	36.19
3	March 1938	−23.46	July 1932	32.68
4	May 1940	−22.02	June 1938	23.49
5	October 1987	−21.64	May 1933	21.10
6	May 1861	−20.29	March 1858	17.59
7	May 1932	−20.21	December 1857	17.24
8	October 1929	−19.56	October 1974	16.80
9	April 1932	−17.87	September 1939	15.95
10	July 1893	−17.81	January 1863	15.72
11	June 1930	−15.66	October 1862	15.43
12	September 1857	−14.31	April 1938	14.36
13	October 1907	−14.00	July 1837	14.10
14	January 1842	−13.84	May 1898	13.88
15	September 1937	−13.45	June 1931	13.75
16	December 1931	−13.34	May 1843	13.64
17	May 1931	−13.27	April 1834	13.53
18	February 1933	−13.19	January 1975	13.48
19	December 1860	−13.08	August 1891	13.40
20	October 1932	−12.89	June 1933	13.38
21	September 1930	−12.32	January 1934	12.96
22	November 1929	−12.04	January 1987	12.82
23	March 1939	−11.86	December 1873	12.81
24	July 1914	−11.70	October 1879	12.79
25	November 1855	−11.64	October 1885	12.60

and August 1893 contain one of the smallest and two of the largest returns, and May–November 1940 contains two of the smallest and one of the largest returns. These brief episodes in stock market history represent 89 percent of the extreme daily returns to aggregate stock portfolios. They are each characterized by high levels of stock market volatility.[3]

Panel B of Table 1 shows the 25 largest increases and decreases in monthly stock percent returns from February 1802 through December 1988. This represents 2243 monthly stock returns. Schwert (1990) describes the construction of this stock return series. Briefly, from 1802–1862 I use Smith and Cole's (1935) portfolios of industrial and railroad stocks. From 1863–1870 I use Macaulay's (1938)portfolio of railroad stocks. From 1871–1885 I use Cowles' (1939) value-weighted portfolio of NYSE listed stocks. From 1885–1925 I use the end-of-month Dow Jones stock returns plus the dividend yield on Cowles' (1939) portfolio. From 1926–1987 I use the Center for Research in Security Prices (CRSP) value-weighted portfolio of NYSE stocks. For 1988 I use the S&P composite portfolio with dividends. The Smith and Cole and Macaulay returns do not include dividends. I use the dividend yields from the Cowles' portfolio from 1871–1938 to estimate the yields from 1802–1870.

The results in panel B of Table 1 reinforce the conclusions drawn from panel A. First, October 1987 is only the fifth lowest return in the 1802–1988 sample. The return for the month is similar to the return on October 19, implying that the large positive and negative returns for the rest of the month net to zero. Second, 17 of the 50 most negative and 12 of the 50 most positive monthly returns are from 1929–1934. The 1937–1939 period includes five of the most negative and five of the most positive returns. One of the largest and one of the smallest returns come from 1987. Again, a large percentage of both the largest and the smallest returns come from brief subperiods in the overall 1802–1988 sample. This shows an increase in stock volatility during these subperiods.

The models in the next section provide a more structured analysis of the time-series properties of stock market volatility. Briefly, these models remove autoregressive and seasonal effects from daily returns to estimate *unexpected returns*. Then the absolute values of the unexpected returns are used in an autoregressive and seasonal model to predict stock volatility.

[3] Cutler, Poterba, and Summers (1989) analyze large daily returns from 1928–1987 to see whether they are related to specific news events. They find that some, but not all, of the large positive or negative returns occur at the same time as major news stories. One reason that return volatility could increase is that the volatility of the "information environment" increases.

2.2 Autoregressive models for daily stock volatility, 1885–1988

There are several stylized facts concerning stock return volatility. First, it is persistent, so an increase in current volatility lasts for many periods [see Poterba and Summers (1986), Schwert (1987), and French, Schwert, and Stambaugh (1987) for alternative estimates of the persistence of stock volatility]. Second, stock volatility increases after stock prices fall [e.g., Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Nelson (1989)]. Third, stock volatility is related to macroeconomic volatility, recessions, and banking crises [Officer (1973), Schwert (1989a,b)]. On the other hand, there are many competing parametric models to represent conditional heteroskedasticity of stock returns.[4] For this article, I adopt a variation of the strategy followed by French, Schwert, and Stambaugh (1987) and Schwert (1989a,b). First, stock returns are regressed on 22 lagged returns (about one month) to estimate short-term movements in conditional expected returns. Dummy variables D_{it} representing the day of the week are included to capture differences in mean returns [e.g., French (1980) and Keim and Stambaugh (1984)]. Half-day Saturday trading occurred from 1885 through May 1952. The residuals from this regression,

$$R_t = \sum_{i=1}^{6} \hat{\alpha}_i D_{it} + \sum_{j=1}^{22} \hat{\beta}_j R_{t-j} + \hat{u}_t \quad (1)$$

estimate the unexpected return on day t, where hats "^" denote estimates. Following Schwert (1989a,b), the absolute residual $|\hat{u}_t|$, multiplied by the factor $(\pi/2)^{1/2}$, estimates the standard deviation of the stock return in period t. This estimator is unbiased if the conditional distribution of returns is normal [hereafter, the absolute residuals $|\hat{u}_t|$ are multiplied by $(\pi/2)^{1/2}$]. To estimate the conditional standard deviation of returns, I estimate the regression,

$$|\hat{u}_t| = \sum_{i=1}^{6} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |\hat{u}_{t-j}| + v_t \quad (2)$$

where the dummy variable coefficients σ_i measure the intercepts for different days of the week, and the autoregressive coefficients ρ_j measure the persistence of volatility.

Table 2 contains estimates of Equations (1) and (2) using daily returns from February 1885 through December 1988. Following Davidian and Carroll (1987), I iterate between Equations (1) and (2) to

[4] In addition to the models used in this article, see Engle (1982), Bollerslev (1986), Engle and Bollerslev (1986), Engle, Lilien, and Robins (1987), Hamilton (1988), Turner, Startz, and Nelson (1990), and Pagan and Schwert (1990).

