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Margin Regulation and Stock Market Volatility

by

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Abstract

Using daily and monthly stock returns we find no convincing evidence that Federal Reserve margin requirements have served to dampen stock market volatility. The contrary conclusion, expressed in recent papers by Hardouvelis (1988a, 1988b), is traced to flaws in his test design. We do detect the expected negative relation between margin requirements and the amount of margin credit outstanding. We also confirm the recent finding by Schwert (1988) that changes in margin requirements by the Fed have tended to follow rather than lead changes in market volatility.

Margin Regulation and Stock Market Volatility

After 55 years, stock market margin requirements are again a source of controversy. The Securities and Exchange Act of 1934 transferred to the Federal Reserve System the authority, hitherto exercised by the New York Stock Exchange and other private-sector exchanges, to set the minimum margins (i.e., down-payments) that securities brokers and dealers (subsequently expanded to all lenders) must require of customers purchasing common stocks on credit. The transfer of authority reflected the view, widely held at the time, that the low initial margins set by the exchanges had fueled the stock market boom of the 1920's, and that the frenzied liquidation of shares in response to margin calls had accelerated the Crash in October 1929, supposedly dragging the economy down with it. The timely raising of margin requirements by the monetary authorities might dampen speculative excesses before they raged out of control; or in today's terms, margin controls might reduce "market volatility."

What the Federal Reserve has done since then with its margin setting authority can be seen from Figure 1 which shows the time paths both of margins and one measure of market volatility from October 1934 to December 1987. Margin requirements were set initially at 45 percent, raised to 55 percent during the boomlet of 1936 and then cut back to a low of 40 percent after the sharp stock-market break in the autumn of 1937. The requirement stayed at that level for the remainder of the 30's and most of the war years, but was stepped up sharply as the war drew to a close, reaching 100 percent (i.e., all cash, no borrowing) for most of 1946. Changes were frequent over the next two and a half decades, averaging once every 18 months or so until January 1974 when margins were set at 50 percent. Since that time there have been no changes whatever.

Difficult as it often is to explain the actions central banks do take, it is harder yet to account for the actions they don't take. The Fed's hesitation to use the tool after 1974 may reflect concerns about possible undesirable side-effects of margin increases. If higher margins reduce speculation, and if speculation is destabilizing, as many in Congress believed in the 1930's, then higher margins would presumably reduce volatility. But in the 1950's and 1960's some economists were suggesting that speculation, under some conditions, might actually be a stabilizing influence. (See, e.g., Friedman (1953) or Telser (1959).) And higher volatility might not be an unmixed curse when it represents the faster incorporation of new information into prices. The Fed's reluctance to tinker with margins after 1974 may, however, simply have reflected its recognition that the impact of margin changes on the stock market or on the economy was unlikely to be large enough to bother with. By the early 1970's, total stock market credit, which, even at the height of the 1929 boom had never amounted to more than 10 percent of the value of listed equities (see the Brady Commission Report, Appendix VIII, esp. p. VIII-2) was down to only 2 percent of market value. Institutional investors, virtually none of whom buy on margin, were steadily supplanting individual investors. The requirements do not apply to market professionals such as investment banks, securities dealers, or exchange specialists. And even for ordinary investors, securities already owned may be pledged as collateral with banks or other lenders on any terms satisfactory to the parties. Substitutes for margin loans to investors thus were, and still are, readily available.

That the transfer of margin authority by the Act of 1934 added little effective firepower to the Fed's arsenal of controls had earlier been the conclusion of two academic studies one by Thomas Moore (1966) and one by Robert Officer (1973). Officer, who constructed a time series on stock market volatility going back to the 1890's, showed that volatility had indeed declined substantially since 1934, but credited the decline not to any policy actions by the Fed or by the S.E.C., but to "a return to normal levels of variability after the abnormally high levels of the 1930's" (p. 452). And, more directly to the present point, Officer noted that: "A more specific examination was made of margin requirements and the greater postwar diversity of stocks listed on the NYSE. The results indicate that neither of these factors affects the variability of the market factor" (pp. 452-3).[1] The Federal Reserve System, in its 1984 study of the margin requirements, came to essentially the same conclusion, noting, in particular, "the lack of any positive demonstration that margin regulation has served to dampen stock price fluctuation" (p. 163).

