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STOCK VOLATILITY AND THE CRASH OF '87

G. William Schwert

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ABSTRACT

This paper analyzes the behavior of stock return volatility using daily data from 1885 through 1987. The October 1987 stock market crash was unusual in many ways relative to prior history. In particular, stock volatility jumped dramatically during and after the crash, but it returned to lower, more normal levels quickly. I use data on implied volatilities from call option prices and estimates of volatility from futures contracts on stock indexes to confirm this result.

G. William Schwert
Simon Graduate School of
Business Administration
University of Rochester
Rochester, NY 14627

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1. Introduction

On October 19, 1987, the Standard & Poor's 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 paper 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. It 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 2 summarizes some of the literature on time-varying stock volatility. Section 3 contains estimates of the conditional standard deviations of daily stock returns from 1885-1987. It shows that stock volatility was unusually high during the 1929-1934 and 1937-1938 depressions, and during the 1973-1974 OPEC recession. Section 4 compares the estimates of daily stock volatility from the stock, options and futures markets during 1987-1988. Section 5 summarizes the empirical results and relates these findings to the October 1987 stock market crash.

2. 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 the Depression as after. So it is difficult to credit the creation of the Securities and Exchange Commission (S.E.C.) with the reduction in stock volatility that occurred 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 S.E.C. began its operations in October 1934. Like Officer, Benston concludes that the activities of the S.E.C. cannot be credited with lowering stock volatility. Schwert [1987] analyzes the relation of stock volatility with real and nominal macroeconomic volatility, financial leverage, stock trading activity, default risk, and firm profitability using monthly data from 1857-1986. Schwert [1989] shows that monthly stock volatility was higher during recessions and following the major banking crises from 1834-1986 (also see 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 1934-1987. There is not 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.

3. Estimates of Conditional Stock Volatility

3.1 Extreme Changes in Stock Prices

Table 1 lists the 50 largest increases and decreases in daily stock returns from February 16, 1885 through 1987. This sample includes 28,884 daily stock 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 (Dow Jones [1972]). From January 1928 to the present, I use the Standard & Poor's composite portfolio (90 stocks until March 1957, and 500 since that time -- see Standard & Poor's [1986]). The Dow Jones portfolios are price-weighted, while the S&P portfolio is value-weighted; neither includes dividends in the returns.[1]

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[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 (that includes

As mentioned at the beginning of the paper, October 19, 1987, is the largest one day percent change in stock prices (-20.4 percent) out of the sample of 28,884 observations. 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. But 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 occur in the October 1929-July 1934 period. The September 1937-September 1939 period accounts for 7 of the most negative and 5 of the most positive returns. The week from October 19 through 26, 1987, accounts for 2 of the most negative and 2 of the most positive returns. March 1907 accounts for 1 large and 1 small return. July and August, 1893 contain 1 of the smallest and 2 of the largest returns, and May-November, 1940 contain 2 of the smallest and 1 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*.[2]

Table 2 lists the 50 largest increases and decreases in monthly stock returns from January 1834 through the end of 1987. This represents 1,848 monthly stock returns. Schwert [1989] describes the construction of this stock return series. Briefly, from 1834-1856 I use Smith and Cole's [1935] portfolio of industrial and railroad stocks. From 1857-1870 I use Macaulay's [1938] portfolio of railroad stocks. From 1871-1925 I use the Cowles [1939] value-weighted portfolio of New York Stock Exchange (NYSE) listed stocks. From 1926-1987 I use the Center for Research in Security

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dividends) with the S&P portfolio (that does not) over the July 1962 - December 1986 period, and there are no important differences in the estimates of stock volatility.

[2]Cutler, Poterba and Summers [1989] analyze large daily returns from 1928-87 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.

Table 1 -- The 50 Largest and Smallest Daily Returns to Market Portfolios, 1885-1987

	Smallest Daily Returns		*Largest Daily Returns*	
1.	October 19, 1987	-.203881	March 15, 1933	.166096
2.	October 28, 1929	-.123362	October 30, 1929	.125306
3.	October 29, 1929	-.101583	October 6, 1931	.123583
4.	November 6, 1929	-.099213	September 21, 1932	.118110
5.	October 18, 1937	-.092749	September 5, 1939	.096271
6.	July 20, 1933	-.088793	April 20, 1933	.095238
7.	July 21, 1933	-.087039	October 21, 1987	.090994
8.	December 20, 1895	-.085162	November 14, 1929	.089468
9.	October 26, 1987	-.082790	August 3, 1932	.088586
10.	October 5, 1932	-.081988	October 8, 1931	.085890
11.	August 12, 1932	-.080158	February 13, 1932	.083744
12.	May 31, 1932	-.078350	December 18, 1931	.082902
13.	July 26, 1934	-.078280	February 11, 1932	.082667
14.	March 14, 1907	-.075887	July 24, 1933	.081359
15.	May 14, 1940	-.074708	June 10, 1932	.076586
16.	July 26, 1893	-.073892	June 3, 1931	.075410
17.	September 24, 1931	-.072917	November 10, 1932	.075144
18.	September 12, 1932	-.071754	October 20, 1937	.074775
19.	May 9, 1901	-.070246	June 19, 1933	.072289
20.	June 15, 1933	-.069723	May 6, 1932	.072183
21.	October 16, 1933	-.067814	April 19, 1933	.072072
22.	September 3, 1946	-.067267	August 15, 1932	.072046
23.	May 28, 1962	-.066756	October 11, 1932	.071651
24.	May 21, 1940	-.066394	January 6, 1932	.070199
25.	September 26, 1955	-.066184	October 14, 1932	.068966
26.	November 11, 1929	-.062323	April 9, 1938	.067568
27.	September 21, 1933	-.061740	June 4, 1932	.067485
28.	October 23, 1929	-.059073	September 23, 1931	.066667
29.	October 5, 1931	-.058698	July 27, 1893	.066109
30.	May 13, 1940	-.058475	August 2, 1893	.065499
31.	March 29, 1938	-.058252	May 10, 1901	.064426
32.	November 19, 1937	-.058244	October 4, 1933	.064116
33.	June 8, 1932	-.057732	March 15, 1907	.063940
34.	September 14, 1932	-.057692	October 25, 1937	.063830
35.	December 18, 1899	-.057639	April 29, 1933	.062580
36.	September 13, 1938	-.057214	August 6, 1932	.061765
37.	November 13, 1929	-.057128	November 4, 1932	.061728
38.	September 7, 1937	-.057124	December 27, 1917	.061241
39.	November 12, 1929	-.056898	June 20, 1931	.060514
40.	June 16, 1930	-.056881	August 22, 1932	.058201
41.	October 21, 1932	-.056708	January 15, 1934	.057654
42.	June 17, 1932	-.056641	November 7, 1940	.055607
43.	September 26, 1932	-.056338	November 15, 1929	.055094
44.	July 30, 1914	-.056296	August 17, 1933	.054902
45.	March 31, 1932	-.055556	March 28, 1898	.054771
46.	October 7, 1932	-.055182	June 2, 1932	.054545
47.	May 27, 1932	-.054795	June 3, 1932	.053879
48.	March 25, 1938	-.054601	June 20, 1938	.053775
49.	October 5, 1937	-.054452	November 10, 1937	.053744
50.	December 12, 1929	-.054066	October 20, 1987	.053327

