NBER WORKING PAPER SERIES

BUSINESS CYCLES, FINANCIAL CRISES AND STOCK VOLATILITY

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Working Paper No. 2957

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 1989

Ben Bernanke, Michael Bordo, Marie Davidian, Franklin Edwards, Michael Gibbons, Jim Hamilton, Gikas Hardouvelis, Charles Nelson, Adrian Pagan, Jim Poterba, Anna Schwartz, Paul Seguin, Robert Schiller, Jack Wilson, and Dennis Sheehan, the referee, provided useful suggestions. The Bradley Policy Research Center at the University of Rochester provided support for this research. This paper is part of NBER's research program in Financial Markets and Monetary Economics. Any opinions expressed are those of the author not those of the National Bureau of Economic Research.

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ABSTRACT

This paper shows that stock volatility increases during recessions and financial crises from 1834-1987. The evidence reinforces the notion that stock prices are an important business cycle indicator. Using two different statistical models for stock volatility, I show that volatility increases after major financial crises. Moreover, stock volatility decreases and stock prices rise before the Fed increases margin requirements. Thus, there is little reason to believe that public policies can control stock volatility. The evidence supports the observation by Black [1976] that stock volatility increases after stock prices fall.

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Introduction

The stock market 'crash' in October 1987 raised considerable concern about the stability of financial institutions and the future of the economy. Not only did broad indexes of stock prices around the world fall about 20 percent on October 19, but for many weeks afterward stock volatility remained at very high levels. As we now know, United States financial institutions survived with very few problems (perhaps due to the calm reaction of government and private institutions). The economy has not entered a major recession. In addition, stock volatility returned to much lower levels by December 1987.[1]

There has been a plethora of research trying to explain the October 1987 crash, including reports from several government and financial industry-sponsored commissions. This paper will not report additional facts about the recent crash. Instead, it documents the relations between business cycles, financial crises and stock volatility in the U.S. from 1834 through 1987. This period covers the entire history of the United States as an industrialized economy. Thus, it provides an exhaustive record of the evidence available to judge whether the October 1987 crash was anomalous. The evidence shows that stock volatility increases after stock prices fall, it increases during recessions, and it increases around major financial crises. The historical record of 150 years justified the concern about both financial stability and future economic growth following the October 1987 crash. While it is possible that the crash foreshadowed a major recession still in the future, the historical evidence suggests that such a long lag is unlikely.

The notion that economic fluctuations have larger amplitude in bad times is not new. Many authors have noted that economic time series behave differently during recessions than expansions. Hamilton [1989] models quarterly real GNP using processes that reflect regime-switching. Stambaugh [1988] shows that the term structure of interest rates behaves differently in expansions and recessions. Schwert [1988] shows that the standard deviation of both stock returns and industrial production growth are higher during recessions than during expansions. He also shows that increases in aggregate financial leverage cannot explain the increase in stock volatility during recessions.

Financial institutions provide one reason that the economy might behave differently in recessions versus expansions. Bernanke [1983], extending the arguments of Friedman and Schwartz [1963], argues that defaults of financial intermediaries play an important role in major recessions. They have permanent negative effects on the long-run growth path of the economy. Gorton [1987] shows that bank failures and financial crises are associated with increased risk. This paper will provide further evidence that crises in financial institutions are linked to economic activity. It is difficult, however, to show that financial crises effect real activity.

Section 2 summarizes the major theoretical arguments linking stock volatility with macroeconomic behavior. Section 3 contains estimates of a linear autoregressive model for both conditional means and standard deviations of stock returns. It also uses Hamilton's [1988, 1989] nonlinear regime switching algorithm to model stock returns. Both of these methods show that stock volatility was noticeably higher during 19^{th} century financial crises, during the post-World War I recession, during the 1929-1934 and 1937-1938 depressions, and during the 1973-1974 OPEC recession. Section 4 contains a brief history of the major financial crises in the 19^{th} and 20^{th} centuries in the United States, and shows how stock volatility behaved during these episodes. Section 5 estimates the relation between stock volatility and margin requirements set by the Federal Reserve Board. Section 6 summarizes the empirical results and relates these findings to policy debates following the October 1987 stock market crash.

Volatility, Crises and Recessions

There are several theories about the relation between stock volatility and macroeconomic behavior. The most controversial, advocated by Shiller [1981a,b,1984] and Summers [1986], is that random or sociological factors have large effects on stock volatility. From this perspective, stock volatility has adverse effects on the economy when rational investors bear unnecessary risk. It is not clear how stock volatility would affect other macroeconomic variables. It is also unclear, however, why such "sociological behavior" would only affect financial asset markets and not capital, labor, or consumption goods markets.[2]

An alternative theory posits that the stock market discounts expected future events into current prices. Thus, the volatility of stock returns reflects uncertainty about future cash flows and discount rates, or uncertainty about the process generating future cash flows and discount rates. From this perspective, stock prices reflect increased uncertainty about the future course of the economy, which shows up later in the realized growth rates of nonfinancial macroeconomic variables such as the money supply, consumption and investment. This rational expectations/efficient markets approach implies that time-varying stock volatility (conditional heteroskedasticity) provides important information about future macroeconomic behavior.

The relation between stock prices and future economic growth has been recognized for many years. It is more complicated, however, to relate conditional heteroskedasticity of stock returns to future economic behavior. Consider the present value model,

$$P_t = \sum_{i=1}^{\infty} \frac{E(D_{t+i})}{[1+r_{t+i}]^i}, \tag{1}$$

where $E(D_{t+i})$ is the cash flow to stockholders expected in period t+i, r_{t+i} is the discount rate and P_t is the stock price, all conditional on information available at time t. Assuming that discount rates are constant over time, stock prices are a fixed linear combination of future expected cash flows. If cash flows follow a first order autoregressive process,

$$(D_t - \mu_d) = \phi\,(D_{t-1} - \mu_d) + u_t, \tag{2}$$

where μ_d is the long-run expected cash flow, then the stock price is

$$P_t = (\mu_d / r) + ([\phi (D_t - \mu_d)] / [1+r-\phi]) , \tag{3}$$

and the variance of the stock price is

$$Var(P_t) = Var(u_t) \phi^2 / [(1+r)^2 - \phi^2]. \tag{4}$$

The variance of the rate of return to the stock, $R_t = (P_t - P_{t-1} + D_t)/P_{t-1}$, is inversely related to the level of stock prices P_t.

These relations do not provide a realistic model for stock prices or dividends.[3] Rather, they illustrate that the conditional variance of prices $Var(P_t)$ is proportional to the conditional variance of cash flows $Var(u_t)$ if cash flows follow a constant parameter ARMA process, and if discount rates are constant over time. In this model, $Var(P_t)$ changes more than $Var(u_t)$ if either (a) the persistence parameter ϕ increases, or (b) the discount rate r falls.

Schwert [1988] concludes that stock return volatility increased too much during the Great Depression to be explained by increases in the volatility of variables that reflect future cash flows. One interpretation is that discount rates changed during the Depression, or that the stochastic process perceived to be generating future cash flows changed. Hamilton's [1989] evidence that recessions typically have shorter duration than expansions predicts that cash flow persistence should decrease during recessions. French, Schwert and Stambaugh's [1987] study of expected risk premiums on stocks shows that discount rates increased with volatility during the Depression. Also, the Fama and French [1988] analysis of the relation between dividend yields and expected stock returns implies that discount rates rise when yields are high. Thus, the empirical evidence for changing persistence or changing discount rates does not help explain the behavior of stock volatility during the Depression using the model in (4).

Of course, alternative specifications of the dividend process (2), or of the process for discount rates, would produce different implications for the relation between conditional volatility of stock prices (returns) and the volatility of cash flows (growth rates). The important point is that stock volatility reflects aggregate uncertainty about future payoffs and discount rates. These factors are important determinants of many macroeconomic variables, including consumption, investment, and employment.

Bernanke [1983] argues that financial crises cause economic losses that exacerbate recessions. In essence, there are large bankruptcy costs associated with failures of financial institutions. It is not possible to eliminate these costs because of the asymmetry of information between banks and depositors about the quality of the bank's loan portfolio (also see Diamond and Dybvig [1983]). Thus, financial crises would lead to high stock volatility because the chance of large permanent losses increases. Of course, exogenous stock volatility could increase the likelihood of a financial crisis. Nevertheless, crises would induce further volatility because of the associated bankruptcy costs.

Gorton [1987] shows that consumers would rationally increase their demand for liquidity as they perceive that a recession is imminent. When consumers expect a recession, they understand that banks suffer larger losses on their loan portfolios. They also expect that consumption will be lower, so the risk of bank deposits increases before recessions. Because banks have better information about the quality of their loan portfolios than depositors, they cannot credibly increase the rate of return on deposits to pay for the increased risk. Instead, they use alternative mechanisms, such as suspension of convertibility of deposits into currency, to avoid insolvency (see Gorton [1985]). Gorton's [1987] evidence suggests that business failures are a leading indicator for both risk and financial crises. He concludes that crises often precede recessions. They occur when business failures and perceived risk reach critically high levels from 1865-1914 in the U.S. Gorton's analysis of risk uses estimates of the covariance of pig iron production with depositor losses. The evidence in this paper using monthly stock volatility data will enhance understanding of the dynamic relations among risk, business cycles and financial crises.

DeLong and Summers [1986] show that the variance of real GNP was not much higher during the financial panics from 1890-1913 than during non-panic periods. They note that money growth was much more variable in the panic periods, and conclude that the private credit system was able to prevent the financial panics from having large effects on real activity.