Table 2
Estimates of autoregressive models for percentage daily stock returns and volatility, 1885–1987 (using 22 lags and iterative weighted least squares)

	Stock returns, R_t		Stock volatility, $\|\hat{u}_t\|$	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Monday	−.1110	−8.86	.2568	16.43
Tuesday	.0353	3.44	.2783	19.74
Wednesday	.0536	5.38	.2507	18.23
Thursday	.0341	3.46	.2584	20.43
Friday	.0894	9.04	.2396	17.58
Saturday	.0608	4.16	.2093	16.98
Lags of dependent variable				
1	.1093	17.07	.0445	6.67
2	−.0174	−3.17	.0221	3.60
3	.0203	3.71	.0267	4.51
4	.0272	4.51	.0456	7.10
5	.0237	4.10	.0320	5.75
6	−.0090	−1.60	.0239	4.27
7	−.0122	−2.19	.0321	5.58
8	.0148	2.46	.0293	5.15
9	.0055	0.98	.0322	5.41
10	.0041	0.71	.0352	5.67
11	.0093	1.64	.0401	7.29
12	.0098	1.63	.0260	4.32
13	−.0078	−1.31	.0350	5.95
14	.0048	0.82	.0276	4.70
15	.0042	0.73	.0254	4.57
16	−.0013	−0.22	.0345	5.97
17	−.0025	−0.42	.0308	5.49
18	.0028	0.48	.0169	2.98
19	.0049	0.88	.0206	3.86
20	.0047	0.79	.0144	2.77
21	−.0004	−0.07	.0190	3.34
22	.0033	0.58	.0129	2.43
Sum of 22 lags	.1981	9.84	.6267	39.87
F-test for equal daily means		35.93		4.76
R^2		0.013		0.236

Equations (1) and (2) are estimated iteratively using weighted least squares (WLS). The t-statistics use Hansen's (1982) correction for autocorrelation and heteroskedasticity to calculate the standard errors, with 44 lags of the residual autocovariances and a damping factor of 0.7. (The RATS computer program was used to perform all calculations.) The coefficient of determination, R^2, is from the ordinary least-squares version of these regressions.

calculate weighted least-squares estimates. The estimate of the equation for stock returns (1) is consistent with previous research. The intercept for Monday is reliably negative (−0.11 percent per day), while the intercepts for the other days of the week are reliably positive.[5] The autoregressive coefficients are positive out to about two weeks (10 to 12 trading days), with the largest estimate at lag 1. The autocorrelation at lag 1 is often attributed to nonsynchronous trading

[5] This so-called weekend effect exists in all of the decades from 1885–1894 up to the present. See Lakonishok and Smidt (1988) and Schwert (1990) for further evidence.

of individual securities [Fisher (1966) and Scholes and Williams (1977)]. The sum of the 22 autoregressive coefficients is 0.20, with a t-statistic of 9.8. Thus, there is a weak tendency for movements in aggregate stock returns to persist. The half-life of a return shock is 0 days.[6] Despite the large t- and F-statistics, the coefficient of determination R^2 is only 0.013, showing that most of the movements in daily stock returns are *not* explained by these factors.

The estimate of the equation for stock volatility (2) is also consistent with previous research. The intercept for Saturday is lower than for the other days of the week. This shows that volatility is expected to be lower than average on Saturday because trading lasted only a half day. There is no evidence that volatility is expected to be higher than average from the close of trading on Friday (or Saturday) to the close on Monday.[7] Both of these effects are seen by Keim and Stambaugh (1984) using the daily S&P composite returns from 1928–1984. Remarkably, the estimates of the autoregressive coefficients are positive for all 22 lags, and all are more than 2 standard errors above zero. The largest coefficients occur in the first six lags. The sum of the 22 autoregressive coefficients is 0.63, with a t-statistic of 39.9. The coefficients decay very slowly, suggesting possible nonstationarity in the autoregressive model.[8] The half-life of a volatility shock is 10 days. The prediction model implied by Equation (2) is a 22-period weighted average of the absolute deviations, adjusted for day-of-the-week seasonal effects.[9] Thus, there is a strong tendency for movements in aggregate stock volatility to persist. The coefficient of determination R^2 is 0.236, showing that movements in daily stock volatility are much more predictable than movements in stock returns.

2.3 "Leverage" effects in the return-volatility relation

Table 3 contains estimates of a model for stock returns that includes lagged values of the volatility measure $|\hat{u}_t|$,

6 The half-life of a shock is calculated from the moving average representation of the autoregressive model in Equation (1), $\psi(L) = 1/\beta(L)$, where L is the lag operator $\mathbf{X}_t L^k \equiv \mathbf{X}_{t-k}$. The long-run effect of a shock u_t on the dependent variable R is $\psi(L{=}1) \equiv \Sigma_{i=0}^{\infty} \psi_i$. The half-life is the number of lags h such that half of the long-run effect has occurred, $\Sigma_{i=0}^{h} \psi_i = \frac{1}{2}\psi(L{=}1)$.

7 A more complicated model, distinguishing between Monday returns with and without Saturday trading, yielded little new insight, so it is not reported.

8 The smallest root for the autoregressive polynomial $\rho(L) = 1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_{22} L^{22}$, is 1.043, which is close to unity. This implies that $\rho(L)$ contains a factor $(1 - 0.959L)$, implying almost nonstationary behavior.

9 The optimal forecast function for an autoregressive integrated moving average (ARIMA)$(p, d, 0)$ process is a $(p + d)$-period rolling average of the past observations, where the weights sum to 1 if $d > 0$. A frequently used predictor of future volatility is to calculate the standard deviation of the last N daily returns. Such an estimator implicitly assumes that the volatility follows a nonstationary ARIMA$(N - 1, 1, 0)$ process, so that the sum of the autoregressive coefficients in Table 2 would equal 1.

Table 3
Estimates of an autoregressive model for percentage daily stock returns, including effects of lagged volatility, 1885–1987 (using 22 lags and iterative weighted least squares)

Variable	Coefficient	*t*-statistic
Monday	−.0965	−5.26
Tuesday	.0222	1.40
Wednesday	.0452	2.88
Thursday	.0287	1.98
Friday	.0936	6.25
Saturday	.0938	4.59

	Lags of R_t		Lags of $\mid\hat{u}_t\mid$	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
1	.1132	17.43	.0470	6.18
2	−.0135	−2.45	.0061	0.84
3	.0187	3.15	−.0108	−1.53
4	.0279	4.56	−.0029	−0.42
5	.0215	3.66	−.0182	−2.65
6	−.0052	−0.88	−.0050	−0.74
7	−.0133	−2.33	.0053	0.78
8	.0142	2.33	−.0122	−1.66
9	.0026	0.45	−.0141	−2.01
10	.0035	0.60	−.0033	−0.44
11	.0093	1.67	.0034	0.51
12	.0101	1.64	−.0104	−1.52
13	−.0055	−0.92	.0078	1.16
14	.0089	1.50	.0032	0.46
15	.0032	0.55	.0007	0.11
16	−.0021	−0.34	−.0030	−0.45
17	−.0027	−0.45	−.0023	−0.31
18	.0049	0.86	.0085	1.24
19	.0066	1.21	−.0001	−0.01
20	.0046	0.77	−.0046	−0.70
21	−.0003	−0.06	.0053	0.79
22	.0056	0.98	.0106	1.56
Sum of 22 lags	.2124	9.63	.0111	0.63
F-test for equal daily means		36.46		
R^2		0.031		