Prices (CRSP) value-weighted portfolio of NYSE stocks. The latter two portfolios include dividends. I use the dividend yields from the Cowles portfolio from 1871-1879 to estimate the yields from 1834-1870.

The results in Table 2 reinforce the conclusions drawn from Table 1. First, it is worth noting that October 1987 is only the fourth lowest return in the 1834-1987 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 out of the 50 most negative and 12 out of the 50 most positive monthly returns are from 1929-1934. The 1937-1939 period includes 5 of the most negative and 5 of the most positive returns. One of the largest and one of the smallest returns come from 1987. Again, a large proportion of both the largest and the smallest returns come from brief subperiods in the overall 1834-1987 sample. This shows an increase in stock volatility during these periods.

The models in the next section provide a more structured analysis of the time series properties of stock market volatility.

3.2 Autoregressive Models for Daily Stock Volatility, 1885-1987

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 [1988]). Third, stock volatility is related to macroeconomic volatility, recessions and to banking crises (Officer [1973], Schwert [1987, 1989]). On the other hand, there are many competing parametric models to represent conditional heteroskedasticity of stock returns.[3] For this paper, I adopt a variation of the strategy followed by French, Schwert and Stambaugh [1987] and by Schwert [1989]. First, stock returns are regressed on 22 lagged returns (about one month) to estimate short-term movements in conditional expected

[3]In addition to the models used in this paper, see Engle [1982], Bollerslev [1986], Engle and Bollerslev [1986], Engle, Lilien and Robins [1987] and Hamilton [1988].

Table 2 -- The 50 Largest and Smallest Monthly Returns to Market Portfolios, 1834-1987

	Smallest Monthly Returns		*Largest Monthly Returns*	
1.	September 1931	-.287943	April 1933	.376807
2.	March 1938	-.234649	August 1932	.361922
3.	May 1940	-.220209	July 1932	.326816
4.	October 1987	-.216432	June 1938	.234906
5.	May 1932	-.202061	May 1933	.210962
6.	October 1929	-.195564	October 1974	.168000
7.	April 1932	-.178743	September 1939	.159539
8.	October 1857	-.159868	May 1843	.150365
9.	June 1930	-.156625	December 1843	.144286
10.	September 1857	-.150544	April 1938	.143594
11.	September 1937	-.134523	November 1857	.138159
12.	December 1931	-.133362	June 1931	.137463
13.	May 1931	-.132673	January 1975	.134829
14.	February 1933	-.131902	June 1933	.133754
15.	October 1932	-.128920	January 1934	.129559
16.	September 1930	-.123243	January 1987	.128229
17.	November 1929	-.120445	January 1863	.127722
18.	March 1939	-.118577	July 1837	.127143
19.	November 1855	-.118571	January 1976	.125243
20.	November 1973	-.116105	August 1982	.125204
21.	November 1860	-.110986	August 1933	.122209
22.	September 1974	-.110282	November 1928	.120004
23.	March 1932	-.109674	October 1982	.115687
24.	July 1934	-.108560	October 1879	.113708
25.	March 1980	-.107585	November 1962	.111819
26.	September 1933	-.105406	August 1984	.111442
27.	January 1842	-.104821	November 1980	.107693
28.	October 1978	-.102213	February 1931	.107665
29.	October 1907	-.102177	February 1855	.105907
30.	September 1946	-.100879	January 1861	.103825
31.	April 1970	-.099774	June 1901	.103602
32.	April 1931	-.097886	July 1939	.101113
33.	July 1933	-.095421	November 1933	.100994
34.	April 1837	-.095345	October 1862	.099834
35.	April 1846	-.095345	June 1929	.098897
36.	October 1937	-.094749	December 1873	.097287
37.	March 1907	-.093834	April 1834	.096906
38.	December 1854	-.093166	May 1863	.096312
39.	January 1846	-.092321	November 1954	.095953
40.	March 1865	-.091938	February 1858	.095089
41.	November 1948	-.090507	December 1971	.090557
42.	May 1837	-.090408	April 1968	.089712
43.	November 1931	-.090172	March 1928	.089423
44.	July 1893	-.088337	April 1935	.089247
45.	August 1974	-.085370	May 1844	.087849
46.	July 1854	-.084593	April 1901	.087279
47.	May 1962	-.084524	February 1845	.085766
48.	May 1893	-.083242	July 1937	.084136
49.	November 1937	-.082932	August 1929	.083753
50.	June 1962	-.082646	April 1978	.083471

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]). The residuals from this regression,

$$u_t = R_t - \sum_{i=1}^{6} \alpha_i D_{it} - \sum_{j=1}^{22} \beta_j R_{t-j} \tag{1}$$

estimate the unexpected return on day t. Following Schwert [1989], the absolute residual $|u_t|$ 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 $|u_t|$ are multiplied by $(\pi/2)^{1/2}$). To estimate the conditional standard deviation of returns, I estimate the regression,

$$|u_t| = \sum_{i=1}^{6} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |u_{t-j}| + v_t , \tag{2}$$

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 3 contains estimates of equations (1) and (2) using the daily data from February 1885 through December 1987. Following Davidian and Carroll [1987], I iterate twice between equations (1) and (2) to calculate weighted least squares estimates. The estimate of the equation for stock returns (1) is consistent with prior research. The intercept for Monday is reliably negative (-.13 percent per day), while the intercepts for the other days of the week are reliably positive.[4] 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 of individual securities (Fisher [1966] and Scholes and Williams [1977]). The sum of the 22 autoregressive coefficients is .18, with a t-statistic of 9.0. Thus, there is a weak tendency for movements in aggregate stock returns to persist. Despite the large t and F-statistics, the coefficient of determination R^2 is only .013, showing that most of the movements in daily stock returns are not

[4]This so-called 'weekend effect' exists in all of the decades from 1885-1894 up to the present.

explained by these factors.