Miron [1986] states that a desire to curb stock market speculation led the Federal Reserve Board to restrict credit following the death of Benjamin Strong (the governor of the New York Fed) in October 1928. He argues that this restrictive credit policy exacerbated the severity of the 1929-1933 recession. Hardouvelis [1988] says that increases in margin requirements by the Fed since October 1934 have reduced stock volatility (and decreases in margin requirements have increased volatility). This conclusion differs from Officer's [1973] analysis of the same question. If Federal Reserve policy can curb 'excess' stock volatility of the type discussed by Shiller and Summers, it would increase economic welfare. On the other hand, if the Federal Reserve adjusts its credit policy in response to stock volatility, and this has adverse effects on other sectors of the economy, it would reduce welfare. This question is analyzed empirically in Section 5.

Thus, there are many reasons to believe that stock volatility will change over time, and that it is related to business cycles and financial crises. The problem of assigning causality is particularly difficult here. Exogenous 'sociological' stock volatility could cause bank runs if depositors worry that defaults on stock market related loans will rise (or if the Fed adjusts its credit policies to respond to the volatility). Alternatively, stock volatility could simply reflect the present discounted uncertainty about future economic growth. In both cases, stock volatility would precede or coincide with bank failures, recessions, and crises.

Statistical Models for Stock Volatility

It is useful to characterize 'normal' behavior of stock volatility before analyzing unusual volatility associated with crises and recessions. This section presents two methods of modeling volatility. The first is from Schwert [1988], who relates stock volatility to the volatility of many macroeconomic series. It is a two-step autoregressive filter for both the conditional mean and the conditional standard deviation. The second is an extension of Hamilton's [1988, 1989] nonlinear Markov filter applied to stock returns. It assumes that stock returns are generated by one of two regimes with different means and variances. It yields estimates of the means and variances of the regimes, along with the probabilities of remaining in a given regime. Both methods identify periods when stock returns were unusually volatile. Later sections of the paper relate these high volatility periods to crises and recessions.

Autoregressive Models for Conditional Means and Standard Deviations

Schwert [1988] uses monthly return data for a large portfolio of common stocks from 1857 through 1986 to measure the behavior of the standard deviation of stock returns through time. He uses the following procedure to estimate the conditional standard deviation of stock returns:

(i) estimate a 12^{th} order autoregression for the returns, including dummy variables D_{jt} to allow for different monthly mean returns, using all data available for the series,

$$R_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{i=1}^{12} \beta_i R_{t-i} + \epsilon_t, \qquad (5a)$$

(ii) estimate a 12^{th} order autoregression for the absolute values of the residuals from (5a), including dummy variables to allow for different average monthly standard deviations,

$$|\hat{\epsilon}_t| = \sum_{j=1}^{12} \gamma_j D_{jt} + \sum_{i=1}^{12} \rho_i |\hat{\epsilon}_{t-i}| + u_t, \qquad (5b)$$

(iii) the regressand $|\hat{\varepsilon}_t|$ is an estimate of the standard deviation of the stock return for month t, σ_t (using just 1 observation). The fitted values from (5b) estimate the conditional standard deviation of R_t, given information available before month t.[4]

This method is a generalization of the 12-month rolling standard deviation estimator used by Officer [1973], Fama [1976], Merton [1980] and others. It allows the conditional mean return to vary over time in (5a), and it allows different weights for lagged absolute unexpected returns in (5b). It is similar to the autoregressive conditional heteroskedasticity (ARCH) model of Engle [1982]. Davidian and Carroll [1987] argue that standard deviation specifications such as (5b) are more robust than variance specifications based on $\hat{\varepsilon}_t^2$. Following their suggestion, I iterate twice between (5a) and (5b), using the predicted values from (5b) to create weighted least squares (WLS) estimates of (5a). Experiments with further iteration produced only small changes in the parameter values and standard errors.

Table 1 contains the estimates of (5b) from 1836-1987, along with diagnostic tests for the adequacy of the model specification. The stock return data are from Smith and Cole [1935] for 1834-1856, from Macaulay [1938] for 1857-1870, from Cowles [1939] for 1871-1925. and from the Center for Research in Security Prices (CRSP) at the University of Chicago for 1926-1987. The data begin in 1834 because that is the first year when many railroad stocks were actively traded.[5] The Smith and Cole data represent all of the actively traded railroad, bank and insurance stocks for that period. The Smith and Cole and Macaulay series do not include dividends, so I added the average monthly dividend yield from the Cowles series from 1871-1879 to calculate the returns from 1834-1870. This does not affect the variation of these series, but it does raise the mean return by about 6 percent per year during this period.

There are measurement problems with the older stock return series. For example, the Cowles returns are based on the average of the high and low prices for each stock within a

Table 1 -- Estimates of the Autoregressive Model for Stock Volatility $|\hat{\epsilon}_t|$, Eq.(5b)

Monthly Data, 1836-1987, T=1824

Parameter	Estimate	Std Error	T-statistic
ρ_1	.1540	.0462	3.33
ρ_2	.0916	.0384	2.38
ρ_3	.1105	.0408	2.71
ρ_4	.0063	.0336	.19
ρ_5	.0483	.0328	1.47
ρ_6	.0005	.0326	.02
ρ_7	.0404	.0323	1.25
ρ_8	.0666	.0497	1.34
ρ_9	.1521	.0479	3.18
ρ_{10}	-.0068	.0464	-.15
ρ_{11}	.0694	.0426	1.63
ρ_{12}	.0189	.0333	.57
Sum of AR coefficients and unit root test	.7518	.0888	2.79
F-test for equal monthly intercepts and its p-value	2.42	.0052	
Box-Pierce test of residual autocorrelation for 24 lags and its p-value	25.2	.0138	
Coefficient of Determination	.195		

Note: Asymptotic standard errors, t and F-tests use White's [1980] correction for heteroskedasticity. The unit root test is a Dickey-Fuller test (see Fuller [1976]). The Box-Pierce [1970] test should be distributed as χ^2 with 12 degrees of freedom.

month. This is similar to the time-averaging effect analyzed by Working [1960]. It creates artificial first order autocorrelation of returns and lowers the variance of returns by about 20 percent (e.g., see Wilson, Sylla and Jones [1988]). Smith and Cole and Macaulay use point-sampled prices, although it is not clear when during the month the prices were available. The CRSP returns are based on end-of-month point-sampled prices. All of these series represent the broadest available coverage of stock prices. While the stock market certainly grew over this 150 year period, so did the economy. The industries represented by publicly traded stocks in the 19th century were the major large corporations at that time. Schwert [1988] shows that the size and industrial diversification of this 'market portfolio' does not explain important movements in stock volatility over time.

The monthly dummy variable coefficients are not shown, but the F-test for equality of monthly intercepts, $\gamma_1=...=\gamma_{12}$, is 2.42, with a p-value of .005, showing there is seasonal variation in stock volatility. The sum of the autoregressive coefficients, $\rho_1+...+\rho_{12}$, equals .752, with an asymptotic standard error of .089, showing there is a high degree of persistence in stock return volatility. Once volatility increases, (5b) predicts that it would remain high for many future periods. Schwert [1987, 1989a] argues that this test understates the persistence in stock volatility for at least two reasons (also see Pagan and Ullah [1988]). First, estimates of autoregressive parameters are biased toward zero in finite samples. Second, and more important in this situation, the absolute residuals from (5a) $|\hat{\epsilon}_t|$ measure current volatility with error. Each value of $|\hat{\epsilon}_t|$ is an estimate of the true unobserved standard deviation σ_t based on a single data point, so there is large sampling error in $|\hat{\epsilon}_t|$. This is a classic errors-in-variables problem if the autoregressive process in (5b) has constant parameters. The sum of the autoregressive parameters in (5b) will be biased towards zero, even in large finite samples.[6] Schwert [1987, 1989a] shows that the bias is large even for large samples (over 1,000 observations) in situations such as this where the measurement error is large. From this perspective, the coefficient of determination $R^2=.19$ is strong evidence that stock return volatility is persistent over time. The Box-Pierce statistic for 24 lags of the residual autocorrelations from (5b) is 25.2, with a p-value of .014 from a χ^2 distribution with 12 degrees of freedom.[7] This suggests there may be additional autocorrelation in stock volatility that is not captured by the AR(12) model in (5b), although the autocorrelations are small.[8]

Table 2 contains several tests based on the standardized errors, $\hat{\epsilon}_t/\hat{\sigma}_t$, the ratio of the residual from (5a) to the fitted value from (5b). The skewness coefficient is -.14 and the kurtosis coefficient is .91. While the p-values for these statistics are small, the comparable statistics for the raw stock returns are .24 and 8.73. The studentized range (SR) statistic

Table 2 -- Tests for Normality and Independence of the Standardized Errors from (5a)-(5b), $\hat{\epsilon}_t/|\hat{\epsilon}_t|$

Tests	Test Statistic	P-value
Skewness	-.137	.0173
Excess Kurtosis	.913	<.0001
Studentized Range	8.10	.010
Box-Pierce test for residual autocorrelation for 24 lags	20.8	.054
Brock-Dechert-Scheinkman Test for Independence	-.36	.719

Note: All tests are based on the errors from (5a), standardized by reciprocals of the fitted values from (5b). David, Hartley and Pearson [1954] describe the studentized range statistic. Brock, Dechert and Scheinkman [1987] develop the BDS test.

(David, Hartley and Pearson [1954]) is 8.10, which is not strong evidence against a stationary normal distribution (SR is 14.60 for the raw stock returns.) Thus, the two-step filter in (5a)-(5b) reduces the excess kurtosis typically found in stock return data.