Equation (3) is estimated iteratively using weighted least squares, along with Equation (4) (see Table 4). The *t*-statistics use Hansen's (1982) correction for autocorrelation and heteroskedasticity to calculate the standard errors, with 44 lags of the residual autocovariances and a damping factor of 0.7. (The RATS computer program was used to perform all calculations.) The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

$$R_t = \sum_{i=1}^{6} \alpha_i D_{it} + \sum_{j=1}^{22} \beta_j R_{t-j} + \sum_{k=1}^{22} \delta_k \mid \hat{u}_{t-k} \mid + \hat{u}_t \qquad (3)$$

where Equation (1) is used in the first stage of an iterative process. Then Equations (3) and (4) below are repeated to generate successive values of $\hat{u}_t$ and $\mid \hat{u}_t \mid$. The day-of-the-week intercepts and the autoregressive coefficients β_j are similar to the estimates in Table 2. The coefficients δ_k measure the effect of higher volatility on future stock returns. The estimate at lag 1 is reliably positive (0.047, with a t-statistic of 6.2), but the remaining 21 coefficients have random signs and most are less than 2 standard errors from 0. The sum of the 22 δ_k's is 0.01, with a t-statistic of 0.63. Thus, there is weak evidence that an increase in volatility increases the expected future return to stocks.

Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Nelson (1989) all note that stock volatility is negatively related to stock returns. In particular, an unexpected negative return is associated with an unexpected increase in volatility. To represent the possible asymmetry in the relation between stock returns and stock volatility, I add lagged unexpected returns to the volatility equation,

$$|\hat{u}_t| = \sum_{i=1}^{6} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |\hat{u}_{t-j}| + \sum_{k=1}^{22} \gamma_k \hat{u}_{t-k} + v_t \qquad (4)$$

where the coefficients γ_k measure the relation between past return shocks and current conditional volatility. If the distribution of the return shocks $\hat{u}_t$ is symmetric, $\hat{u}_t$ and $|\hat{u}_t|$ are uncorrelated. Negative correlation between $|\hat{u}_t|$ and $\hat{u}_t$ is evidence of negative skewness of the distribution of $\hat{u}_t$. The prior evidence suggests that these coefficients should be negative.

There are two hypotheses that predict such a negative relation. First, since the firms in the market portfolio have financial leverage, a drop in the relative value of stocks versus bonds increases the volatility of the stocks [see Christie (1982)]. Black (1976) argues that operating leverage (large fixed costs of production) has a similar effect. Second, if increases in predictable volatility increase discount rates of future cash flows to stockholders, but not the expected cash flows, then unexpected increases in volatility will cause a drop in stock prices [see, for example, Poterba and Summers (1986)].

Table 4 contains estimates of Equation (4), the model relating stock volatility to lagged stock returns and volatility. The day-of-the-week intercepts are similar to the estimates in Table 2. The coefficients γ_k measure the effect of lagged unexpected stock returns on stock volatility. The estimates of γ_k for lags 1 to 22 are all negative, and several are more than 2 standard errors from 0. The sum of the 22 lag coefficients is -0.17, with a t-statistic of -6.30. The sum of the autoregressive estimates ρ_j is 0.62, which is similar to Table 2. One interpretation of this regression model is that volatility is related to lagged stock returns. The coefficient of lagged positive returns is $(\gamma_j + \rho_j)$, while the coefficient for lagged negative returns is $(\gamma_j - \rho_j)$. A negative

Table 4
Estimates of an autoregressive model for percentage daily stock volatility, including effects of lagged unexpected stock returns, 1885–1987 (using 22 lags and iterative weighted least squares)

Variable	Coefficient	*t*-statistic
Monday	.2532	14.96
Tuesday	.2748	18.32
Wednesday	.2478	16.86
Thursday	.2545	18.54
Friday	.2358	16.20
Saturday	.2174	15.40

	Lags of $\lvert \hat{u}_t \rvert$		Lags of $\hat{u}_t$	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
1	.0448	6.68	−.0173	−3.08
2	.0192	3.28	−.0152	−2.81
3	.0258	4.32	−.0033	−0.66
4	.0412	6.49	−.0122	−2.30
5	.0330	5.91	−.0013	−0.28
6	.0282	4.89	−.0050	−0.99
7	.0292	5.04	−.0065	−1.40
8	.0295	5.08	−.0048	−0.94
9	.0296	4.79	−.0000	−0.01
10	.0365	5.88	−.0132	−2.66
11	.0367	6.66	−.0063	−1.28
12	.0237	3.90	−.0168	−3.31
13	.0340	5.89	−.0030	−0.61
14	.0312	5.25	−.0054	−1.12
15	.0239	4.31	−.0006	−0.13
16	.0350	5.99	−.0148	−3.01
17	.0334	5.85	−.0015	−0.32
18	.0139	2.50	−.0114	−2.40
19	.0202	3.75	−.0117	−2.56
20	.0159	3.16	−.0085	−1.85
21	.0227	3.93	−.0046	−0.99
22	.0144	2.71	−.0024	−0.52
Sum of 22 lags	.6220	34.80	−.1660	−6.30
F-test for equal daily means		3.67		
R^2		0.259		

Equation (4) is estimated iteratively using weighted least squares, along with Equation (3) (see Table 3). The *t*-statistics use Hansen's (1982) correction for autocorrelation and heteroskedasticity to calculate the standard errors, with 44 lags of the residual autocovariances and a damping factor of 0.7. (The RATS computer program was used to perform all calculations.) The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

return shock has about 2.5 times as large an effect on volatility as a positive return shock.[10]

I also have estimated the model in Equations (3) and (4) using 44 lagged returns and volatility measures. The estimate of the return

[10] Using the moving average representation from note 6, $\psi(L) = 1 / \phi(L)$, $\phi_i = (\rho_i + \gamma_i)$ for positive shocks and $\phi_i = (\rho_i - \gamma_i)$ for negative shocks. The long-run effect of a positive shock is $\psi(L{=}1) = 1 / (1 - 0.622 + 0.166) = 1.838$. The long-run effect of a negative shock is $\psi(L{=}1) = 1 / (1 - 0.622 - 0.166) = 4.717$.