The estimate of the equation for stock volatility (2) is also consistent with prior research. The intercept for Monday is higher than for the other days of the week, and the intercept for Saturday is lower. This shows that volatility is expected to be lower than average from the close of trading on Friday to the close on Saturday. The negative intercept does **not** imply negative volatility predictions, since there is much persistence in volatility. Saturday trading occurred from 1885 through May 1952, but it lasted for only a half day. Similarly, volatility is expected to be higher than average from the close of trading on Friday (or Saturday, when there was Saturday trading) to the close on Monday. This represents more calendar time. Both of these effects are seen by Keim and Stambaugh [1984] using the daily S&P composite returns from 1928-1984. The autoregressive coefficients are positive for all 22 lags, and many are more than 3 standard errors above zero. The largest coefficients occur in the first 6 lags. The sum of the 22 autoregressive coefficients is .69, with a t-statistic of 52.2. The prediction model implied by (2) is a 22 period weighted average of the absolute deviations, adjusted for day-of-the-week seasonal effects.[5] Thus, there is a strong tendency for movements in aggregate stock returns to persist. The coefficient of determination R^2 is .237, showing that movements in daily stock volatility are much more predictable than movements in stock returns.

I have also estimated the model in equations (1) and (2) using 44 lagged returns and volatility measures. The estimate of the return equation (1) is unaffected, in that the sum of the incremental 22 lag coefficients is .0083 with a t-statistic of .37. On the other hand, the sum of the incremental 22 lag coefficients in equation (2) is .183 with a t-statistic of 6.45 (the sum for lags 1 through 44 is .888). Thus, the persistence in conditional volatility is stronger than the results in Table 3 show.

3.3 'Leverage' Effects in the Return-Volatility Relation

Black [1976], Christie [1982], French, Schwert and Stambaugh [1987] and Nelson [1988] all

[5]The optimal forecast function for an 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 3 would equal 1.

Table 3 -- Estimates of Autoregressive Models for Daily Stock Returns and Volatility, 1885-1987, (using 22 lags and iterative weighted least squares)

	Stock Returns, R_t		*Stock Volatility, $\|u_t\|$*	
Variable	Coefficient	T-stat	Coefficient	T-stat
MON	-.001257	-9.92	.002328	12.80
TUE	.000185	1.78	.001881	11.60
WED	.000400	3.98	.001745	12.12
THU	.000166	1.68	.001113	6.83
FRI	.000710	7.08	.001341	9.21
SAT	.000451	3.08	-.001212	-6.16
Lags of dependent variable:				
1	.1033	16.65	.1520	7.87
2	-.0177	-3.22	.1215	10.12
3	.0182	3.32	.0875	8.29
4	.0262	4.33	.0526	5.07
5	.0228	3.91	.0592	5.55
6	-.0092	-1.63	.0702	6.26
7	-.0134	-2.40	.0229	1.96
8	.0143	2.39	.0332	2.51
9	.0064	1.14	.0187	1.45
10	.0040	.69	.0124	1.07
11	.0098	1.70	.0217	2.07
12	.0093	1.53	.0326	2.79
13	-.0087	-1.44	.0021	.20
14	.0040	.68	.0104	1.15
15	.0027	.47	.0181	1.92
16	-.0016	-.26	.0029	.26
17	-.0025	-.42	.0156	1.48
18	.0026	.45	.0268	2.89
19	.0043	.77	.0093	.94
20	.0055	.93	.0339	3.83
21	-.0001	-.97	.0002	.22
22	.0035	.61	.0338	3.67
Sum of 22 lags	.1838	9.04	.6856	52.19
F-test for Equal Daily Means		34.07		75.89
R^2		.013		.237

Note: 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 .7 (the RATS computer program was used to perform all of the calculations). The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

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,

$$|u_t| = \sum_{i=1}^{6} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |u_{t-j}| + \sum_{k=1}^{22} \gamma_k u_{t-k} + v_t, \tag{3}$$

where the coefficients γ_k measure the relation between past return shocks and current conditional volatility. If the distribution of the return shocks u_t is symmetric, u_t and $|u_t|$ are uncorrelated. Negative correlation between $|u_t|$ and u_{t-k} is evidence of negative conditional skewness. 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 stock (see Christie [1982]). 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 4a contains estimates of a model for stock returns that includes lagged values of the volatility measure $|u_t|$,

$$R_t = \sum_{i=1}^{6} \alpha_i D_{it} + \sum_{j=1}^{22} \beta_j R_{t-j} + \sum_{k=1}^{22} \delta_k |u_{t-k}| + u_t, \tag{4}$$

where equation (1) is used in the first stage of an iterative process. Then (3) and (4) are repeated to generate successive values of u_t and $|u_t|$.[6] The day-of-the-week intercepts and the autoregressive coefficients β_j are similar to the estimates in Table 3. The coefficients δ_k measure the effect of higher volatility on future stock returns. The coefficient at lag 1 is reliably positive (3.52, with a

[6]This iterative process would not yield consistent estimates if there was a strong relation between stock returns and lagged volatility in (4). Since the proportion of variation of returns explained by lagged returns or volatilities is low, this problem is not likely to be important.