The negative skewness in the standardized errors is similar to that found by French, Schwert and Stambaugh [1987] when analyzing errors from a generalized autoregressive conditional heteroskedasticity in mean (GARCH-M) model for daily returns to the Standard & Poor's composite portfolio of stocks from 1928-1984. They argue that this nonnormality of the standardized errors has an important effect on the estimate of the relation between the conditional mean return and the conditional variance, although the estimates of the conditional variance are not affected by this specification error. The Box-Pierce statistic for 24 lags of the standardized errors is 20.8, with a p-value of .054. The Brock, Dechert and Scheinkman [1987] test for independent and identically distributed (i.i.d.) errors is designed to detect a variety of forms of nonlinear dependence. I calculated several versions of this test varying ξ (the spread parameter) and m (the dimension parameter). Table 2 contains the BDS statistic for ξ=1 standard deviation and m=6. The statistic is -.36, which should have an asymptotic normal distribution. Based on Monte Carlo experiments by Hsieh and LeBaron [1988a,b], a BDS statistic of -.36 with a sample size over 1,000 represents strong evidence for the i.i.d. null hypothesis. Thus, the model in equations (5a)-(5b) seems to fit the stock return data well.

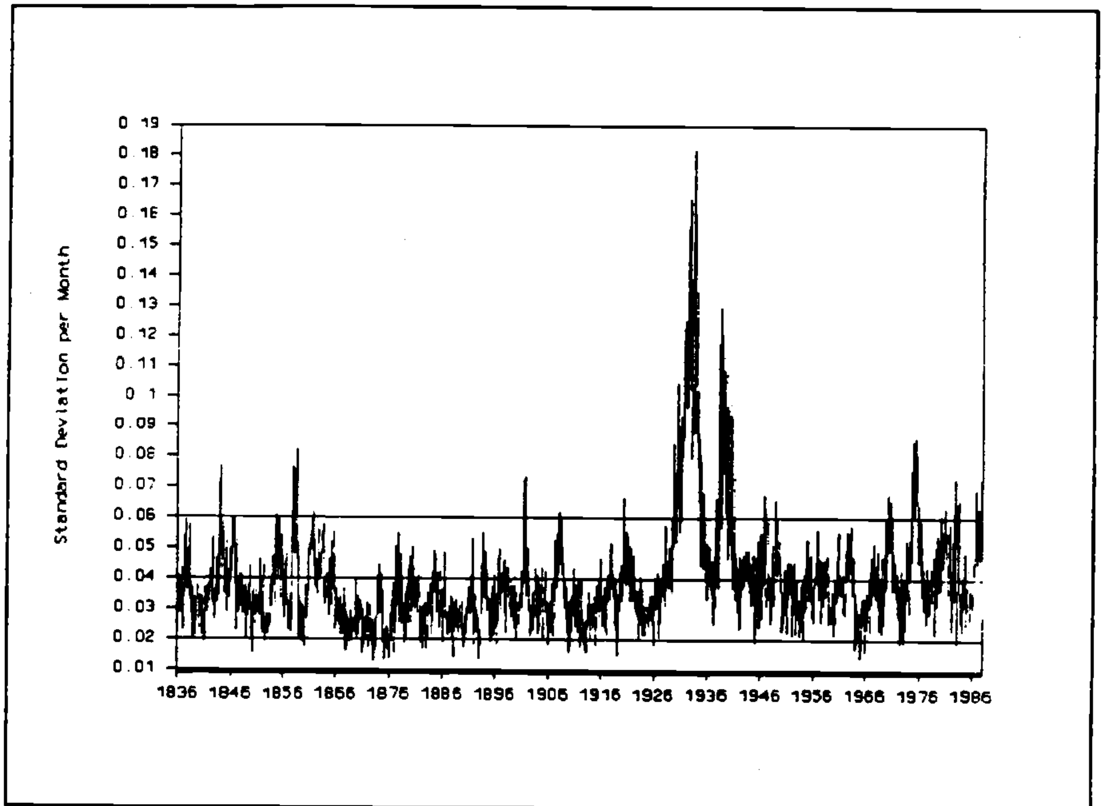

Figure 1 -- Conditional Standard Deviations of Monthly Stock Returns, 1836-1987 (Fitted Values from Estimate of Equation (5b))

Figure 1 shows estimates of conditional stock return volatility (the fitted values from (5b)) for 1836-1987. Stock volatility was in the range from 2 to 6 percent per month from 1836-1928 and from 1940-1987. During the Great Depression from 1929-1939 stock volatility was much higher, often above 10 percent per month. There are some periods when stock volatility increased temporarily, including the 1857 and 1907 recessions and the 1973-1974 OPEC oil crisis.

Before considering the role of financial crises in explaining the time series behavior of stock volatility, I will consider an alternative method for modeling stock return behavior.

It does not impose a linear structure such as (5a)-(5b), so it is capable of representing more complex types of time series behavior.

State-dependent Behavior of Stock Returns

Hamilton [1989] proposes a switching-regime Markov model for GNP growth rates as a model for recessions and expansions. Briefly, consider a variable y_t that follows the stochastic process,

$$\begin{aligned} y_t - \mu(S_t) = \phi_1 [y_{t-1} - \mu(S_{t-1})] + \phi_2 [y_{t-2} - \mu(S_{t-2})] + \\ \ldots + \phi_m [y_{t-m} - \mu(S_{t-m})] + \sigma(S_t)v_t \end{aligned} \tag{6}$$

where v_t is NID(0,1) and the autoregressive polynomial $\phi(L) = (1 - \phi_1 L - \ldots - \phi_m L^m)$ has roots outside the unit circle. This is an m^{th} order autoregressive (AR(m)) model, except that the mean, $\mu(S_t)$, and the residual standard deviation, $\sigma(S_t)$, are a function of the 'regime' in period t. The regimes are assumed to follow a two-state first order Markov process,

$$\begin{aligned} P(S_t=1 \mid S_{t-1}=1) &= p \\ P(S_t=0 \mid S_{t-1}=1) &= 1-p \\ P(S_t=1 \mid S_{t-1}=0) &= 1-q \\ P(S_t=0 \mid S_{t-1}=0) &= q, \end{aligned} \tag{7}$$

and the parameters of (6) are modeled as,

$$\begin{aligned} \mu(S_t) &= \alpha_0 + \alpha_1 S_t \\ \sigma(S_t) &= \omega_0 + \omega_1 S_t. \end{aligned} \tag{8}$$

Finally, the errors v_t are assumed to be independent of all S_{t-j}. Given this structure, it is straightforward to use numerical procedures to maximize the likelihood as a function of the parameters $\{\phi_1,..,\phi_m,p,q,\alpha_0,\alpha_1,\omega_0,\omega_1\}$.[9] In addition to point estimates and asymptotic standard errors, Hamilton's algorithm estimates the probability that the variable is in "regime 1" conditional on data available at date t. The unconditional probability of being in regime 1 is

$$P(S_t=1) = \rho = (1-q)/[(1-p)+(1-q)],$$

and the expected future value of the state variable S_{t+j} given information about the current state of the system $S_t=s_t$ is,

$$E(S_{t+j}|S_t=s_t) = \rho + \lambda^j (s_t-\rho) \tag{9}$$

where $\lambda = -1+p+q$. Note also that the conditional variance of y_t is a function of the state variable S_t. If the variable was in regime 1 last period ($S_{t-1}=1$), the variance of the squared forecast error for period t is,

$$E\{\sigma^2(S_t)|S_{t-1}=1\} + Var\{\mu(S_t)|S_{t-1}=1\}$$

$$= [E\{\sigma(S_t)|S_{t-1}=1\}]^2 + Var\{\sigma(S_t)|S_{t-1}=1\} + E\{[\mu(S_t) - E(\mu(S_t)]^2|S_{t-1}=1\}$$

$$= [\omega_0 + \omega_1 p]^2 + \omega_1^2\, p(1-p) + \alpha_1^2\, p(1-p). \tag{10a}$$

If the variable was in regime 0 last period ($S_{t-1}=0$), the variance of the squared forecast error for period t is,

$$E\{\sigma^2(S_t)|S_{t-1}=0\} + Var\{\mu(S_t)|S_{t-1}=0\}$$

$$= [E\{\sigma(S_t)|S_{t-1}=0\}]^2 + Var\{\sigma(S_t)|S_{t-1}=0\} + E\{[\mu(S_t) - E(\mu(S_t)]^2|S_{t-1}=0\}$$

$$= [\omega_0 + \omega_1(1-q)]^2 + \omega_1^2\, q(1-q)+ \alpha_1^2\, q(1-q). \tag{10b}$$

Thus, if the probability of staying in the same regime is high (both p and q are well above .5), the parameter ω_1 plays a large role in determining the conditional variance of the process in (6)-(8). As noted by Hamilton [1989], the Markov process in (7) contributes to the heteroskedasticity of the forecast error from (6) when p and q differ. In essence, uncertainty about the regime in period t given knowledge of the regime in period t-1 (e.g., p or q close to .5) adds uncertainty to the conventional forecast error $\sigma(S_t)v_t$. If p=q=.5, the variance of the forecast error is the same no matter which regime exists in period t-1.