equation (3) is unaffected, in that the sum of the incremental 22 autoregressive coefficients ($\beta_{23} + \cdots + \beta_{44}$) is 0.0351, with a t-statistic of 1.06. The sum of the incremental coefficients of lagged volatility ($\delta_{23} + \cdots + \delta_{44}$) is -0.097, with a t-statistic of -0.98. On the other hand, there is evidence that the volatility model in Table 4 truncates the true lag distribution by stopping at 22 lags. The sum of the incremental 22 autoregressive coefficients in Equation (4) ($\rho_{23} + \cdots + \rho_{44}$) is 0.301, with a t-statistic of 10.67 (the sum for lags 1 through 44 is 0.675). The sum of the incremental coefficients of lagged unexpected returns in Equation (4) ($\gamma_{23} + \cdots + \gamma_{44}$) is -0.124, with a t-statistic of -3.87. (The sum for lags 1 through 44 is -0.227.) Thus, the persistence in conditional volatility is even stronger than the results in Table 4 show.

2.4 Models for daily stock volatility using high–low spreads

Parkinson (1980) and Garman and Klass (1980) create efficient estimators of the variance of returns using extreme values of prices. Garman and Klass show that a variance estimator based on the percentage (high–low) spread is over five times more efficient than the estimator based on daily stock returns. They note, however, that infrequent trading biases downward the extreme values estimator and reduces its efficiency.[11] Nonsynchronous trading of individual stocks would have similar effects for measuring the volatility of portfolio returns.

I took high, low, and closing values of the S&P composite portfolio since 1980 from COMPUSERVE. I estimate the following model for daily stock returns:

$$R_t = \sum_{i=1}^{5} \alpha_i D_{it} + \sum_{j=1}^{22} \beta_j R_{t-j} + \sum_{k=1}^{22} \delta_{1k} | u_{t-k} | + \sum_{m=1}^{22} \delta_{2m} \ln \frac{H_{t-m}}{L_{t-m}} + u_t \quad (5)$$

where $\ln(H_t/L_t)$ is the percent spread for day t. The model for daily volatility uses lags of the spread, of the absolute residuals $|\hat{u}_t|$, and of the residuals $\hat{u}_t$ from Equation (5),

$$|\hat{u}_t| = \sum_{i=1}^{5} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |\hat{u}_{tj}| + \sum_{k=1}^{22} \gamma_k \hat{u}_{tk} + \sum_{m=1}^{22} \theta_m \ln \frac{H_{tm}}{L_{tm}} + v_t \quad (6)$$

where the coefficients θ_m measure the relation between past spreads and current conditional volatility. Both equations also include a dummy variable equal to 1 from January 1980–December 1983, and

[11] Beckers (1983) finds that the high–low spread variance estimator does help predict future close-to-close variance estimates for individual stocks, although the improvements are not as large as the Garman–Klass analysis suggests.

0 after 1984. Standard & Poors changed the way they calculate the high–low values in January 1984. A plot of the high–low spread for the S&P portfolio compared with the spread for the Dow Jones Industrial Average from 1980–1988 shows that S&P spreads drop noticeably in January 1984.[12] The dummy variable, SPDUM, adjusts for the change in the level of measured spreads in 1984.

The spread data do not help predict stock returns, so the results are not reported in detail. Only one of the spread coefficient estimates, δ_{2m}, is more than 2 standard errors from 0, and the sum is negative. If spreads proxy for volatility, these coefficients should be positive. Lagged spreads do add significant information in predicting volatility. The coefficient of the spread at lag 1, θ_1, is almost 3 standard errors above 0. The sum of 22 lags is 0.42, over 4 standard errors above 0. The coefficient on SPDUM is reliably negative, adjusting for the higher level of spreads in 1980–1983. Compared with Table 4, the coefficients on lagged values of $\hat{u}_t$ and $|\hat{u}_t|$ are smaller, and they have smaller t-statistics. The sum for 22 lags is 0.098 for $|\hat{u}_t|$ and -0.105 for $\hat{u}_t$. Again, volatility increases more following a large negative return than following a large positive return, but the size of the effect is smaller. Because the spread contains less estimation error than lagged absolute residuals, it is not surprising that including lagged spreads reduces the predictive ability of lagged absolute residuals.

2.5 Models for monthly stock volatility, 1885–1988

One disadvantage of the results in Tables 2, 3, and 4 is that it is difficult to graph so many estimates of daily volatility.[13] It is also difficult to determine the persistence of volatility using high-order autoregressions.[14] Following French, Schwert, and Stambaugh (1987), I calculate the sample standard deviation within each month from 1885–1988,

$$\hat{\sigma}_m = \left[\sum_{i=1}^{N_t} (R_{i,m} - \bar{R}_m)^2 \right]^{1/2} \tag{7}$$

[12] A copy of this plot is available from the author on request. It seems that S&P used the highest and lowest prices for each stock in the portfolio during the day to create the high–low values for the portfolio prior to 1984. Since 1984, they apparently evaluate the value of the entire portfolio frequently throughout the day. The latter procedure matches the theory behind the Parkinson estimator and produces a smaller measured spread and volatility estimate.

[13] For example, a 9-inch-wide graph on a 300 dots-per-inch laser printer can accommodate only 2700 data items.

[14] For example, using a 6-MB virtual machine on an IBM 4361 using a CMS operating system, I was unable to estimate more complicated models than those in this article using the mainframe version of the RATS computer program without running out of available memory.

where there are N_t daily returns $R_{t,m}$ in month m, with an average return of $\bar{R}_m$. This has the dimension of a monthly return standard deviation because it is not divided by the number of days N_t. Next, I estimate an autoregressive model for the standard deviation estimate for month m, $\hat{\sigma}_m$,

$$\hat{\sigma}_m = \sum_{i=1}^{12} \alpha_i D_{im} + \sum_{j=1}^{12} \phi_j \hat{\sigma}_{m-j} + v_m \tag{8}$$

When daily volatility changes slowly, this procedure is a useful approximation. The errors-in-variables problem for estimating the true process for volatility stressed by Pagan and Ullah (1988) is reduced, since the monthly regressors $\hat{\sigma}_{m-j}$ contain less estimation error than the daily regressors $|\hat{u}_{t-j}|$. Table 5 contains estimates of the twelfth-order autoregressive model for $\hat{\sigma}_m$, including different monthly intercepts α_i. There is weak evidence that the monthly intercepts are not equal ($F = 4.35$, with a P-value $< .0001$). The coefficient of determination R^2 from the monthly model in Table 5 (0.559) is much larger than from the daily model in Table 2 (0.236). There is also more evidence of persistence in the monthly volatility model. The sum of the autoregressive coefficients from the monthly model (0.893) is larger than from the daily model (0.627).[15] The half-life of a volatility shock is 18 months. Moreover, the smallest root in the autoregressive polynomial is 1.034, which implies a factor $(1 - 0.967L)$ in the autoregressive polynomial $\phi(L)$ in Equation (8).