Table 4a -- Estimates of Autoregressive Model for Daily Stock Returns, Including Effects of Lagged Volatility, 1885-1987, (using 22 lags and iterative weighted least squares)

Variable	Coefficient	T-stat	Coefficient	T-stat
MON	-.000986	-7.44		
TUE	.000060	.54		
WED	.000302	2.76		
THU	.000131	1.23		
FRI	.000784	7.22		
SAT	.000792	4.48		
	Lags of R_t		Lags of $\lvert u_t \rvert$	
1	.1058	16.78	3.5203	4.60
2	-.0116	-2.13	1.2732	1.57
3	.0208	3.58	-.6818	-.91
4	.0295	4.83	-.3772	-.46
5	.0225	3.79	-1.7406	-2.23
6	-.0040	-.68	.3874	.55
7	-.0143	-2.52	.0387	.49
8	.0146	2.43	-1.2369	-1.36
9	.0031	.55	-1.2669	-1.51
10	.0029	.49	.2546	.30
11	.0086	1.54	1.1101	1.47
12	.0091	1.46	-1.2546	-1.73
13	-.0084	-1.38	-.0145	-.20
14	.0071	1.20	.2611	.37
15	.0011	.18	.1450	.19
16	-.0025	-.41	-.2778	-.38
17	-.0036	-.60	.5093	.74
18	.0044	.77	1.0052	1.39
19	.0058	1.04	-1.5081	-2.04
20	.0057	.96	-.2122	-.28
21	-.0007	-.12	.0607	.08
22	.0057	1.00	.8097	1.20
Sum of 22 lags	.2018	8.83	.8045	.90
F-test for Equal Daily Means		30.61		
R^2		.026		

Note: Equation (4) is estimated iteratively using weighted least squares, along with equation (3) (see Table 4b). 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 .7 (the RATS computer program was used to perform all of the calculations). The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

Table 4b -- Estimates of Autoregressive Model for Daily Stock Volatility, Including Effects of Lagged Unexpected Stock Returns, 1885-1987, (using 22 lags and iterative weighted least squares)

Variable	Coefficient	T-stat	Coefficient	T-stat
MON	.002352	12.75		
TUE	.001898	10.37		
WED	.001864	11.36		
THU	.001265	6.49		
FRI	.001477	8.42		
SAT	-.001131	-5.20		
	Lags of $\|u_t\|$		Lags of u_t	
1	.1162	8.23	-.0770	-5.19
2	.0947	8.30	-.0836	-8.69
3	.0825	7.48	-.0624	-7.05
4	.0469	3.89	-.0488	-4.21
5	.0495	5.34	-.0415	-4.63
6	.0693	6.06	-.0408	-4.23
7	.0237	1.99	-.0330	-3.73
8	.0380	2.74	-.0307	-2.89
9	.0232	1.95	-.0315	-3.15
10	.0182	1.63	-.0155	-1.56
11	.0328	2.97	-.0118	-1.35
12	.0372	3.62	.0086	.84
13	.0094	.91	-.0152	-1.87
14	.0224	2.40	.0013	.14
15	.0250	2.81	-.0049	-.52
16	.0066	.67	.0102	1.12
17	.0205	2.11	-.0061	-.70
18	.0305	3.12	.0164	2.02
19	.0158	1.63	.0071	.79
20	.0295	3.82	.0066	.81
21	.0018	.20	-.0018	-.24
22	.0343	3.44	-.0090	-1.20
Sum of 22 lags	.8281	41.76	-.4636	-6.49
F-test for Equal Daily Means		78.62		
R^2		.265		

Note: Equation (3) is estimated iteratively using weighted least squares, along with equation (4) (see Table 4a). 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 .7 (the RATS computer program was used to perform all of the calculations). The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

t-statistic of 4.6), 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 .8045, with a t-statistic of .90. Thus, there is weak evidence that an increase in volatility increases the expected future return to stocks.

Table 4b contains estimates of (3), the model relating stock volatility to lagged stock returns and volatility. The day-of-the-week intercepts are similar to the estimates in Table 3. The coefficients γ_k measure the effect of lagged unexpected stock returns on stock volatility. The coefficients from lags 1 to 11 are all negative, and most are more than 3 standard errors from 0. The sum of the 22 lag coefficients is -.46, with a t-statistic of -6.49. The sum of the autoregressive coefficients ρ_j is .8281, about 20 percent larger than the sum in Table 3. One interpretation of this regression model is that volatility is related to lagged stock returns. The coefficient of lagged positive returns is ρ_j, while the coefficient for lagged negative returns is $(\gamma_j-\rho_j)$. Thus, there is strong evidence that a large negative stock return increases predictions of future volatility more than an equivalent positive return. This extends the earlier evidence on the asymmetric reaction of volatility to return shocks.

3.4 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 5 times as efficient as the estimator based on daily stock returns. They note, however, that infrequent trading biases downward the extreme values estimator and would reduce its efficiency.[7]

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

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

[7]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 Garman-Klass analysis suggests.

where $\ell n(H_t/L_t)$ is the percent spread for day t. The model for daily volatility uses lags of the spread, of the absolute errors $|u_t|$, and of the errors u_t from (5),

$$|u_t| = \sum_{i=1}^{5} \sigma_i D_{it} + \sum_{j=1}^{22} \rho_j |u_{t-j}| + \sum_{k=1}^{22} \gamma_k u_{t-k} + \sum_{m=1}^{22} \theta_m \ell n(H_{t-m}/L_{t-m}) + v_t, \tag{6}$$

where the coefficients θ_m measure the relation between past spreads and current conditional volatility. Table 5a contains estimates of the return equation (5). Table 5b contains estimates of the volatility model (6). Both equations also include a dummy variable equal to 1 from January 1980 - December 1983, and 0 after 1984. Standard & Poor's 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 over the 1980-1988 period shows that S&P spreads drop noticeably at that time.[8] 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 in Table 5a. Only one of the spread coefficient estimates, δ_{2m}, is more than two standard errors from 0, and the sum is negative. If spreads proxy for volatility, these coefficients should be positive. The estimates in Table 5a for the 1980-1987 sample are different from the estimates for the 1885-1987 sample in Tables 3 and 4a. For example, while the intercept for Monday returns is negative, it is only ½ standard error from 0. The autoregressive coefficient at lag 1, ρ_1 = .09, is close to the value in Table 3 (.10), but the pattern of negative coefficients after lag 10 results in the sum of the 22 lags close to 0. The coefficients on lagged volatility δ_{1k} are larger than the estimates in Table 4a, and the sum for 22 lags is 9.6. Nevertheless, the estimates are imprecise, so there is only weak evidence that expected returns are related to past volatility.

Table 5b shows evidence that lagged spreads 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

[8]One possibility is 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, it seems that they evaluate the value of the portfolio frequently throughout the day. The latter procedure matches the theory behind the Parkinson estimator, and is bound to produce a smaller measured spread.