Table 3 contains maximum likelihood estimates of (6)-(8) for a fourth order autoregressive process (AR(4)) for the monthly stock return series from 1834-1987.[10] It is interesting that the regime-switching algorithm seems to identify periods with a higher

Table 3 -- Estimates of Switching Regime Model for Monthly Stock Returns, 1834-1987

Maximum Likelihood Estimates of Hamilton's Two-state Markov Autoregressive Model, Equations (6)-(8)

Parameter	Estimate	Std Error	T-statistic
"Regime 0" Mean, α_0	.0086	.0011	7.97
Incremental "Regime 1" Mean, α_1	-.0122	.0076	-1.60
"Regime 0" Standard Deviation, ω_0	.0319	.0010	31.27
Incremental "Regime 1" Std Dev, ω_1	.0580	.0059	9.85
AR(1) parameter, ϕ_1	.1864	.0244	7.64
AR(2) parameter, ϕ_2	-.0320	.0240	-1.33
AR(3) parameter, ϕ_3	.0022	.0242	0.09
AR(4) parameter, ϕ_4	.0411	.0234	1.76
Probability of remaining in "Regime 0", q	.9810	.0061	160.10
Probability of remaining in "Regime 1", p	.8839	.0313	28.26
Negative log-likelihood	5062.40		

Note: A numerical optimization algorithm was used to find the maximum likelihood estimates of the model parameters. Asymptotic standard errors and the t-statistics are based on the inverse of the negative of the estimated matrix of second derivatives of the likelihood function at the maximum.

standard deviation of returns. The incremental standard deviation, ω_1, is reliably above 0, with an asymptotic t-statistic of 9.8. The incremental mean return, α_1, is -1.12 percent, but the t-statistic is only -1.60. The estimate of mean return in regime 1, $\alpha_0+\alpha_1$, is also negative, but its t-statistic is only -.48. The estimate of the mean return in regime 0 is .86 percent per month with a t-statistic of 7.97.

The estimate of the standard deviation in regime 1, $\omega_0+\omega_1$, is .090, with an asymptotic t-statistic of 14.09. This is almost 3 times higher than the estimate of the standard deviation in regime 0. Thus, the main factor that distinguishes the regimes identified by Hamilton's algorithm is the difference in volatility.

The probabilities of remaining in a given regime are quite high. Conditional on being in the low variance regime in period t, the probability of remaining in that regime in the next period is $q = .98$. If you are in the high variance regime in period t, the probability of remaining in that regime in period t+1 is $p = .88$. Both of these estimates are more than 3 standard errors from 1 using conventional t-tests, although the reliability of such tests against values on the boundaries of the admissible parameter space is questionable.[11] The unconditional probability of being in the high variance regime is $\rho = .141$, and the decay parameter for the switching process in (9) is $\lambda = .86$. Thus, the high variance regime represents a small proportion of the overall 1834-1987 sample. Once in it, however, there is a high likelihood that it will persist. The expected duration of high variance episodes is $(1-p)^{-1} = 8.6$ months, while the expected duration of the low variance episodes is $(1-q)^{-1} = 52.7$ months. The asymptotic t-statistic for the hypothesis that $p = q$ is -3.35, so these estimates of duration are reliably different.

Figure 2 plots the estimates of conditional standard deviation of returns from the model in (6)-(8).[12] There were several short episodes of high volatility in the 19th century, including 1837, 1843, 1847, 1857, the Civil War period 1862-1865, 1873 and 1893. During the 20th century, episodes of high volatility occurred in 1907, 1919-1920, and virtually the entire 1929-1934 and 1937-1938 periods and 1973-74. Also, there seem to be several periods of high volatility in the post-1973 period.

Summary of the Evidence on Conditional Stock Volatility

The alternative statistical models provide similar pictures of stock volatility. The major difference between them occurs during the Great Depression. One limitation of Hamilton's model in (6)-(8) is that it only allows two regimes. In Figure 1, stock return volatility is much higher during the Great Depression than during other parts of the sample. The two-state model underlying Figure 2 forces all "high volatility" periods to have the same

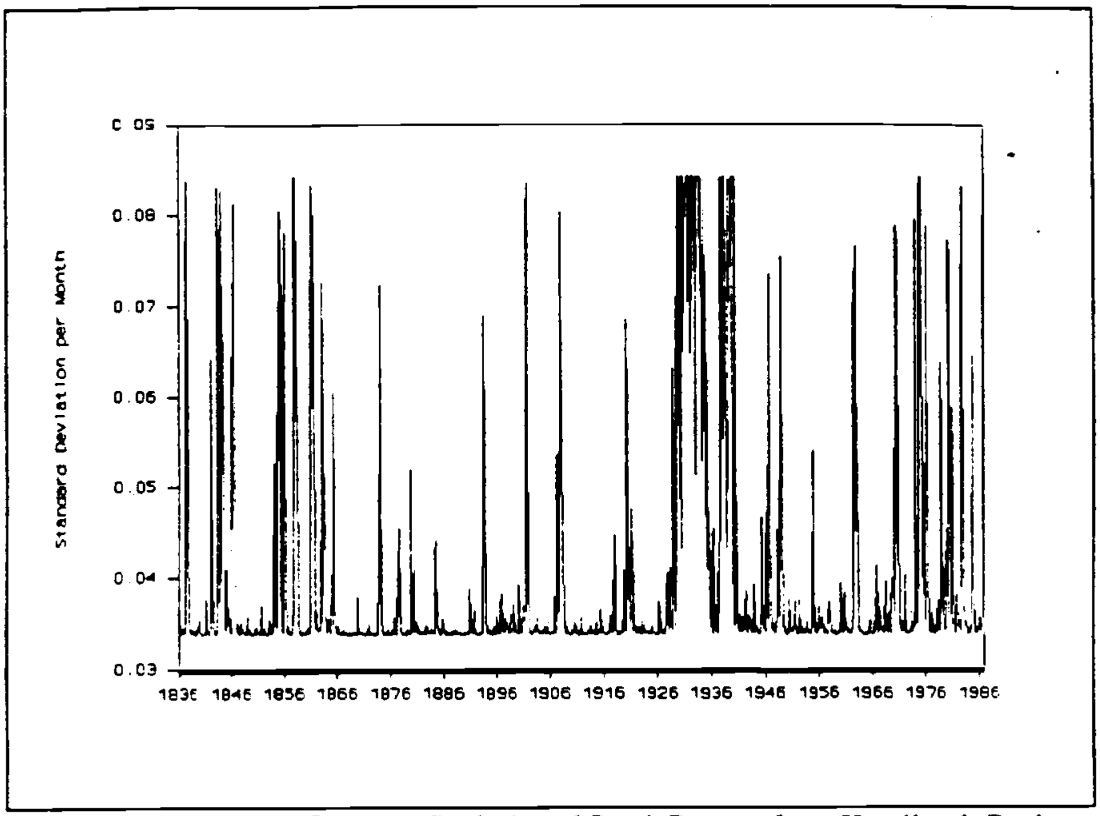

Figure 2 -- Conditional Standard Deviation of Stock Returns from Hamilton's Regime-switching Model, 1836 - 1987

distribution. While it is possible to generalize the Markov model to allow for more states, or to allow the process in (6) to include autoregressive conditional heteroskedasticity (ARCH), these extensions involve much more complicated computational procedures. I suspect that the benefits from such extensions would not exceed the costs.

To compare the ability of the two models to explain the behavior of stock returns, I follow a strategy suggested by Hamilton [1989]. Define a variable S_{t-1} as the estimate of the probability of being in the high variance regime in period t-1, based on information available in period t-1. Then add S_{t-1} as an additional regressor to both equations (5a) and (5b). The t-tests for these regression coefficients tell whether the estimate of the regime probability adds incremental explanatory power. The t-test for the mean equation (5a) is 1.20, and the t-test for the volatility equation (5b) is 1.05. Thus, there is weak evidence that the Markov regime-switching model adds information to the autoregressive models in (5a) and (5b).

A Brief History of Panics and Recessions, 1854-1987

N.B.E.R. Recessions

Table 4 -- Dates and Descriptions of N.B.E.R. Recessions, 1854-1987

Dates	Description	Dates	Description
July,1857-December,1858		September,1918-March,1919	mild
November,1860-June,1861		February,1920-July,1921	severe
May,1865-December,1867		June,1923-July,1924	mild
July,1869-December,1870		November,1926-November,1927	mild
November,1873-March,1879	severe	September,1929-March,1933	severe
April,1882-May,1885	mild	June,1937-June,1938	severe
April,1887-April,1888	mild	March,1945-October,1945	mild
August,1890-May,1891	mild	December,1948-October,1949	mild
February,1893-June,1894	severe	August,1953-May,1954	mild
January,1896-June,1897	mild	September,1957-April,1958	mild
July,1899-December,1900	mild	May,1960-February,1961	mild
October,1902-August,1904	mild	January,1970-November,1970	
June,1907-June,1908	severe	December,1973-March,1975	
February,1910-January,1912	mild	February,1980-July,1980	
February,1913-December,1914	mild	August,1981-November,1982	

Table 4 contains a list of recessions as determined by the National Bureau of Economic Research (N.B.E.R.) from 1854 through 1987, along with a brief description of the severity of the economic contraction. The descriptions of severity are from Friedman and Schwartz [1963], so they are not available for the post-1970 recessions. It is clear from a comparison of Table 4 with Figures 1 and 2 that severe recessions are associated with higher stock volatility. The recessions of 1857-1858, 1860, 1893-1894, 1907-1908, 1920-1921, 1929-1933, 1937-1938 and 1973-1975 correspond to high predicted volatility in Figures 1 and 2. Of course, the Great Depression, 1929-1933 and 1937-1938, is the most severe contraction and it is also the period when volatility was the highest during the 1834-1987 sample period.

Schwert [1988] notes that stock volatility is higher during recessions, and that industrial production volatility is also higher during recessions. For many other macroeconomic time series, however, there is only weak evidence that volatility increases during recessions. Stambaugh [1988] notes that the behavior of the term structure of interest rates is related to the stage of the business cycle. He argues that one interpretation of this phenomenon is that the variance of expected future consumption growth is higher during recessions than during expansions. This is consistent with Hamilton's [1989] model for GNP growth if recessions have shorter duration than expansions, which his estimates predict.