By 1984, the year of the Fed Staff Study, the long-run future of the Fed's control over margin requirements was in doubt. So weak was the empirical case in the Fed's staff study for the efficacy of the requirements and so perfunctory was the recommendation to retain them that it became possible to believe that the wave of deregulation might someday soon sweep the responsibility for margins back to the private sector from which it had been transferred 50 years earlier. The likelihood of such a step, however, has been much reduced by two recent events. One, of course, was the great stock market crash of October 19, 1987. Unlike the 1929 episode, few observers this time were actually blaming stock market margin rules for the disaster; the amount of margin credit involved was far too small for that to be credible. The critics focussed instead on the supposedly low margins for stock index futures contracts. Those margins were still set by the commodity exchanges with no direct regulatory oversight. The Brady Commission called attention to this disparity and recommended that margins in the two markets be "harmonized." That term was nowhere actually defined by the Brady Commission, but their call for harmonization was widely taken as a code word for making futures margins, as well as stock margins, a responsibility of the Federal Reserve System. Several bills to that effect are currently pending in the Congress.

Proposals to extend the Fed's margin-setting authority to futures must contend, inevitably, with Fed's own seeming lack of confidence in the efficacy of the powers it already had. The case for the effectiveness of the Fed's margin controls appeared to have been revived, however, by the publication in mid-1988 in the Bulletin of the Federal Reserve Bank of New York (subject, of course, to the standard disclaimer) of an empirical study (Hardouvelis 1988a), given extensive press coverage at the time and purporting to show that "The empirical evidence reveals an economically and statistically significant negative relationship between initial margin requirements and stock market volatility." (p. 81) Timely increases in margin requirements thus might well serve to reduce market volatility, exactly as Congress had anticipated when it granted the authority to the System in 1934.

This claim by Hardouvelis, so strikingly at variance with results in the earlier study by Officer (1973) and with the Board's staff study (as well with a number of other recent studies to be noted later), has reopened what had seemed to be a dead issue. We propose here to take a fresh look at the data using newer statistical techniques not available when Officer undertook his original investigation. Even so, we can find no relation, either in the short or the long run between changes in margin requirements and subsequent changes in market volatility. We do find a negative association over time between the level of margin requirements and the level of volatility, but the association is weak and comes mainly from a few observations in the late 1930's and early 1940's. The claim to the contrary by Hardouvelis that the negative association is "economically and statistically significant" we trace largely to flaws in his test design. He relies on methods that are strongly biased in favor of finding a relation between stock market volatility and margin requirements even when they may be truly unrelated; and his basic estimating equation is misspecified. When the necessary corrections are made, the "significant" effect that Hardouvelis reported vanishes.

Our findings are not entirely negative, however. We do detect the expected negative relation between margin requirements and the amount of stock market margin credit outstanding. We also confirm the recent finding by Schwert (1988) that changes in margin requirements by the Fed have tended to follow rather than lead changes in volatility. The Fed apparently raised margins when the market was booming and cut them after it fell. Because volatility normally rises when the market falls, a negative association between margins and volatility may well be detected in the data even though the causation runs in the opposite way from that envisaged by Hardouvelis.

I. Margins and Volatility: A Fresh Look at the Data

A connection between margin requirements and volatility as strong as Hardouvelis suggests would surely leave a readily detectable track in the raw data. Calibrating a weak connection precisely might well require refined econometric techniques, but a strong connection should show itself even in a relatively crude preliminary data analysis. This section offers two such preliminary searches. First, using daily data, we test for signs of short-term or impact relations between the 22 historical changes in margin requirements and the immediately subsequent levels of volatility. We find a small but positive correlation between margins and volatility, which is contrary to the claims in Hardouvelis. Then, taking a longer-term perspective, and switching to monthly data, we present a test that asks essentially whether knowing the true margin requirements month by month makes the observed patterns of volatility over time appear more coherent and explainable. We conclude that it does not. Checking further, we observe that a regression of average volatility on the level of margin requirements yields a weak negative association, traceable mainly to the late 1930's and early 1940's.