Table 5a -- Estimates of the Relation Between Stock Returns, Lagged Stock Returns, Day-of-the-Week Intercepts, Lagged Stock Volatility and Lagged Spreads, Eq. (5) (S&P Composite Portfolio, 1980-87)

Variable	Coef	T-stat	Coef	T-stat	Coef	T-stat
MON	-.000441	-.52				
TUE	.000527	.69				
WED	.001373	2.22				
THU	.000246	.35				
FRI	.001021	1.47				
SPDUM	.000342	.28				
	Lags of R_t		Lags of $\|u_t\|$		Lags of $\ell n(H_t/L_t)$	
1	.0929	5.20	.2503	.10	-.0489	-1.31
2	.0042	.21	6.4470	2.29	-.0196	-.57
3	-.0059	-.29	-.5886	-.20	-.0642	-2.07
4	-.0038	-.18	.1484	.05	.0247	.62
5	.0003	.02	-3.7487	-1.19	.0436	1.18
6	-.0066	-.31	.8697	.37	-.0456	-1.37
7	.0037	.17	5.7284	1.82	-.0147	-.45
8	.0164	.83	-.7434	-.24	.0106	.32
9	.0067	.32	.5386	.19	.0547	1.53
10	-.0114	-.53	1.1126	.43	-.0485	-1.39
11	-.0201	-1.00	3.3033	1.18	-.0500	-1.60
12	.0266	1.22	-.5188	-.19	.0140	.36
13	-.0020	-.09	1.0094	.42	.0326	.92
14	-.0178	-.83	-2.7541	-1.11	-.0299	-.81
15	-.0090	-.43	-1.5764	-.47	.0221	.55
16	-.0211	-.85	-4.6921	-2 05	.0290	.96
17	.0053	.21	.5486	.20	.0334	.78
18	-.0210	-1.18	5.0628	1.27	-.0055	-.18
19	-.0031	-.15	-4.7302	-1.89	.0338	1.18
20	-.0133	-.58	3.5107	1.59	-.0333	-1.13
21	-.0085	-.33	-4.8909	-1.88	-.0126	-.35
22	-.0128	-.55	5.3360	2.05	.0080	.26
Sum of 22 lags	-.0002	-.00	9.6224	1.20	-.0662	-.67
F-test for Equal Daily Means		1.98				
R^2		.063				

Note: Equation (5) is estimated iteratively using weighted least squares, along with equation (6) (see Table 7b). 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 .7 (the RATS computer program was used to perform all of the calculations). The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

Table 5b -- Estimates of the Relation Between Stock Volatility, Lagged Stock Volatility, Day-of-the-Week Intercepts, Lagged Stock Return Shocks and Lagged Spreads, Eq.(6) (S&P Composite Portfolio, 1980-87)

Variable	Coef	T-stat	Coef	T-stat	Coef	T-stat
MON	.0044	5.97				
TUE	.0035	5.55				
WED	.0028	5.17				
THU	.0027	4.25				
FRI	.0024	4.60				
SPDUM	-.0037	-4.26				
	Lags of $\lvert u_t \rvert$		Lags of u_t		Lags of $\ell n(H_t/L_t)$	
1	.0341	.68	-.1069	-1.85	.1730	2.78
2	-.0341	-.66	-.0604	-2.30	.0282	.35
3	.0531	1.07	-.0132	-.50	.0463	1.11
4	.0691	1.34	.0243	.78	-.0669	-.80
5	.0543	1.11	-.0359	-1.74	.0111	.17
6	-.0462	-1.53	.0182	.92	.0716	1.28
7	.0389	1.21	-.0653	-2.57	-.0064	-.11
8	-.0501	-1.49	-.0145	-.67	.1236	2.93
9	-.0198	-.49	-.0145	-.73	-.0150	-.31
10	.0020	.07	.0029	.13	-.0189	-.40
11	.0564	2.23	.0130	.67	-.0108	-.28
12	.0089	.24	.0205	.79	-.0558	-1.25
13	.0127	.29	.0417	2.04	.0125	.32
14	-.0014	-.04	-.0276	-1.55	-.0082	-.17
15	.0376	1.23	.0234	1.30	.0174	.31
16	-.0824	-2.56	-.0005	-.03	.0652	1.34
17	.0608	1.36	.0180	.78	-.0681	-1.13
18	.0124	.36	.0124	.69	.0064	.10
19	.0197	.54	.0346	.79	.0035	.06
20	-.0266	-.66	-.0181	-.99	.0340	.52
21	-.0259	-.81	.0067	.35	.0011	.02
22	-.0756	-2.45	.0359	2.10	.0751	1.81
Sum of 22 lags	.0978	.70	-.1051	-.95	.4187	4.44
F-test for Equal Daily Means		2.34				
R^2		.156				

Note: Equation (6) is estimated iteratively using weighted least squares, along with equation (5) (see Table 7a). 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 .7 (the RATS computer program was used to perform all of the calculations). The coefficient of determination, R^2, is from the ordinary least squares version of these regressions.

for 22 lags is .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 4b, the coefficients on lagged values of u_t and $|u_t|$ are smaller and they have smaller t-statistics. The sum for 22 lags is .098 for $|u_t|$ and -.105 for u_t. Again, volatility increases more following a large negative return than following a large positive return, but the size of the effect seems to be 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.

3.5 Models for Monthly Stock Volatility, 1885-1987

One disadvantage of the results in Tables 3, 4a and 4b is that it is difficult to graph so many estimates of daily volatility.[9] It is also difficult to determine the persistence of volatility using high order autoregressions.[10] Following French, Schwert and Stambaugh [1987], I calculate the sample standard deviation within each month from 1885-1987. Next, I estimate an autoregressive model for the standard deviation estimate for month m σ_m,

$$\sigma_m = \sum_{i=1}^{12} \alpha_i D_{im} + \sum_{j=1}^{12} \phi_j \sigma_{m-j} + v_m. \tag{7}$$

When daily volatility changes slowly, this procedure is a useful approximation. The errors-in-variables problem stressed by Pagan and Ullah [1988] is reduced, since the monthly regressors σ_{m-i} contain less estimation error than the daily regressors $|u_{t-j}|$. Table 6 contains estimates of the 12[th] order autoregressive model for σ_m, including different monthly intercepts α_i. The coefficient of determination R^2 from the monthly model in Table 6 (.556) is much larger than from the daily model in Table 3 (.237). The sum of the autoregressive coefficients from the monthly model (.898) is larger

[9]For example, a 9 inch wide graph on a 300 dots-per-inch laser printer can accommodate only 2,700 data items.

[10]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 paper using the mainframe version of the RATS computer program without running out of available memory.

than from the daily model (.686).[11] There is weak evidence that the monthly intercepts are not equal ($F = 3.33$, with a p-value = .0001).