Table 5 -- Estimates of Differential Mean and Standard Deviation of Stock Returns During Recessions, 1855-1987

Coefficients of Dummy Variables Added to Equations (5a), (5b) and (11)

	Coefficient	Std Error	T-statistic
Differential Mean (5a)	-.0115	.0026	-4.44
Differential Volatility (5b)	.0054	.0019	2.80
Differential Probability of Being in High Variance Regime (11)	.0152	.0074	2.05

Note: Asymptotic standard errors and t-statistics use White's [1980] correction for heteroskedasticity. A dummy variable equal to 1 during NBER recessions, and 0 otherwise, is added to equations (5a), (5b) and (11) to estimate these coefficients.

Table 5 contains estimates of the coefficients of dummy variables equal to 1 during the recessions in Table 4, and 0 otherwise, when they are added to equations (5a) and (5b). Stock prices have been a business cycle indicator since at least Macaulay [1938], so it is not surprising that the average return to stocks is significantly lower during recessions. The estimate of -.01 is similar in size to the monthly intercepts, implying that the average return to stocks is near 0 during recessions. The estimate of differential volatility is .0054, about 60 percent larger than the average monthly intercept in (5b), implying that volatility is much higher during recessions.

Table 5 also contains estimates of the coefficient of the recession dummy variable D_{rt} in the regression,

$$S_t = p_0 + \lambda S_{t-1} + p_1 D_{rt} + v_t, \tag{11}$$

where S_t is the estimate of the probability of being in the high variance regime in period t from the model estimated in Table 3. Equation (11) is an empirical version of (9), except the N.B.E.R. recession variable is added. The estimate of the persistence parameter λ is .85, close to the value implied by the parameter estimates in Table 3. The constant term p_0 in (11) is .0157. Thus, the unconditional probability of being in the high variance state during an expansion is .10 = .0157/(1-.85). The estimate of the recession variable coefficient p_1 is .0152, with a standard error of .0074, which implies that the probability of being in the high variance regime increases by about 60 percent after the recession has gone on for 6 months. and almost doubles after the recession has gone on for 18 months.[13] This difference is reliably larger than 0. The N.B.E.R. announces that a recession or expansion has begun at least 6 months after it starts. Thus, the regressions in Table 5 are not forecasting models. Rather, they show that stock return behavior is related to the factors the N.B.E.R. uses to decide when the economy is in a recession.

Financial Panics

Table 6 contains a list of the major bank panics and financial crises from 1834-1987. Friedman and Schwartz [1963], Gorton [1985,1987] and Miron [1986] provide further analysis of these events. I put the crises into severe ("Fail") and less severe ("Panic") groups in the right column based on the descriptions available in these sources. One thing that identifies severe crises is that many banks suspended the convertibility of demand deposits into currency. During the 19th century, the banking system was subject to brief periods when depositors sought to withdraw cash from many banks simultaneously. Gorton [1987] argues that the banking panics before the founding of the Federal Reserve in 1914 were due to expectations of an imminent recession. The desire for liquidity, along with a forecast of future dissaving due to the recession, caused many depositors to try withdrawals simultaneously. He focuses most of his analysis on the behavior of the currency/deposit ratio for national banks.

Table 6 -- Major U.S. Bank Panics and Financial Crises, 1834 - 1987

Dates	Description	Type
5/1837	Bank panic	Fail
10/1839	Bank panic	Fail
10/1857	Bank panic	Fail
1/1862	convertibility of Union currency into specie suspended (resumed 1/1/1879); flexible exchange rates; greenback standard; UK on gold standard	Panic
9/1873	Bank panic	Fail
6/1884	Bank panic - no suspension of convertibility	Panic
8/1890	Bank panic - no suspension of convertibility	Panic
5/1893	Bank panic (suspension of convertibility of deposits into currency -- ends in Sept)	Fail
12/1896	Bank panic - no suspension of convertibility	Panic
12/1899	Bank panic - no suspension of convertibility	Panic
5/1901	Morgan/Harriman fight for North Pacific collapses (more stock sold than issued)	Panic
3/1903	Bank panic - no suspension of convertibility	Panic
10/1907	Bank panic (suspension of convertibility of deposits into currency -- lifted in early 1908)	Fail
8/1914	NYSE closed due to World War I (trading resumed 12/12/1914)	Panic
10/1930	first banking crisis	Panic
3/1931	second banking crisis	Panic
1/1933	Banking panic	Panic
3/1933	National Banking Holiday 3/6-3/13 (US off gold standard)	Fail

Sources: Friedman and Schwartz [1963], Gorton [1985,1987] and Miron [1986].

In many instances, a stock market panic accompanied these financial crises. Sobel [1968] discusses stock market panics in 1837, 1857, 1869, 1873, 1884, 1893, 1901, 1907, 1914, 1929 and 1962. In addition, he identifies less dramatic crises in 1847, 1860, 1878, 1889, 1898, 1903, 1920, 1937, 1940, 1955 and 1963. Certainly, an updated version of his work would include the 1973-1974 bear market and the October 1987 crash. Stock market crashes are *defined* by the size and the volatility of stock returns. To avoid a tautology, I do not measure the relation between stock market crashes and stock returns or volatility.

I use dummy variables to measure the behavior of stock returns and volatility for six months before and after the crises listed in Table 6. $D_{ft} = 1$ in the months severe crises began (Fail), $D_{pt} = 1$ in the months less severe crises began (Panic), and they equal 0 otherwise. Thus, the model for stock returns in (5a) becomes,

$$R_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{i=1}^{12} \beta_i R_{t-i} + \sum_{k=-6}^{6} \delta_{fk} D_{ft-k} + \sum_{m=-6}^{6} \delta_{pm} D_{pt-m} + \epsilon_t, \tag{12a}$$

and the model for stock volatility in (5b) becomes,

$$|\hat{\epsilon}_t| = \sum_{j=1}^{12} \gamma_j D_{jt} + \sum_{i=1}^{12} \rho_i |\hat{\epsilon}_{t-i}| + \sum_{k=-6}^{6} \gamma_{fk} D_{ft-k} + \sum_{m=-6}^{6} \gamma_{pm} D_{pt-m} + u_t. \tag{12b}$$

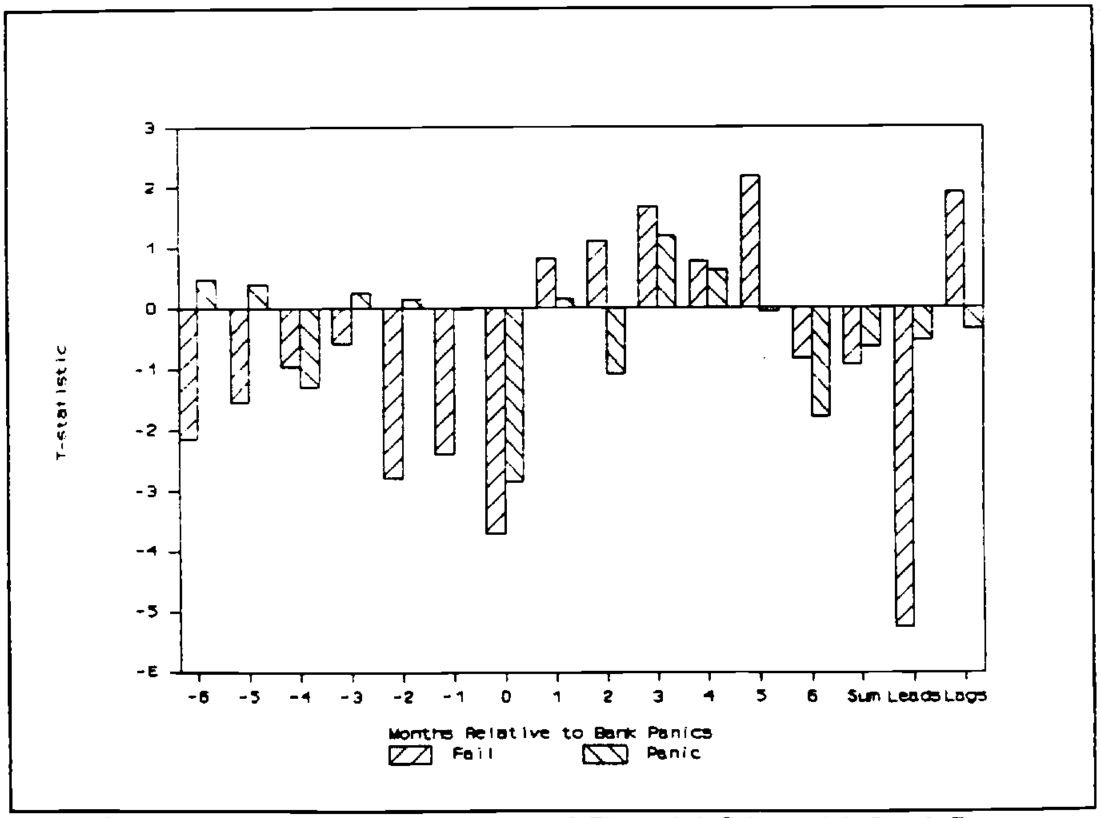

Figure 3a -- T-statistics for the Relation of Financial Crises with Stock Returns (Dummy variables in Equation (12a))

Figures 3a and 3b plot the t-statistics for 6 leads and lags of D_{ft} and D_{pt} in (12a) and (12b). They also show the t-statistics for the sums of all of the coefficients (-6,...,6), of the lead coefficients (-6,...,0), and of the lag coefficients (1,...,6).[14] Not surprisingly, stock returns are reliably negative for both Fail and Panic events (the coefficient estimates at lag 0 are -.07 and -.038, respectively). For the major crises, labeled Fail, the average return is reliably negative for several months before the date of the crisis. The t-statistic for the sum of the lead coefficients is -5.25. The t-statistic for the sum of the 6 lag coefficients is 1.92, showing that stock prices rose on average after the crisis. Stock volatility increases following both types of crises, shown by the t-statistics of 2.90 and 2.42 for Fail and Panic crises, respectively. There are individual months before these crises that have large t-statistics, but some are positive and some negative, and the sum of the lead coefficients is not reliably different from 0. Thus, the average behavior for stock prices surrounding these crises is for