Figure 1 shows the predictions of monthly stock volatility from Table 5. From 1886–1926, using the Dow Jones portfolios to estimate volatility, the conditional standard deviation is between 0.02 and 0.08 per month. It increases in 1893 and in the financial panic of 1907. Otherwise, there are no dramatic movements in conditional volatility during this period.

The number of stocks in the Dow Jones portfolio increases from 12 in 1885 to 50 by 1926. Nevertheless, there are no obvious changes in the portfolio standard deviation in the months near the changes in portfolio size. Moreover, the Dow Jones portfolio volatility is similar to the S&P portfolio volatility in 1928. Thus, there is little reason to believe that the size or composition of the portfolio has important effects on the time-series behavior of volatility.[16]

[15] Nevertheless, the sum for the daily model is equivalent to a one-month period, and the first monthly coefficient is only 0.468. This shows that the assumption of constant volatility within the month that is implicit in Table 5 is not accurate.

[16] There is also no significant change in volatility when the S&P portfolio expanded from 90 to 500 stocks in March 1957.

Table 5
Estimates of a twelfth-order autoregressive model for monthly percent stock volatility, where monthly volatility is estimated using the daily returns in the month, including differing monthly intercepts, 1885–1987

Variable	Coefficient	*t*-statistic
Monthly intercepts		
January	.0671	0.22
February	−.0008	−0.01
March	.5863	2.46
April	.1605	0.60
May	.5930	2.04
June	.4288	4.49
July	.3058	1.23
August	.5231	2.34
September	.8291	3.35
October	1.108	3.55
November	.4254	1.45
December	.2276	0.82
Lags of dependent variable		
1	.4683	9.32
2	.0642	1.40
3	.0469	1.27
4	.0501	0.99
5	.0282	0.54
6	.0857	2.43
7	.0449	1.66
8	.0736	1.78
9	−.0381	−0.86
10	.0370	1.56
11	.0056	0.52
12	.0265	1.20
Sum of 12 lags	.8929	16.24
F-test for equal monthly means		4.35
R^2		0.559

The *t*-statistics use Hansen's (1982) correction for heteroskedasticity to calculate the standard errors. The volatility for month *m* is estimated from the daily returns in the month [Equation (7)] where there are N_t daily returns $R_{t,m}$ in month *m*, with an average return of $\bar{R}_m$. This has the dimension of a monthly return standard deviation because it is not divided by the number of days N_t.

The most notable episodes of high volatility are from 1929–1934, 1937–1938, 1946, 1973–1974, and 1987. Officer (1973) and Schwert (1989b) have documented that many macroeconomic time series, such as the money growth rate and industrial production, were also more volatile during the Great Depression (1929–1939). Nevertheless, as stressed by Schwert (1989b), the increase in macroeconomic volatility is not large enough to explain all of the increase in stock volatility during this period. Schwert also shows that changes in aggregate financial leverage following the stock market crash of 1929 are too small to explain the sharp rise in stock volatility during the Depression.

Thus, the plot in Figure 1 confirms the analysis of Table 1. Episodes

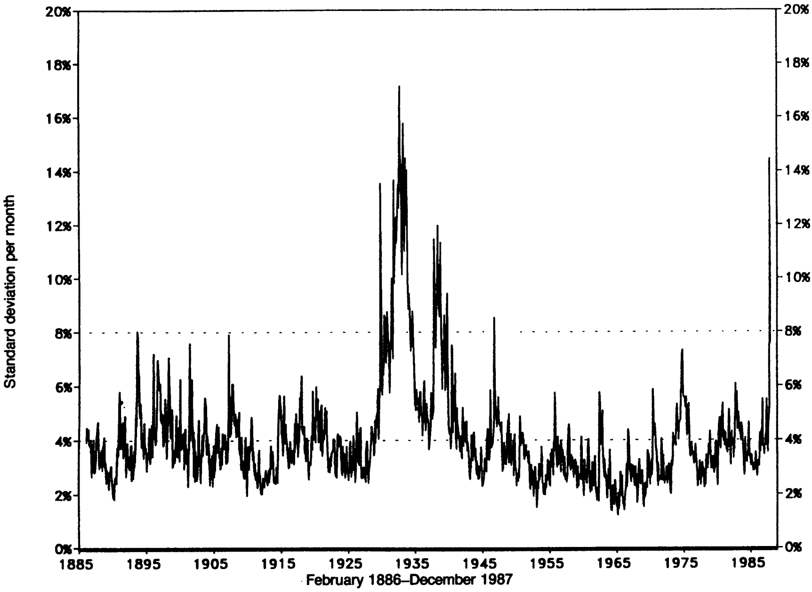

Figure 1
Predictions of percentage monthly stock return standard deviations from Table 5, 1886–1988
Fitted values from a twelfth-order autoregression for monthly stock return standard deviations with different monthly intercepts.

of high stock volatility in the past have occurred in a few spans of time. The plot also confirms the analysis of Tables 2, 4, and 5 that volatility is persistent. Once it rises, it usually remains high for many months. As noted by Schwert (1989a), many periods of high volatility correspond to business cycle recessions or crises in the banking system.