Table 6 -- Estimates of 12th Autoregressive Model for Monthly Stock Volatility, Including Different Monthly Intercepts, 1885-1987

Variable	Coefficient	T-statistics
Jan	.0001	.03
Feb	.0002	.11
Mar	.0058	2.54
Apr	.0014	.65
May	.0057	2.23
Jun	.0045	2.06
Jul	.0028	1.24
Aug	.0054	2.60
Sep	.0084	3.49
Oct	.0112	3.13
Nov	.0042	1.79
Dec	.0025	1.01
Lags of dependent variable:		
1	.4613	8.04
2	.0765	1.78
3	.0112	.25
4	.0777	1.58
5	.0318	.71
6	.0793	1.72
7	.0546	1.30
8	.0805	1.75
9	-.0511	-1.28
10	.0470	1.16
11	.0102	.27
12	.0186	.48
Sum of 22 lags	.8976	20.89
F-test for Equal Daily Means		3.33
R^2		.556

Note: Estimates of a 12th order autoregressive model for monthly stock volatility, including different intercepts for each month of the year. The t-statistics use Hansen's [1982] correction for heteroskedasticity to calculate the standard errors.

[11] On the other hand, the sum for the daily model is equivalent to a one month period, and the first monthly coefficient is only .461. This shows that the assumption of constant volatility within the month that is implicit in Table 6 is not accurate.

Figure 1 shows the predictions of monthly stock volatility from Table 6. From 1886-1926, using the Dow Jones portfolios to estimate volatility, the conditional standard deviation is between .02 and .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.

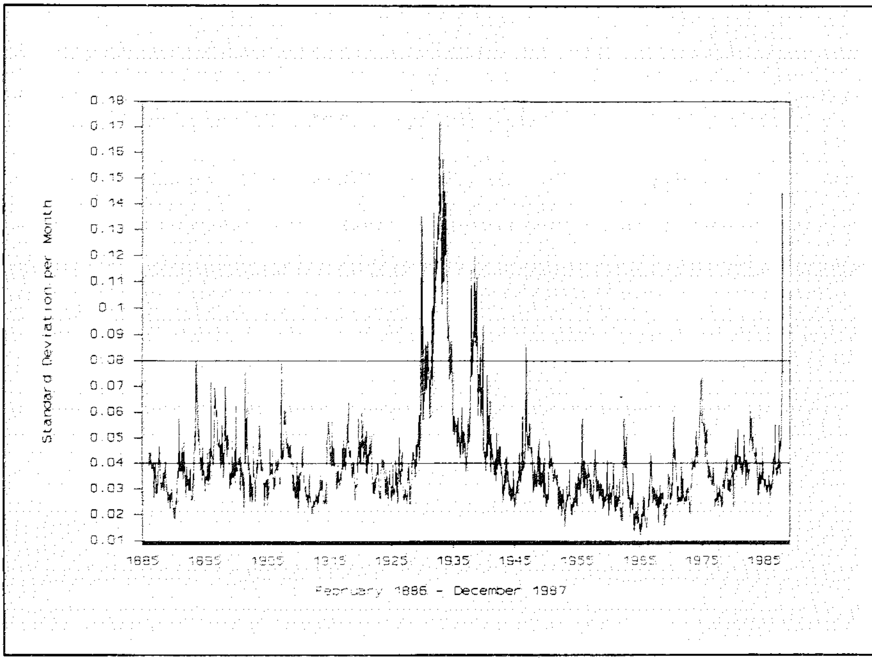

Figure 1 -- Estimates of Monthly Stock Return Volatility from Table 6, 1886-1987

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. 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.[12]

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

The most notable episodes of high volatility are from 1929-1934, 1937-1938, 1946, 1973-1974 and 1987. Officer [1973] and Schwert [1987] have documented that many macroeconomic time series, such as the money growth rate and industrial production, were also more volatile during the Great Depression (1929-1938). Nevertheless, as stressed by Schwert [1987], the increase in macroeconomic volatility is not large enough to explain all of the increase in stock market 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 Tables 1 and 2. Episodes of high stock volatility in the past have occurred in a few brief spans of time. The plot also confirms the analysis of Tables 3, 4b and 5b, that volatility is persistent. Once it rises, it usually remains high for many months. As noted by Schwert [1989], many periods of high volatility correspond to business cycle recessions or crises in the banking system.

4. How Unusual Was the '87 Crash?

4.1 Daily S&P returns

There are many ways to measure the extent to which the October 1987 crash and its aftermath was 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, and

N87 = 1, from November 2-30, 1987, and 0 otherwise,

are used to estimate the effects of the crash on returns and volatility. Table 7 contains estimates and t-statistics for the dummy variable coefficients. The autoregressive model for returns predicts that the 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 7 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,

Table 7 -- Effects of the Crash of 1987: Estimates of Differential Intercepts in Autoregressive Models for Daily Stock Returns and Volatility, Eq. (3) and (4), (using 22 lags and iterative weighted least squares)

	October, 1987	*November, 1987*	*Joint F-test*
Effect on Returns, R_t			
Coefficient	.0213	-.0079	18.31
(t-statistic/p-value)	(4.63)	(-3.97)	(.0000)
Effect on Volatility, $\|u_t\|$			
Coefficient	-.0108	-.0051	23.06
(t-statistic/p-value)	(-5.52)	(-3.43)	(.0000)

Note: The models in equations (4) (for daily stock returns) and (3) (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 coefficient estimates in Tables 4a and 4b are not reported because they are similar. The dummy variable coefficient estimates and their Hansen [1982] t-statistics are reported here. 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 4a and 4b for more information.

1987. Both of these coefficient estimates have t-statistics near 4 in absolute value. Since the October dummy variable equals 1 for 9 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 4b, the large drop in stock prices on October 19 predicts future volatility to be much higher. The estimates of the October and November coefficients for stock volatility are both negative and several standard errors below 0. Thus, 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 4a and 4b. In essence, the stock market returned to relatively normal levels of volatility quickly at the end of 1987.

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 4b, $|u_t|$, for the 10 most negative daily stock returns in Table 1 (excluding October 19, 1987) for 66 days (about 3 months) before and after these 'crashes.' It also plots $|u_t|$ for the October 19, 1987 crash. All of these values are expressed in units of monthly standard deviations (i.e., they are multiplied by $(253/12)^{½}$).