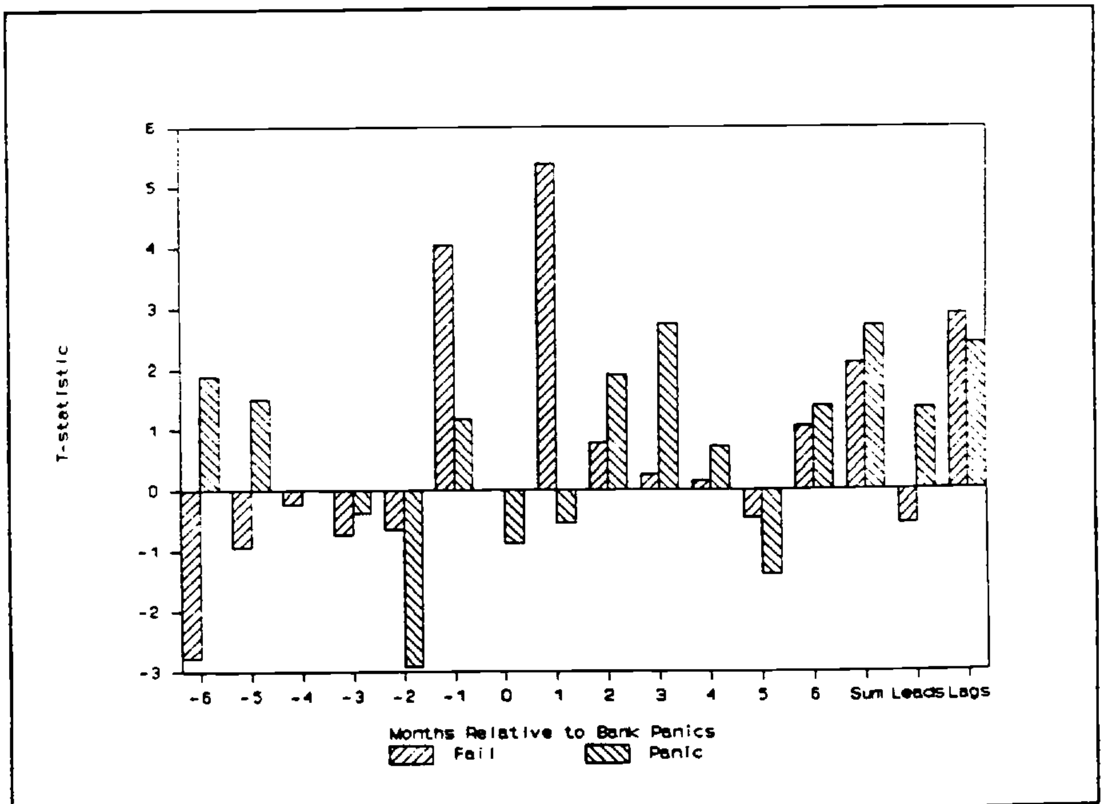

Figure 3b -- T-statistics for the Relation of Financial Crises with Stock Volatility (Dummy variables in Equation (12b))

prices to fall before and at the time of the crisis, and for return volatility to rise after the crisis.

Figure 4 plots the t-statistics for 6 leads and lags of D_{ft} and D_{pt}, when these variables are added to equation (11), showing the relation between these financial crises and the probability of being in the high variance regime ($S_t = 1$) for stock returns. Consistent with the

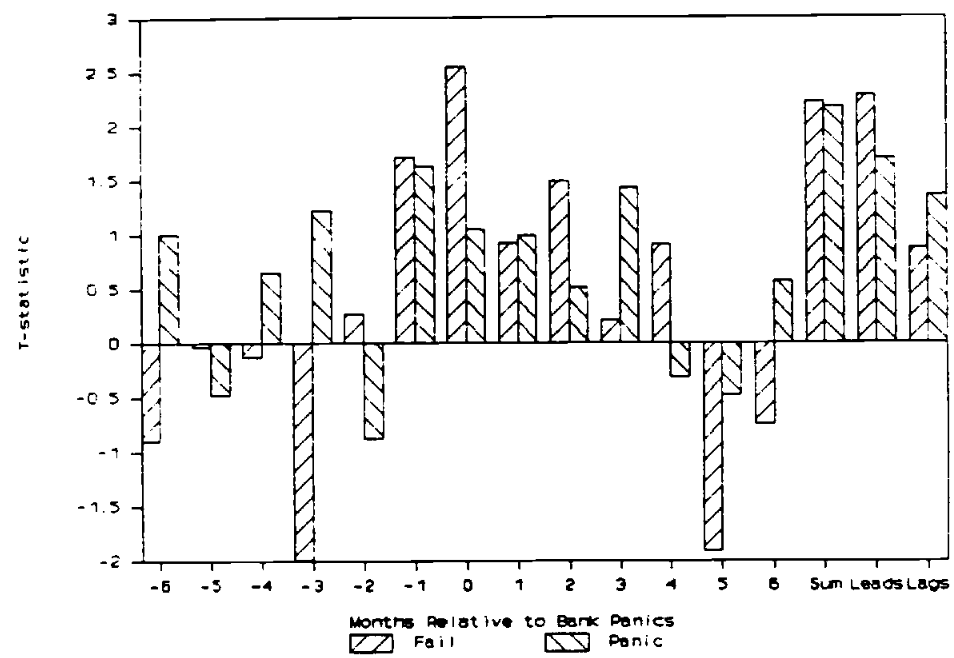

Figure 4 -- T-statistics for the Relation of Financial Crises with Probability of Being in the High Variance Regime, (Dummy Variables added to Equation (11))

results in Figures 3a and 3b, the probability of being in the high variance regime is reliably higher in the months before and of severe crises (the coefficient estimates are .254 and .245 for months -1 and 0, with t-statistics of 1.70 and 2.54). The effects of the less severe crises (Panic) are weaker, although the sum of all lead and lag coefficients has a t-statistic of 2.16.

Since many of the panics occurred before or during recessions, I also estimated the regressions underlying Figures 3a, 3b and 4 including the recession dummy variable D_{rt} along with the leads and lags of D_{fi} and D_{pi}. Although the estimates change somewhat, the general pattern of the results is the same as that displayed in the figures above.

Figures 5a and 5b plot the t-statistics for 6 leads and lags of D_{fi} and D_{pi} in equations like (12a) and (12b), except that short-term interest rates are the regressands instead of stock returns.[15] There is strong evidence that interest rates rose during the period before the major

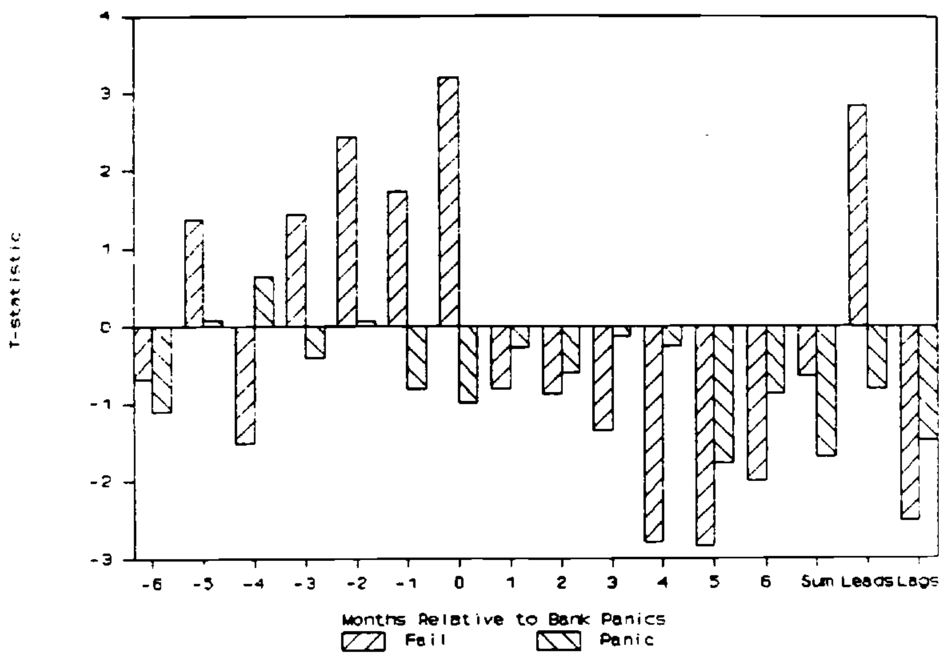

Figure 5a -- T-statistics for the Relation of Financial Crises with Interest Rates (Dummy variables in Equation (12a), using interest rates instead of stock returns)

crises and fell in the six months after these crises (t-statistics of 2.83 and -2.51). There is little evidence that short-term interest rates behave unusually during the less severe crises. Interest rate volatility increased during the three months surrounding the major crises (Fail), with t-statistics of 2.29, 4.61 and 4.05, for months -1, 0 and 1.

Thus, one thing that distinguishes the major crises from the minor ones is the behavior of short-term interest rates. Short rates rose before and fell after the major crises.