3. How Unusual Was the 1987 Crash?

3.1 Daily S&P returns

There are many ways to measure the extent to which the October 1987 crash and its aftermath were unusual. One somewhat mechanical method is to add dummy variables to Equations (3) and (4). Two dummy variables

O87 = 1   from October 20–30, 1987, and 0 otherwise
N87 = 1   from November 2–30, 1987, and 0 otherwise.

are used to estimate the effects of the crash on returns and volatility. Table 6 contains estimates and *t*-statistics for the dummy variable coefficients. The autoregressive model for returns predicts that the

Table 6
Effects of the crash of 1987: estimates of differential intercepts in autoregressive models for daily percent stock returns and volatility (using 22 lags and iterative weighted least squares)

$$R_t = \sum_{i=1}^{6} \alpha_i D_{it} + \sum_{j=1}^{22} \beta_j R_{t-j} + \sum_{k=1}^{22} \delta_k \,|\hat{u}_{t-k}| + \mu_{or} O87_t + \mu_{nr} N87_t + u_t$$

$$|\hat{u}_t| = \sum_{i=1}^{6} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |\hat{u}_{t-j}| + \sum_{k=1}^{22} \gamma_k \hat{u}_{t-k} + \mu_{os} O87_t + \mu_{ns} N87_t + v_t$$

	October 1987, μ_o	November 1987, μ_n	Joint F-test
Effect on returns, R_t			
Coefficient	1.671	−.7849	32.32
(t-statistic/P-value)	(5.21)	(−5.98)	(.0000)
Effect on volatility, $\|\hat{u}_t\|$			
Coefficient	−.6519	.5163	11.76
(t-statistic/P-value)	(−3.59)	(3.10)	(.0000)

The models in Equations (3) (for daily stock returns) and (4) (for daily stock volatility) are estimated, along with dummy variables: O87 = 1 from October 20–30, 1987, and N87 = 1, from November 2–30, 1987, and 0 otherwise. The dummy variable coefficient estimates and their Hansen (1982) t-statistics are reported here. The other coefficient estimates are not reported because they are similar to the comparable estimates in Tables 3 and 4. The F-statistic tests whether the two coefficients are jointly different from 0. Its P-value is in parentheses below the F-test. See notes to Tables 3 and 4 for more information.

large drop in stock prices on October 19 would persist for the next month. On the other hand, the positive effect of lagged volatility on returns predicts higher-than-average returns after October 19. The estimates in Table 6 say that stock returns were higher than predicted from October 20–30 relative to the model in Equations (3) and (4). They are lower than predicted from November 2–30, 1987. Both of these coefficient estimates have t-statistics over 5 in absolute value. Since the October dummy variable equals 1 for nine days and the November dummy variable equals 1 for 20 days, the net effect of these two months on the S&P index is close to zero.

From Table 4, the large drop in stock prices on October 19 predicts future volatility to be much higher. The estimate of the October coefficient for stock volatility is negative, with a t-statistic of −3.59. Thus, volatility was significantly *lower* than the model in Table 4 predicts during the remainder of October 1987. The estimate of the November coefficient for stock volatility is positive, with a t-statistic of 3.10. This means that volatility was higher during November than would have been predicted, *given that it was unusually low at the end of October.* While volatility was high relative to its historical average in the weeks after the October 1987 crash, it was below the prediction of the model for stock returns and volatility in Tables 3 and 4. In essence, the stock market returned to relatively normal levels of volatility quickly at the end of 1987.

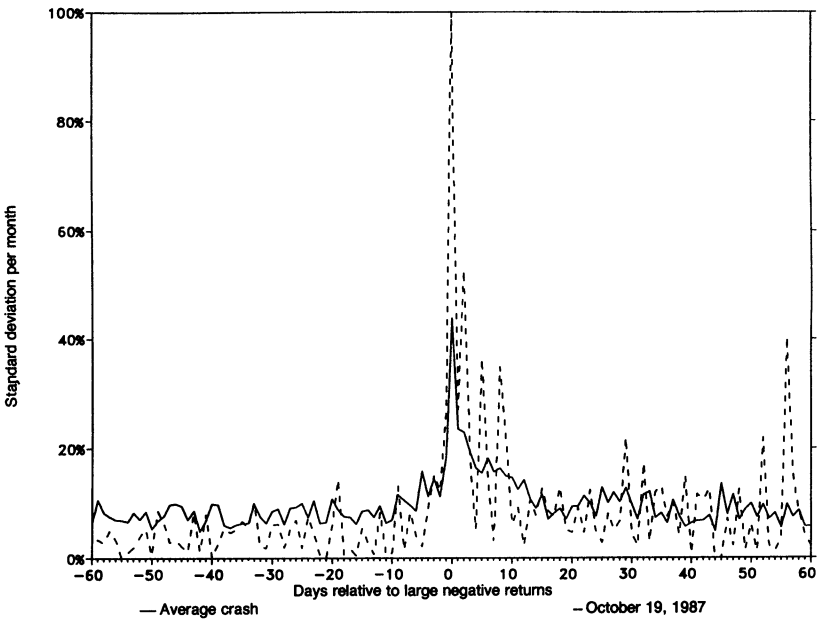

Figure 2
Average standard deviation of daily percent stock returns around 20 "crashes," compared with the behavior around the October 19, 1987 crash
Expressed in units of monthly standard deviations.

Another way to tell whether the 1987 crash was unusual is to compare it to previous crashes. Figure 2 plots the average absolute error from the estimate of Equation (4) in Table 4, $|\hat{u}_t|$, for the 20 most negative daily stock returns in panel A of Table 1 (excluding October 19, 1987) for 60 days (about three months) before and after these "crashes." It also plots $|\hat{u}_t|$ for the October 19, 1987, crash. All of these values are expressed in units of monthly standard deviations [i.e., they are multiplied by $(253/12)^{1/2}$]. This graph shows that volatility typically declines after crashes, and that the October 1987 crash looks like the average crash, except that it has a much larger value on day 0. It also shows that volatility was lower before the October 1987 crash than for the average of the other crashes.

Figure 3 is similar to Figure 2, except that it plots the predictions of volatility from Equation (4) in Table 4 for October 19, 1987, versus the 20 next largest crashes. There are two notable differences between the October 1987 crash and the average crash. First, the level of predicted volatility was lower in 1987 than for the average. Second, for the five days after October 19, predicted volatility remained above the average for the other crashes. After that, the conditional volatility of stock returns behaved like the average for previous crashes. Relative