I.A The Short-Term Relation Between Margins and Volatility

To examine the short-term relation between margins and volatility, we ask whether the standard deviation of daily stock returns changes when margins change, taking the logarithmic difference in the Standard and Poors stock index as a measure of daily stock returns. This index has been used in previous work, such as Largay (1973), Largay and West (1973), and Grube, Joy, and Panton (1979), to examine the relation between margins and the means rather than the standard deviations of stock returns, using the "event study" method of Fama, Fisher, Jensen, and Roll (1969).[2] Table I compares the volatility as measured by standard deviations of returns for the 25 trading days before and after margin changes. We exclude the days immediately before and after the margin changes, although the results are not sensitive to the number of days excluded.

Ferris and Chance (1988) have previously conducted a similar study in which they calculated the variances for the 100 days before and the 100 days after a margin change, and used the F statistic to test the equality of the two variances. Out of 19 margin changes since 1945, they found 15 occasions when the variances before the margin changes were different from the variances afterwards. In 10 cases, the variances changed in the same direction as the margins, and in the remaining 5 cases, the opposite change occurred. They therefore concluded that higher margins do not consistently reduce volatility. A problem with their method, however, is that the F statistic is valid only if the data are Normally distributed. In a simulation experiment, Brown and Forsythe (1974) show that the F statistic rejects the null hypothesis of equal variances too frequently, if the data have heavier tails than the Normal distribution (as we show later they do), but that the modified Levene statistic is not sensitive to departures from Normality.[3]

We therefore use the modified Levene statistic to test whether the standard deviation of stock returns in the 25 days preceding margin changes is the same as that in the succeeding 25 days. We chose 25 days because 25 days is half the smallest number of trading days between two margin changes (i.e., the 51 trading days between August 5, 1958 and October 16, 1958). To assess the distribution of the modified Levene statistic in our application, we randomly select 1000 days from our sample of 14118 daily stock returns, and calculate the corresponding 1000 modified Levene statistics for the 25 days before and after. This gives us a "bootstrap" distribution of the modified Levene statistic. (See Efron (1982).) The location of the observed statistics in the bootstrap distribution is given in the seventh column of Table I. Our results show many fewer significant changes than in Ferris and Chance (1988). We find only three occasions in which the modified Levene statistics lie in the upper 5% tail of the bootstrap distribution. In one case, the volatility increased when margins declined. In the other two cases, the volatility declined when margins declined. This absence of strong and consistent impact effects of margin changes is particularly relevant for policy discussions. Margin requirements are not at all like the beryllium rods used to control nuclear reactors.

I.B The Long-Term Relation Between Margins and Volatility

Twenty-five days may perhaps be too short an interval for volatility to respond to initial margin requirements. To examine the possibly longer-term relation between margins and volatility, we turn to monthly real returns of the Standard and Poors stock index (from Ibbotson Associates). We begin the analysis in October 1934, when, as noted, the Federal Reserve was first empowered to set the initial margin requirement. We end the sample in December 1987, to coincide with the sample in Hardouvelis (1988b). Monthly returns show little autocorrelation, but the distribution of returns departs from Normality. The coefficient of kurtosis is 6.67, noticeably higher than 3, the value under the Normal distribution.

To test whether margin requirements influence stock market volatility over the long term, we divide our sample of stock returns into 23 periods, according to the 22 changes in margin requirements. If our goal were merely to test whether the standard deviations are different across the 23 periods, we could use the modified Levene statistic. If stock returns are independent and identically distributed and if margins do not affect volatility, the modified Levene test is distributed as an F(22,616), whose 1% and 5% critical values are, respectively, 1.86 and 1.56. The value 2.33 that we find for our sample lies in the 0.058% tail of the F(22,616) distribution. Thus, the modified Levene test suggests that stock volatility is different over the 23 periods, a result which is hardly surprising, given the many studies that have documented changes in stock return volatility (e.g. French, Schwert, and Stambaugh (1987)).

Our real goal, however, is to discover whether the volatility in periods with high margins differs systematically from that in periods with low margins. To answer this question, we seek the distribution of the modified Levene statistic, but computed somehow without having to assume as the null hypothesis that stock returns are independent and identically distributed within the 23 margin periods (which is clearly not true for our data). How to construct such a distribution can be seen from the following thought experiment. Suppose the margin requirement has changed three times in the course of 60 months. Say it is 40% in the first 10 months, 60% in the next 20 months, and 50% in the last 30 months. We can observe stock returns over the entire 60 months, and calculate the modified Levene statistic. Next we can randomly rearrange the ordering of the these periods: say 60% in the first 20 months, 50% in the next 30 months, and 40% in the last 10 months. If we calculate the modified Levene statistic using the randomly permuted margin requirements and the <u>original</u> stock returns, what should we find? If margin requirements do affect stock volatility, the first statistic should be large (rejecting the null hypothesis). The 20 months with the 60% margin requirement will have a substantially lower volatility than the 30 months with