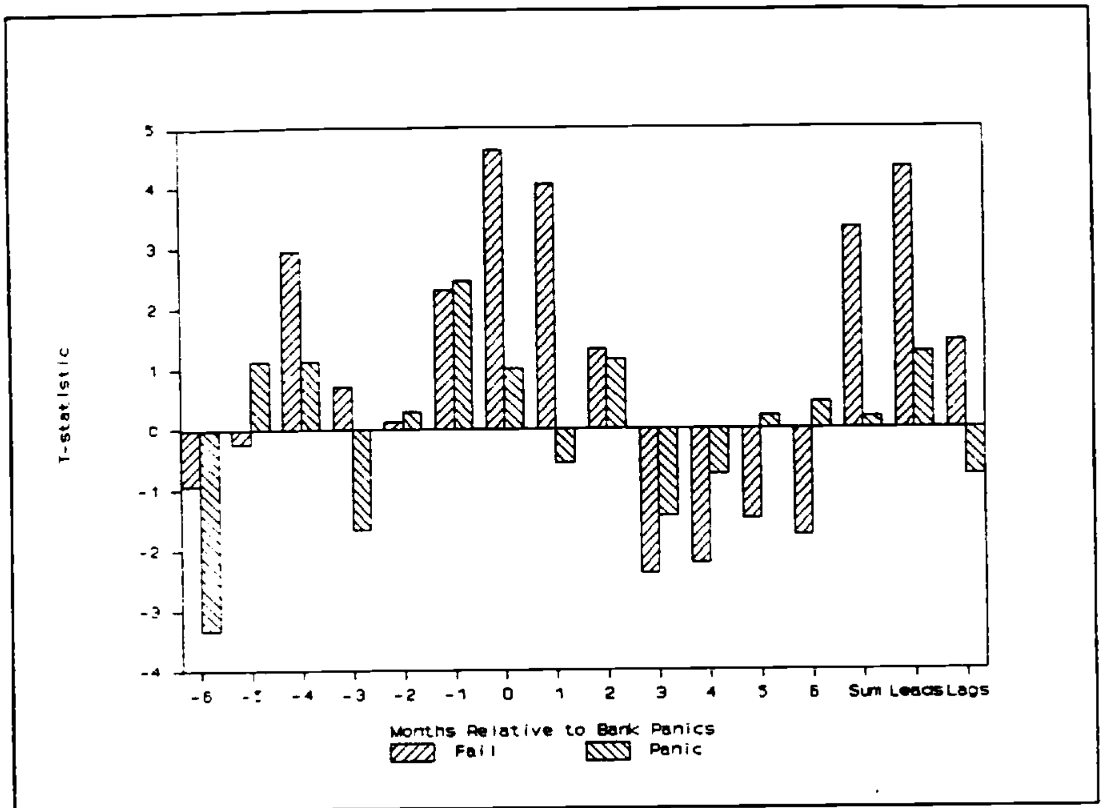

Figure 5b -- T-statistics for the Relation of Financial Crises with Interest Rate Volatility, (Dummy variables in Equation (12b), using interest rates instead of stock returns)

and there was an increase in interest rate volatility during the 3 months surrounding these crises (Fail). There is no reliable evidence of unusual behavior of short rates during the minor crises (Panic). Since money market yields increased **before** the major crises, and banks did not increase their yields in response, it is not surprising that the quantity of deposits in banks declined.

There is some disagreement among economic historians about which of the events in Table 6 were really crises. To check the sensitivity of my results to alternative specifications, I also estimated regressions where the dummy variable Fail only covered the 1873, 1893 and 1907 crises. The results were qualitatively similar. Also, the analysis by Wilson, Sylla and Jones [1988] of stock volatility during the panics of 1873, 1884, 1893 and 1907 supports the results in Figure 3b.

Finally, it is worth noting that the dummy variable coefficients measure the difference between the predictions from equations (5a) and (5b) and the realizations for a small subset of the total sample. The Fail variable equals 1 in only 7 of the 1,848 months. Thus, Figure 3b shows whether a standard deviation estimate based on 7 observations is significantly different from the standard deviation estimated from the full sample. Even though the total sample is large, there are only a few major bank crises, so the power of this test is not high.

Interpretation

What can be gleaned from such evidence? These results raise questions about Gorton's [1987] claim that risk increased *before* crises. While default risk for bank deposits may have increased before panics, stock and interest rate volatility increased during or after the major crises.

Another interpretation of this evidence is that I have formalized the measures used by economic historians to define a financial panic -- short-term interest rates rise quickly and stock prices fall and become volatile. Nevertheless, Gorton [1987] documents rises in the currency/deposit ratio and in the losses suffered by depositors during these episodes. He notes that many of the major crises were also associated with the failure of at least one large corporation or bank.

Is it possible to blame stock volatility for creating these crises? That seems unlikely. Stock volatility increases *after* the crises.[16] If interest rates rise and stock prices fall, it is not surprising that volatility also increases at the time of these crises (e.g., French, Schwert and Stambaugh [1987]). I have estimated the regressions underlying Figures 3a, 3b, 4, 5a and 5b including the recession dummy variable D_R and, while some of the t-statistics are smaller, the qualitative picture remains the same. Thus, even though these panics often began during or immediately before major recessions (compare Tables 4 and 6), the 13 months surrounding the panics are reliably different from the remaining recession months. The t-statistics for the recession dummy variable are smaller than in Table 5, but they remain reliably different from 0.

Margin Requirements and Stock Volatility

Officer [1973] and Hardouvelis [1988] analyze the relation between stock volatility and margin requirements set by the Federal Reserve Board. Officer concludes that the Fed increases margin requirements after stock return volatility has fallen. Hardouvelis concludes that margin requirements cause a decrease in stock volatility. Both papers use rolling 12-month volatility estimates to measure stock volatility. The rolling 12-month estimator of volatility implicitly assumes volatility is nonstationary.[17] Moreover, the time path of margin requirements is persistent. Thus, the 'spurious regressions' problem (see, for example, Plosser and Schwert [1978]) is likely to be serious in this case.

Table 7 -- Initial Margin Requirements Set by S.E.C., 1934 - 1987

Dates	Rate	Dates	Rate
10/15/1934	45	1/16/1958	50
2/1/1936	55	8/5/1958	70
11/1/1937	40	10/16/1958	90
2/5/1945	50	7/28/1960	70
7/5/1945	75	7/10/1962	50
1/21/1946	100	11/6/1963	70
2/1/1947	75	6/8/1968	80
3/30/1949	50	5/6/1970	65
1/17/1951	75	12/6/1971	55
2/20/1953	50	11/24/1972	65
1/4/1955	60	1/3/1974	50
4/23/1955	70		

Source: *New York Stock Exchange Fact Book, 1983*, p. 45. Gikas Hardouvelis informs me that the *NYSE Fact Book* contains a data error. Using annual reports of the Federal Reserve System, he finds that the margin requirement was lowered to 50 percent on 7/10/1962, not raised to 90 percent as the *Fact Book* shows.

Table 7 lists the level of initial margin requirements m_t set by the Federal Reserve Board from October 1934 to the present. This policy variable affects the credit terms for investors who borrow money to buy stock. A 100 percent margin requirement means that stock cannot be used as collateral for loans, and a 50 percent margin means that a loan can pay for half of the cost of stock. Some analysts claim that personal leverage contributed to the severity of the 1929 stock market crash, as margin investors sold securities quickly to repay loans when stock prices fell. They claim that induced selling further depressed stock prices. Miron [1986] argues that the Federal Reserve Board was concerned about the effect of bank credit to securities purchasers before the 1929 crash. Thus, they restricted general credit conditions in 1928-1929 to dampen speculation in the stock market. Consistent with this argument, the 1934 Securities and Exchange Act gave the Fed the power to set margin requirements. This created a policy instrument directly focused on credit to the securities markets.

Table 8 -- Relation of Changes in Margin Requirements with Stock Returns and Stock Volatility, 1935-1987

	Sum	Std Error	T-statistic
Tests for Returns			
All leads and lags (-12,..,12)	.6449	.2290	2.82
Leads (-12,..,0)	.4867	.1508	3.23
Lags (1,..,12)	.1582	.1393	1.14
Tests for Volatility, $\lvert\varepsilon_t\rvert$			
All leads and lags (-12,..,12)	-.3234	.1576	-2.05
Leads (-12,..,0)	-.2117	.1102	-1.92
Lags (1,..,12)	-.1118	.1001	-1.12

Note: Asymptotic standard errors, t-statistics and p-values use White's [1980] correction for heteroskedasticity. Twenty-five leads and lags (-12,..,12) of the change in margin requirements are added to equations (5a) and (5b) to estimate the relation of changes in margin requirements with stock returns or stock volatility from October 1935 through December 1987.

Table 8 contains tests for the relation between changes in margin requirements and both stock returns and volatility. Twelve leads and lags of changes in margin requirements, $dm_t = m_t - m_{t-1}$, are added to both (5a) and (5b). Table 8 contains the sum of all 25 coefficients, and the sums for the leads (-12 to 0) and the lags (1 to 12). The results strongly support Officer's interpretation that the Federal Reserve Board has increased(decreased) margin requirements after stock prices have risen(fallen). The coefficients of margin changes in the return equation are reliably positive for the leads and only about one standard error above 0 for the lags. Moreover, increases(decreases) in margin requirements seem to follow periods when stock volatility is low(high). The coefficients of margin changes in the volatility equation are reliably negative for the leads and only about one standard error below 0 for the lags.

When the recession dummy variable D_n is included in these regressions, the results are slightly stronger: margin requirements are increased after stock prices have risen and stock volatility is relatively low. There is no evidence that stock return behavior is different from normal in the 12 months following a change in margin requirements. The obvious interpretation of this result is that the Fed responds to stock market conditions. The policy actions have little or no effect on stock return behavior.

Summary and Conclusions

This paper provides evidence on the behavior of stock prices and volatility during the last 150 years. Two different statistical models present similar pictures of the time series behavior of stock volatility. One model allows the conditional mean and standard deviation of returns to follow a high-order autoregressive process. The second model, adopted from Hamilton [1988, 1989], allows stock returns to come from two different distributions, depending on which regime occurs in time t. Diagnostic tests for these models suggest they are adequate representations of the data. Both of these statistical methods show that stock volatility was high during the Great Depression from 1929-1939 and it was also high for several shorter periods.