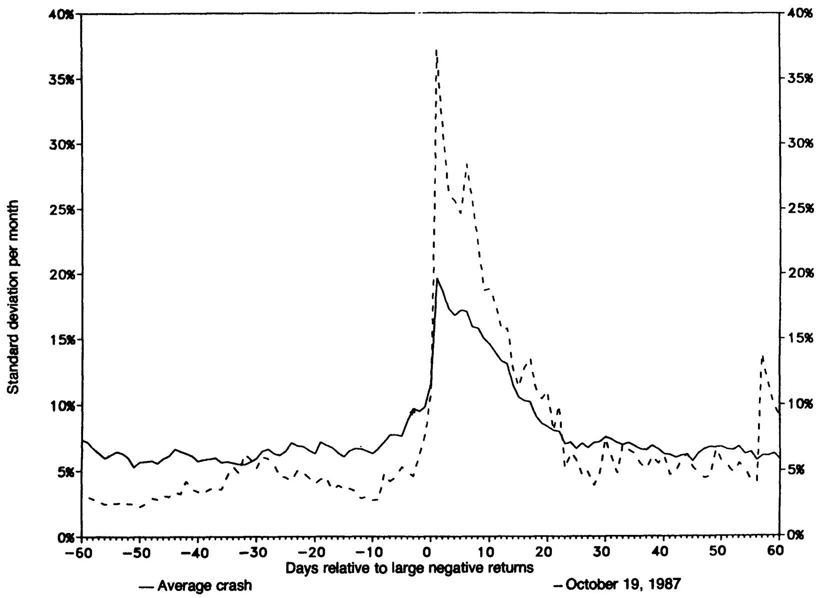

Figure 3
Average predicted standard deviation of daily percent stock returns around 20 "crashes," compared with the behavior around the October 19, 1987, crash
Expressed in units of monthly standard deviations.

to precrash levels, stock volatility rose and fell faster around October 19 than the evidence from the next largest 20 crashes would imply.

Together, Figures 2 and 3 confirm the evidence in Table 6. Stock volatility fell faster after the October 19, 1987, crash than either the model in Table 4 or than evidence from previous crashes imply. While the stock market remained quite volatile in the days after "Black Monday," it was not as volatile as historical evidence would predict.

3.2 Implied volatility from the options market

Figure 4 plots the implied volatility from call options on the S&P 500 portfolio along with the predictions from Equation (4) daily from April 1987 through December 1988. I took daily option prices from the Dow Jones News Retrieval Service. I used Merton's (1973) option pricing model for stocks paying continuous dividends to solve for the level of stock return volatility that is consistent with the option prices.[17] I used the option with an exercise price that was closest to the index level and closest to maturity (but not in the maturity month)

[17] I used an interest rate of 6 percent in these calculations. Since short-term interest rates were relatively stable during this period, using a more accurate measure of the interest rate for each day would have little effect on the implied volatility calculations. I used the dividend yield on the S&P portfolio, 3.7 percent.

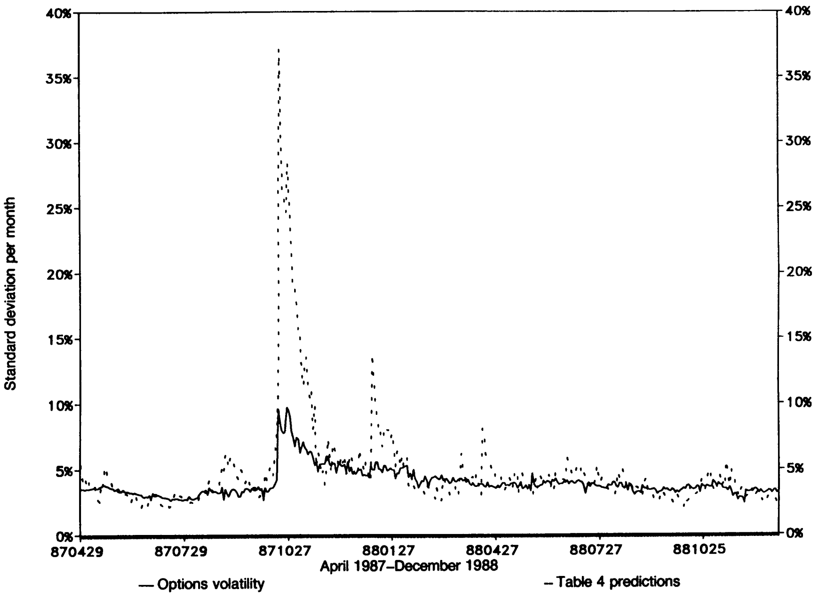

Figure 4
Implied monthly standard deviations of percent returns to the S&P 500 portfolio from daily call option prices, April 1987–December 1988
Using Merton's (1973) continuous dividend option pricing model, at-the-money and close-to-maturity options.

to calculate the implied volatility. Many studies have shown that close-to-the-money option prices convey the most information about the expectations of the options market concerning future volatility [Day and Lewis (1988)].[18]

Several things are clear from this plot. First, option traders' perceptions of stock volatility did not rise until October 19, and they remained high for the next couple of months.[19] The implied standard deviation rose from less than 0.04 per month to over 0.09 per month on October 19. It decayed back to its precrash level by March 1988 and remained at that level throughout 1988. It is also clear that the predictions of daily volatility (expressed at a monthly rate) from Table 4 rose much higher than the implied volatility from the options prices.

One reason that the level of the implied volatility series is lower

[18] I also calculated several average measures of implied volatility, averaging across options with different exercise prices for a given maturity date, and none of these alternatives yielded substantially different results.

[19] Franks and Schwartz's (1988, table 1) report implied standard deviations from weekly data for call options on the Financial Times Stock Exchange (FTSE) portfolio from May 1984 through November 1987. Implied standard deviations almost tripled from the week ended October 16 to the week of the crash. Volatility declined faster in the United States than in the United Kingdom during the remainder of October and November.

than the prediction from Table 4 is because the option price estimates the *average* volatility of returns over the life of the option. These options have from 20 to 110 days to maturity. If daily volatility is expected to decrease in the future, the implied volatility from option prices will be below the current one-day prediction of volatility. Thus, the lower levels of volatility implied by option prices following the October 19 crash are a further indication that traders expected volatility to return to lower levels soon.

Merton's model assumes that volatility is nonstochastic. Nevertheless, Wiggins (1987) suggests that implied volatilities from models such as Merton's are likely to be similar to those from models that incorporate stochastic volatility effects for near-the-money options. Of course, the 20 percent drop in stock prices on October 19 meant that there were few near-the-money options immediately following the crash. Nevertheless, Wiggins' results suggest that volatility estimates from Merton's model would be too high for short-maturity out-of-the-money stock index options. Thus, it is unlikely that the use of Merton's option pricing model explains the lower level of implied volatilities from the options market.