50% margins which in turn will be systematically lower than in the 10 months with only 40% required margin. The second modified Levene statistic, however, should be noticeably smaller (perhaps even not rejecting the null hypothesis). The random rearrangement will assign some months with high volatility to periods with high margins and vice versa. Recall that the margin periods are of different lengths and that is crucial to the test. Suppose, on the other hand, that margin requirements do not affect stock volatility. Then the second test statistic should be similar to the first. The two arrangements of the margin intervals are "equally random" as it were.

This thought experiment can actually be carried out using the bootstrap method.[4] We randomly rearrange the path of margin requirements 1000 times,[5] obtaining 1000 modified Levene statistics. Their distribution approximates that of the modified Levene statistics under the null hypothesis that margin requirements do not affect stock volatility, but without assuming that stock returns are independent and identically distributed (since we preserve the original stock return series). It turns out that the original modified Levene statistic of 2.33 is actually less than 953 of the 1000 simulated statistics, signifying that 2.33 is not an "unusual" occurrence. The years with the true margin requirements appear to be indistinguishable from those with the imaginary margin requirements.

The question naturally arises as to the statistical power of the bootstrap modified Levene test. As with any statistical test against unspecified alternatives, the modified Levene test may have difficulty finding a weak relation between margins and volatility. However, the simulation experiment in Table II suggests that it could detect a strong relation between margin requirements and volatility if it existed. As a further check, we present in Figure 2 a scatter plot of average standard deviation during each margin period against the level of initial margins required during the period. A negative association is apparent, but it is clearly very weak.[6] Rather than a pervasive relation, moreover, the association appears to stem mainly from a single observation, representing the reduced margins after the market break in 1937.

II. Re-examination of Previous Results

Our preliminary analysis of the data thus conforms to the finding in Officer (1973) that initial margin requirements have little or no effect on stock market volatility. How then can we explain the vastly different conclusion in Hardouvelis (1988a, 1988b), that higher margin requirements definitely reduce price volatility? Our answer is that the correlation found by Hardouvelis is "spurious," in the technical sense of that term. His method strongly biases in favor of finding correlation between margin and volatility, even when they are truly unrelated.

To explain how and why the spurious results arise, we shall proceed in three steps. First, we consider the issue of which proxy should be used to measure stock market volatility on a month-to-month basis. Second, we conduct a bivariate analysis of the time series relation between margin requirements and stock volatility. This allows us to use two-dimensional scatter diagrams to illustrate more clearly the problem of spurious regression. Finally, we reexamine the multiple regression of volatility on margin requirements and other macroeconomic variables, presented in Hardouvelis (1988b).

II.A Proxies for Stock Market Volatility

Since volatility is not directly observable, Hardouvelis (1988b) constructs two proxies from the monthly real stock returns, denoted by r_t:

$$\sigma_{y,t} = [\ (1/11)\ \Sigma_{j=0}^{11}\ \{\ r_{t-j} - (1/12)\ \Sigma_{i=0}^{11}\ r_{t-i}\ \}^2\ ]^{1/2} \tag{1}$$

$$\sigma_{m,t} = (\pi/2)^{1/2}\ |u_t|, \tag{2}$$

where u_t is the residual from the regression:

$$r_t = \Sigma_{i=1}^{12}\ \alpha_i D_{i,t} + \Sigma_{j=1}^{12}\ \beta_j r_{t-j} + u_t\ , \tag{3}$$

where $D_{i,t}$ are monthly dummies.

The first proxy $\sigma_{y,t}$, a twelve month moving average of volatility, is similar at first sight to that used by Officer (1973). Officer, however, uses for his tests only one standard deviation per calendar year based on the twelve monthly returns during that year. That approach limits his sample size but at least leaves his regression equations correctly specified. (See the discussion in Section II.B.) Hardouvelis (1988b), on the other hand, in an attempt to expand his sample size, uses one standard deviation per month based on the past twelve monthly returns. Any monthly measure of volatility, such as the standard deviation of daily stock returns within each month, will show strong autocorrelation in volatility. (See French, Schwert, and Stambaugh (1987).) But the overlapping nature of a moving average like $\sigma_{y,t}$ further compounds the problem by inducing substantial additional autocorrelation in Hardouvelis' regression residuals, leading to spurious results.