Confirming the evidence in Schwert [1988], I show that stock volatility is higher on average during recessions. This fact reinforces the notion that the stock market is an important business cycle indicator. While the volatility effect is not as reliable as the relatively low level of stock returns during recessions, it does suggest that stock volatility could be used as an additional factor in assessing the state of the economy. Moreover, this evidence supports the notion that business cycles are asymmetric (see Neftci [1984]), since the duration of high volatility episodes is reliably shorter than the duration of low volatility episodes.

I show that the stock market reacted strongly to major and minor banking crises. Stock prices fell and short-term interest rates rose immediately before the major panics. Interest rates fell and stock volatility rose following the major panics. These events explain many of the larger increases in stock volatility during the 1834-1934 period. While it is impossible to prove that the stock market did not cause these panics, the facts are consistent with Gorton's [1987] interpretation that panics resulted from of a large increase in the probability of a recession. Whether panics also exacerbated the severity of subsequent recessions (as argued by Bernanke [1983]) cannot be determined from these data.

The evidence for the relation between margin requirements and stock volatility during the 1934-1987 period suggests that the Fed reacts to stock price behavior. There is no evidence that the Fed's policy changes effect stock price behavior.

Thus, analysis of credit markets and the stock market for 1834-1987 is consistent with the notion that stock prices reflect rational anticipations of future economic events. There is little evidence to suggest that speculative bubbles or fads induced crises in credit markets. Nevertheless, many analysts believe this concern motivated the actions of the Federal Reserve Board even before the 1934 Securities and Exchange Act gave the Fed power to set margin requirements.

What implications does this evidence have for current policy debates caused by the October 1987 crash? The evidence on margin requirements has an interesting parallel in the current policy debate concerning contingent claims contracts on stock market indexes. There has been much debate about whether trading in financial futures contracts and options contracts on stock indexes exacerbated the October 1987 crash. One of the policy prescriptions favored by the stock markets is to increase margins for financial futures, perhaps to the same level as margins for stocks, which would increase transactions costs in the futures market. Since the historical evidence from the stock market is the only available basis for assessing the efficacy of margin requirements, I conclude there is little basis for these recent policy recommendations.

How unusual was the October 1987 Crash? The drop of over 20 percent on October 19th is the largest one day decrease in the Dow-Jones or Standard & Poor's composite portfolios from 1885 to 1987.[18] The next largest one day declines were 12 and 10 percent on October 28 and 29, 1929. On the other hand, the drop of 21 percent for October 1987 is only the fourth largest monthly percentage decline from 1834-1987 (September 1931, March 1938, and May 1940 all had larger losses).

What does the October 1987 crash portend for the future of the economy? If the drop in stock prices and the brief spurt of high volatility in October 1987 was either a forecast or a cause of a major financial crisis or a recession, those events should have happened by now. The historical evidence suggests very close timing relations among volatility, crises and recessions. Since it is now 12 months after the crash and there has been no recession, the

October 1987 crash was not similar to the 19th and early 20th century bank crises or the national banking holiday in 1933.

Friedman and Schwartz [1963], among others, conclude that the financial crisis of 1907 led to the passage of the Aldrich-Vreeland Act in 1908. They also say that this Act led to the creation of the Federal Reserve Board in 1914. One of the first actions of the Fed was to close the New York Stock Exchange in August 1914 when World War I began in Europe. Historical accounts of this episode report that stock trading eventually resumed in December 1914. The Fed imposed rules that prices could be no lower than they had been when trading halted at the end of July. Trading had occurred off the floor of the Exchange during this period, and prices were neither falling nor particularly volatile. Thus, one interpretation of that episode is that the newly appointed Fed panicked and halted trading for over four months in fear of a nonexistent financial crisis.

The National Banking Holiday in March 1933, resulted in the closing of over 4,000 banks. This event caused the creation of the Federal Deposit Insurance Corporation since it was clear that the Fed was incapable of assuring depositors that their claims were safe during a severe recession.

The drop in stock prices and highly volatile stock returns during this period led to the 1934 Securities and Exchange Act, creating the Securities and Exchange Commission (S.E.C.). Several authors have tried to determine whether the creation of the S.E.C. caused an increase in public confidence and an associated reduction in stock volatility. Officer [1973] concludes that this explanation is inconsistent with the fact that stock volatility returned to pre-1929 levels in about 1940, and that it had not been as high as the 1929-1933 episode anytime from 1897-1928. Benston [1973] also concludes that the beginning of S.E.C. activity in October 1934 was not associated with a decrease in stock volatility. This paper presents additional evidence that stock volatility was lower throughout 1834-1928 than 1929-1933. Moreover, volatility was very high again during the 1937-1938 recession, long after the S.E.C. began its activities. Thus, as with margin requirements, major innovations in financial regulation follow increases in stock volatility. There is little evidence that the actions of these regulatory agencies directly reduce volatility.

One message from this analysis is that new regulatory initiatives following the October 1987 crash should be cautious. Efforts to control stock volatility can have important negative effects on other parts of the economy. For example, if the Fed restricted general credit in 1928-1929 to reduce the extent of stock market speculation (Miron [1986]), this probably increased the severity of the 1929-1933 recession (Friedman and Schwartz [1963]).

Proposals to impose trading halts, increase margin requirements, or to restrict trading in financial futures or options contracts would be innocuous if they do not effect credit costs or investment opportunities. If these proposals create large frictions in capital markets, however, the costs of regulatory solutions could easily exceed any hypothetical benefits from reducing stock volatility.

1. Implied monthly standard deviation estimates from prices of call options on the S&P composite index were about .035 during 1987 until October 19, when they rose to above .08. They dropped below .06 by November 17 and gradually declined to about .04 by the end of April 1988.

2. Indeed, the evidence on the relation between aggregate consumption growth rates and stock returns suggests that there is *too little* variation in aggregate consumption.

3. An alternative model proposed by Kleidon [1986] assumes that cash flows follow a geometric random walk with drift. In that case, the variance of stock returns would be proportional to the variance of dividend growth rates, and it would be unrelated to the level of the stock price.

4. Since the expected value of the absolute error is less than the standard deviation from a Normal distribution, $E|\epsilon_t| = \sigma_t(2/\pi)^{1/2}$, all absolute errors are multiplied by the constant $(2/\pi)^{-1/2}$. Dan Nelson suggested this correction.

5. The volatility of the Smith and Cole index of bank and insurance stock returns from 1792-1833 is much lower than for the composite index from 1834-1856. I omitted the early data because the composition of the sample apparently affected the behavior of the index.

6. Fuller [1976] shows how a p^{th} order autoregression can be transformed into a first order autoregression, along with 11 lagged changes in the series. This transformation is used in the Dickey-Fuller tests for unit roots in autoregressions. The autoregressive coefficient in the transformed model is equal to the sum of the autoregressive coefficients in the original p^{th} order autoregression.

7. All Box-Pierce tests are corrected for small sample bias.

8. Since the sample size is so large (T=1824), small residual autocorrelations cause the Box-Pierce statistic to be large. In effect, the test is so powerful that it rejects at very small significance levels even when the model misspecification seems trivial.

9. Hamilton [1988, 1989] provides additional information about the statistical model and the related estimation procedures. I am grateful to Jim Hamilton for providing the FORTRAN source code used to estimate these models.

10. The autoregressive model is limited to order 4 because of computational considerations. The largest coefficients in the estimates of equations (5a) and (5b) are in the first few lags, so this should not impair the comparison of the two modeling approaches.

11. If either p or q equals either 0 or 1, the model in (6)-(8) degenerates to the AR(4) model in (6). Similarly, if both α_1 and ω_1 equal 0, there is no difference between the two regimes.

12. Hamilton [1988,1989] describes the process used to calculate the probability of being in a given regime based on information at time t. It assumes that the parameter estimates from the whole sample are known; otherwise, only data through time t are used to estimate this probability. I use the estimates of $P(S_{t-1}=1 \mid y_{t-1}, \ldots)$ and $P(S_{t-1}=0 \mid y_{t-1}, \ldots)$, with the transition probabilities in (7) and the formulas in (10a) and (10b) to estimate the conditional standard deviation of stock returns in period t based on data through time t-1.

13. I am grateful to Bob Shiller for correcting an error in this calculation in an earlier version of this paper.

14. Geweke, Meese and Dent [1983] discuss this type of single equation 'causality test,' where lags of the dependent variable, along with leads and lags of the independent variable are included in the same regression. Also, see Nelson and Schwert [1982] for an analysis and comparison of various types of causality tests.

15. I use high-grade commercial paper rates from Macaulay [1938] for 1834-1925, spliced to match the short-term Treasury bill yields from the CRSP Bond File for 1926-1987. See Schwert [1988] for more information about the construction of this series.

16. As mentioned previously, and as I discuss in detail in Schwert [1979], it is generally difficult to assign causality based on estimated predictive relations. For example, if stock volatility had increased before the crises. there are several competing hypotheses that would predict such behavior. Nevertheless, since volatility didn't increase until after the panics, it is difficult to imagine reverse causality scenarios where depositors descend on banks in anticipation of future stock volatility.

17. 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. Thus, the 12-month rolling average implicitly assumes that the volatility process follows a nonstationary ARIMA(11,1,0) process with equal autoregressive parameters.

18. I use a weighted average of the Dow-Jones indexes of railroad and industrial stock prices from 1885-1927, and the Standard & Poor's composite index from 1928-1987. See Schwert [1989b] for further analysis of the behavior of daily stock market returns from 1885-1988.

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