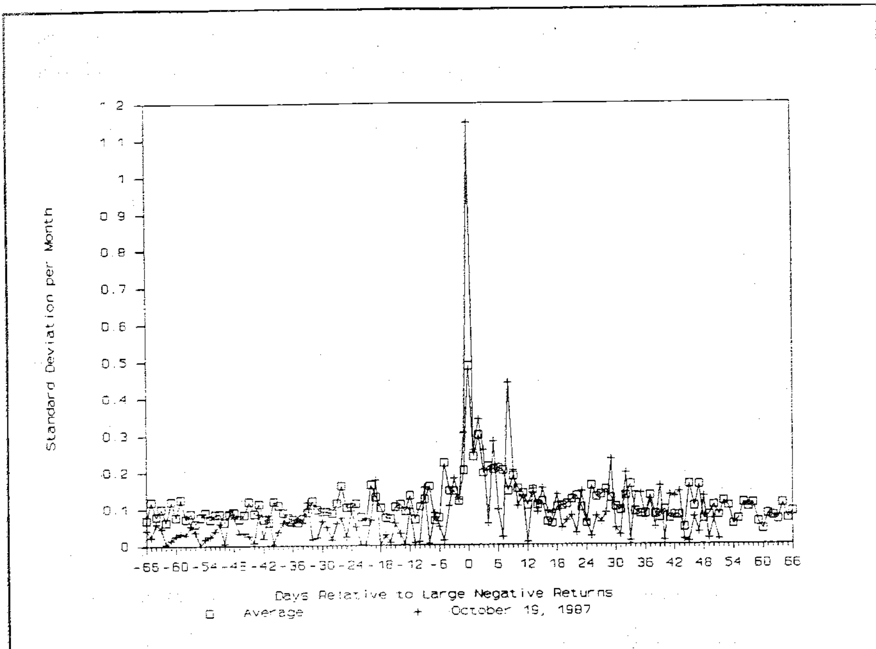

Figure 2 -- Average Standard Deviation of Daily Stock Returns Around Crashes, Relative to the Behavior Around the October 19, 1987 Crash, (expressed in units of monthly standard deviations)

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 seems 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 from equation (3) in Table 4b. 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 to pre-crash levels, stock volatility rose and fell faster around October 19 than the evidence from the next largest 10 crashes would imply.

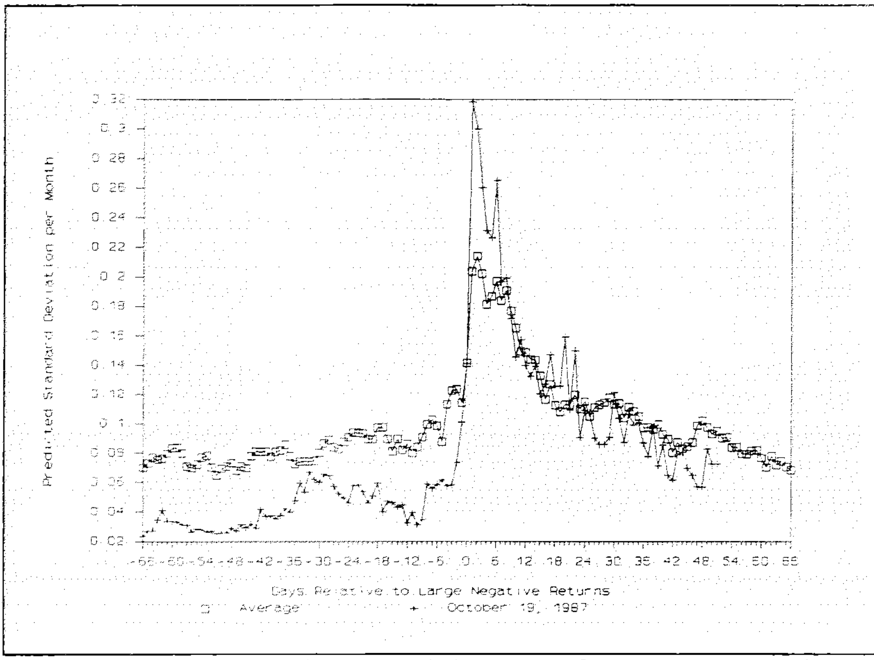

Figure 3 -- Average Predicted Standard Deviation of Daily Stock Returns Around Crashes, Relative to the Behavior Around the October 19, 1987 Crash, (expressed in units of monthly standard deviations)

Together, Figures 2 and 3 confirm the evidence in Table 7. Stock volatility fell faster after the October 19, 1987 crash than either the model in Table 4b, 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.

4.2 Implied Volatility from the Options Market

Figure 4 plots the implied volatility from call options on the S&P 500 portfolio. I got daily option prices from the Dow Jones News Retrieval Service from April 1987 - December 1988. I use Merton's [1973] option pricing model for stocks paying continuous dividends to solve for the level

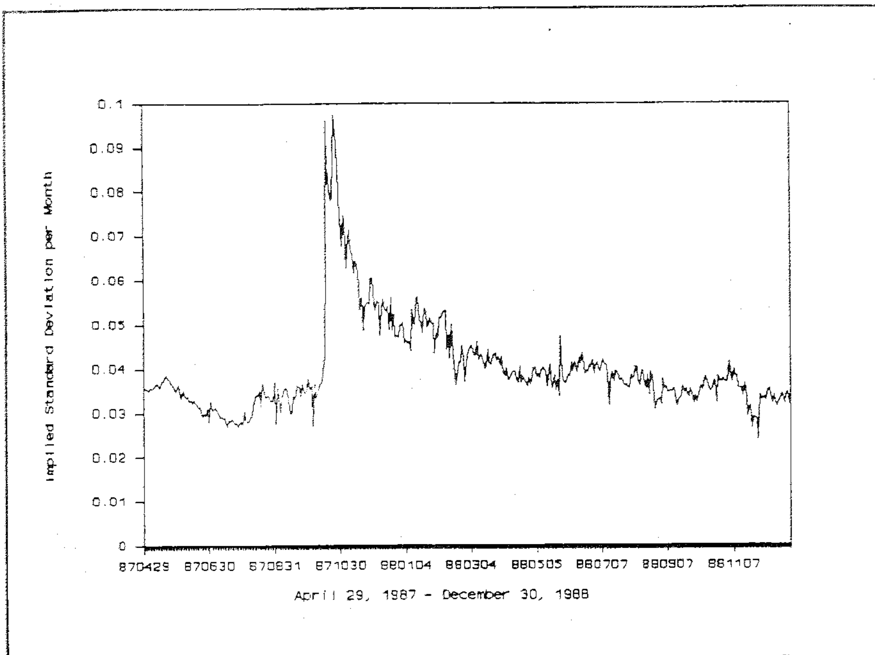

Figure 4 -- Implied Monthly Standard Deviation of Standard & Poor's 500 Portfolio from Daily Call Option Prices, April 1987 - December 1988

of stock return volatility that is consistent with the option prices.[13] I use the option whose exercise price is closest to the current stock price 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.[14]

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

[14]Day and Lewis [1988]. 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.