The second proxy $\sigma_{m,t}$ is similar to but not the same as the proxy of volatility in Schwert (1988). Schwert actually uses the fitted values of a second stage regression:

$$|u_t| = \Sigma_{i=1}^{12}\ \lambda_i D_{i,t} + \Sigma_{j=1}^{12}\ \rho_j |u_{t-j}| + v_t\ , \tag{4}$$

based on a suggestion in Davidian and Carroll (1987). As a matter of fact, Schwert's proxy turns out to be quite similar to $\sigma_{y,t}$ and very different from $\sigma_{m,t}$.

Before turning to the regressions of volatility on margins, it is useful to check first whether these are in fact reasonable proxies of stock market volatility, a step not taken in Hardouvelis (1988b). Denote the mean and standard deviation of r_t as μ_t and σ_t, respectively. If $\hat{\mu}_t$ and $\hat{\sigma}_t$ are estimates of μ_t and σ_t, then the "standardized" return, $[r_t-\hat{\mu}_t]/\hat{\sigma}_t$, should have mean zero and standard deviation one.

The definition of $\sigma_{y,t}$ implies that the mean of r_t is $\mu_{y,t} = (1/12)\ \Sigma_{j=0}^{11}\ r_{t-i}$. The mean of the standardized return, $[r_t-\mu_{y,t}]/\sigma_{y,t}$, is -0.0404 (which is close to zero), and its standard deviation is 0.9722 (which is close to one). Thus $\mu_{y,t}$ and $\sigma_{y,t}$ are reasonable estimates of μ_t and σ_t. In fact, $[r_t-\mu_{y,t}]/\sigma_{y,t}$ is well-behaved, with its maximum value at 2.61, its minimum value at -2.73, and its coefficient of kurtosis being 2.68.

The definition of $\sigma_{m,t}$ implies that the mean of r_t is $\mu_{m,t} = \Sigma_{i=1}^{12}\ \alpha_i\ D_{i,t} + \Sigma_{i=1}^{12}\ \beta_j\ r_{t-j}$. This definition, however, leads to the unsatisfactory result that the standardized return is either +1, -1, or undefined, depending on whether u_t is positive, negative, or zero. Suppose we choose $\mu_{m,t}$ to be the sample average. The mean of the standardized return, $[r_t-\mu_{m,t}]/\sigma_{m,t}$, is 0.6263, and its standard deviation is 17.65 (which is much larger than the desired value of one). In fact, $[r_t-\mu_{m,t}]/\sigma_{m,t}$ is so ill-behaved that its maximum value is 379.6, its minimum value is -155.7, and its coefficient of kurtosis is 379.61! The problem does not lie with $\mu_{m,t}$, but with $\sigma_{m,t}$; whenever $\sigma_{m,t}$ gets close to zero, the standardized return, $[r_t-\mu_{m,t}]/\sigma_{m,t}$, can be arbitrarily large in absolute value. (This criticism does not apply to Schwert's proxy of volatility, because his second stage regression smooths out and avoids extremely small values of the estimates of monthly volatility.) Thus, the single-month proxy $\sigma_{m,t}$ is not satisfactory and, for the remainder of the analysis, we shall concentrate on $\sigma_{y,t}$ as a proxy for stock market volatility.[7]

II.B Bivariate Relation Between Volatility and Margin

To measure margin requirements, Hardouvelis (1988a, 1988b) defines M_t as the margin rate at the end of each month. To conform with his moving average proxy for volatility, he takes a twelve month moving average of margin rates:

$$\overline{M}_t = (1/12) \; [\; \Sigma_{j=0}^{11} M_{t-j} \;]. \qquad (5)$$

Hardouvelis (1988a) provides a scatter plot of $\sigma_{y,t}$ versus $\overline{M}_t$ (Chart 2, p. 87, corresponding to our Figure 3) and a regression of $\sigma_{y,t}$ on $\overline{M}_t$ (Table 3, p. 85, corresponding to our Table IV Column A). He reports a strong negative correlation between margins and volatility. Yet Officer (1973), who uses a seemingly similar proxy for volatility, finds no statistically important relation between margins and volatility. Hardouvelis (1988a, 1988b) has 15 more years of data, it is true, but since the margin requirement has changed only once since 1973, the longer data sample cannot possibly add much information about the relation between margins and volatility.