3.3 Evidence from the futures market

Arbitrage forces the price of the S&P futures contract to mimic the index. Therefore, it is reasonable to expect the volatility of futures prices to be similar to the volatility of stock prices. Nevertheless, Edwards (1988) shows that the variance of daily futures returns has been 40 to 50 percent larger than the variance of S&P stock returns since 1982, when these futures began trading.[20] There are several reasons why this might occur. First, variation in the expected real return or in the dividend yield to the S&P portfolio could explain some of the difference (although preliminary calculations suggest these factors are unlikely to explain the extra variation in futures returns). Second, because not all stocks in the S&P portfolio trade at the end of the day, the measured stock index smooths volatility of the "true" value of the underlying stocks [e.g., Scholes and Williams (1977)]. Third, because transactions costs are lower in futures markets, investors with macroeconomic information are likely to trade in futures markets rather than the stock market. The extra volatility in futures prices may reflect information that would not be worth trading on in the stock market. Arbitrage between futures and stock markets would prevent large disparities between prices to persist, but it would not prevent small short-run variations. Finally, "speculation" or "noise"

[20] Futures returns, $\ln(F_t/F_{t-1})$, measure the percent change in the futures price. Since there is no net investment in a futures contract, these are not rates of return in the usual sense of the word.

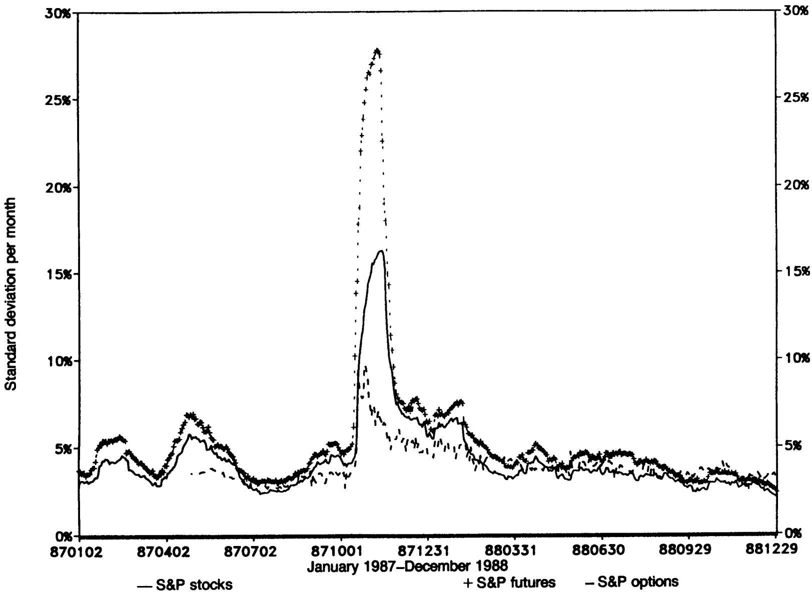

Figure 5
Estimates of standard deviations of daily percentage returns to the S&P 500 portfolio from daily stock prices, call option prices and futures prices, January 1987–December 1988
Using Merton's (1973) continuous dividend option pricing model, at-the-money and close-to-maturity options; stock and futures prices use daily percentage high-low spreads. ln(H/L).

trading in futures markets may induce extra volatility into futures prices [e.g., Shiller (1984), Black (1986), and Summers (1986)].

Futures prices reflect the value of the portfolio at a point in time. Thus, the intraday (high–low) futures spread is probably a better measure of volatility than the (high–low) spread for stocks. If nothing else, there is no problem of nonsynchronous trading. Thus, even though futures volatility is larger than stock volatility, past volatility or spreads from futures may help predict stock return volatility.

Figure 5 plots three estimates of the volatility of the S&P portfolio: (1) the standard deviation estimated from the most recent 21 daily (high–low) spreads for the S&P portfolio, (2) the standard deviation estimated from the most recent 21 S&P futures (high–low) spreads,[21] and (3) the implied standard deviation from the S&P call options for 1987–1988. It is clear from this plot that the volatility estimates from

[21] I use the Parkinson (1980) variance estimator,

$$\hat{\sigma}_t^2 = 0.393\left[\sum_{i=1}^{21} \frac{\ln(H_{t-i}/L_{t-i})}{21}\right]^2$$

where $\ln(H_t/L_t)$ is the percentage (high–low) spread on day t.

the futures market are similar to the estimates from the stock market, except around October 19. The futures price at the end of trading on that day was well below the stock price, and the swings within the day were larger. In part, this was due to the lack of timely quotes in the stock market. The increase in estimated volatility in both the futures and stock markets was much larger than in the options market. Nevertheless, before October 19, 1987, and after January 1988, the three measures of stock market volatility are similar. All three measures show that stock volatility returned to precrash levels by early 1988 and remained low throughout the remainder of 1988.

4. Conclusions

The stock market crash of October 19, 1987, already has been studied under a variety of microscopes. This article focuses on the effect of the 20 percent drop in stock prices on the volatility of stock market returns. In particular, it analyzes whether the behavior of daily returns before and after the 1987 crash was unusual relative to the experience of over 100 years of daily data. While the 1987 crash was the largest one-day percentage change in prices in over 29,000 observations, it was also unusual in that stock market volatility returned to low precrash levels quickly. Two comparisons support this conclusion. First, the prediction model for stock volatility includes significant negative differential intercepts for the days from October 20 through October 30, 1987. Second, compared with the next 20 most negative daily stock returns, volatility rose faster at the time of the October 19 crash, and it fell faster afterwards.

Evidence from the options and futures markets also supports this conclusion. Estimates from these markets from 1987–1988 show that stock volatility dropped to precrash levels by early 1988 and remained low. These data are only available for the last six years, so they cannot be used to study previous crashes. Nevertheless, they provide more accurate estimates of volatility than do the methods using daily stock returns. When they are available, they corroborate the conclusions from the much larger sample of stock returns.

This article also estimates new models for the behavior of stock volatility. I parameterize the asymmetric reaction of volatility to negative returns using lagged return shocks along with lagged measures of volatility. I also use lagged (high–low) spreads to help predict volatility when these data are available.

Schwert (1989a,b) shows that stock volatility was higher during recessions and around the major banking panics in the nineteenth and early twentieth centuries. In part, this is an example of the asymmetry in the return–volatility relation. Negative returns lead to larger increases in volatility than do positive returns. Nevertheless, this historical evidence points out another difference between the 1987 crash and earlier periods of high volatility. There has been no major crisis in the U.S. financial system, and there has been no recession accompanying the 1987 crash.

Instead of a microscope, the plots of volatility in this article can be thought of as an electrocardiogram. They reflect the pulse of financial markets by measuring the rate of price changes. They show the risk borne by investors in the stock market, and where stock volatility reflects uncertainty about more fundamental economic aggregates [e.g., Schwert (1989b)], they provide information about the health of the economy.

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