Several things are clear from this graph. First, option traders' perceptions of stock volatility did not rise until October 19, and they remained high for the next couple of months. The implied standard deviation rose from less than .04 per month to over .09 per month on the 19th. It decayed back down to its pre-crash level by March 1988 and remained at that level throughout 1988.

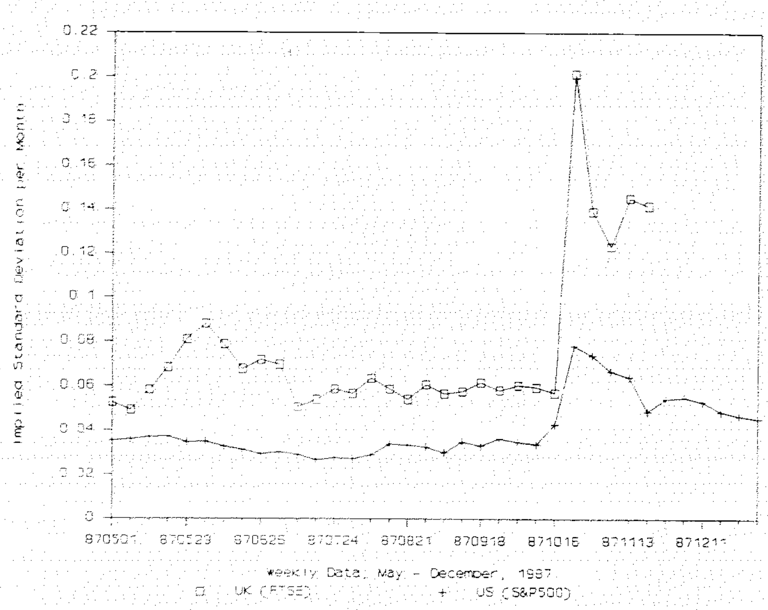

Figure 5 -- Comparison of Implied Market Standard Deviations from Weekly U.S. and U.K. Call Option Prices, 1987

Figure 5 compares implied standard deviations from call options on the S&P portfolio with the implied standard deviations from call options on the Financial Times Stock Exchange portfolio (FTSE) from Franks and Schwartz [1988, Table 1]. Franks and Schwartz use weekly data from May 1984 through November 1987. While the volatility of British stock returns is higher than for the S&P returns, the time pattern is the same. Implied standard deviations almost tripled from the week ended October 16 to the week of the crash. Volatility declined faster in the U.S. than in the U.K.

during the remainder of October and November.

4.3 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.[15] 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 this 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 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 6 plots three estimates of the volatility of the S&P portfolio: (i) the standard deviation estimated from the most recent 21 daily (high-low) spreads for the S&P portfolio; (ii) the standard

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[15]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.

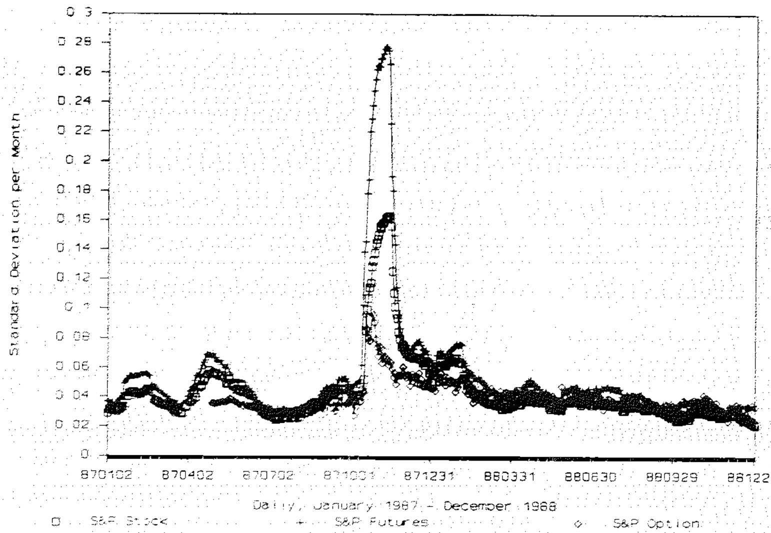

Figure 6 -- Estimates of Standard Deviations from Daily S&P Stock Prices, Futures Prices and Call Option Prices, 1987-88 (Stock and futures prices use spreads $\ell n(H_t/L_t)$)

deviation estimated from the most recent 21 S&P futures (high-low) spreads; and (iii) the implied standard deviation from the S&P call options, for 1987-1988.[16] It is clear from this plot that the volatility estimates from 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

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

$$\hat{\sigma}_t^2 = .393 \{ \sum_{i=1}^{21} \ell n(H_{t-i}/L_{t-i})/21 \}^2$$

where $\ell n(H_t/L_t)$ is the percentage (high-low) spread on day t.

January 1988, the three measures of stock market volatility are similar. All three measures show that stock volatility returned to pre-crash levels by early 1988 and remained low throughout the remainder of 1988.

5. Conclusions

The stock market crash of October 19, 1987 has already been studied under a variety of microscopes. This paper 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 28,000 observations, it was also unusual in that stock market volatility returned to low pre-crash 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 November 30, 1987. Second, compared with the next 10 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 pre-crash levels by early 1988 and remained low. These data are only available for the last 6 years, so they cannot be used to study prior crashes. Nevertheless, they provide more accurate estimates of volatility than the methods using daily stock returns. When they are available, they corroborate the conclusions from the much larger sample of stock returns. Moreover, data from option prices on British stocks have the same pattern of stock volatility.

This paper 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 [1987, 1989] shows that stock volatility was higher during recessions and around the major banking panics in the 19^{th} and early 20^{th} centuries. In part, this is an example of the asymmetry in the return-volatility relation. Negative returns lead to larger increases in volatility than 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 volatility plots in this paper can be thought of like an electrocardiogram (ECG). 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 [1987]), they provide information about the health of the economy.

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