Before resolving this puzzle, we remind readers once again that correlation does not imply causation. Even if margins and volatility are negatively correlated, we cannot infer that changes in margins cause changes in volatility. Federal Reserve policy, for example, may be to increase margins when stock prices are high, and decrease margins when stock prices are low. If so, a negative correlation between margins and volatility may arise, simply because volatility is typically low (high) when stock prices are rising (falling). (See Black (1976).) We shall return to this point later.

With this caveat in mind, we turn now to the Hardouvelis (1988a, 1988b) result that margins and volatility are strongly negatively correlated. That finding traces ultimately to the high autocorrelation of volatility shown in our Table III. Furthermore, both $\overline{M}_t$ and M_t will also appear to be highly autocorrelated if only because they are step functions. (See M_t in Figure 1.) Regressing a highly autocorrelated series such as $\sigma_{y,t}$ on step functions such as M_t and $\overline{M}_t$ can produce a "significant" coefficient even if no true relation exists. To see why, suppose that volatility, by chance, happens to be unusually high during a period when margins are low, as we know was the case when the Fed lowered margin requirements to 40 percent after the market break of 1937. The strong persistence in volatility (signified by the high autocorrelation) means that the volatility in subsequent months is also likely to be high, while margins have not yet changed. Thanks to this persistence, the high volatility-low margin period shows up not as a single point, as in Figure 2, but as a clustering of points in the scatter plot of volatility versus margin, as in Figure 3. If these clustered points are considered <u>independent</u> observations, the evidence of a negative correlation between margins and volatility appears strong. Just such an assumption of independence is made implicitly in computing the standard errors in the regression of volatility on $\overline{M}_t$, presented in Table IV Column A.[8] Note that the coefficient on the margin variable is not merely "significant," but is actually over 8 times its standard error. But the low values of the Durbin-Watson statistics and the high values of the autocorrelation coefficients of the residuals are sending us a strong warning signal that the independence assumption may be failing.[9]

That we are well advised to heed these warnings is shown by the simulation experiment reported in Table V. We generate there an artificial series, y_t, according to the following rule:

$$y_t = \rho\, y_{t-1} + u_t, \tag{6}$$

where u_t is Normal, independent and identically distributed, with zero mean and unit variance. We then regress our artificial y_t on the actual $\overline{M}_t$:

$$y_t = \alpha + \beta\, \overline{M}_t + e_t, \tag{7}$$

and see how often we find a statistically significant regression coefficient as the value of ρ, and hence of the autocorrelation of y_t increases. We perform 10000 replications of this experiment. When ρ=0, the regression satisfies the standard assumptions including that of the independence of the points. If we use a 1% significance level in a one-sided test of β=0 versus β<0, we should reject 1% of the replications. We actually reject 1.07%, which is well within the accuracy of the simulation. The rejection rate increases to 8.13% when ρ=0.5, 32.47% when ρ=0.95, and 38.93% when ρ=1. In fact, ρ=1 is the case of "spurious regression," a term coined by Granger and Newbold (1974). For this case, the regression coefficient converges to a non-degenerate distribution, so that <u>any test of the hypothesis of no correlation between</u> y_t and $\overline{M}_t$ <u>will be rejected with probability 1</u> (as the sample size goes to infinity). (A proof is available upon request.)

If the residuals are autocorrelated, the sampling standard errors of the regression coefficients are understated when computed in the ordinary way. Recognizing that his use of 12-month moving averages will induce serial correlation, Hardouvelis (1988b) computes his standard errors using a correction method proposed by Hansen (1982) with a weighting scheme proposed by Newey and West (1987), which is valid when the regression uses overlapping data, thus inducing a finite order moving average in the residuals. Hardouvelis (1988b) chooses a moving average of order 12 after testing it against a moving average of order 24 using a procedure in Cumby and Huizinga (1988). The power of this test, however, is too low to rule out the possibility that the true order of the moving average is greater than 12. If the order really is greater than 12 -- which is probable, since volatility is highly autocorrelated, even when the volatility proxy does not involve overlapping data, see p. 13 and footnote 11 -- the Newey-West method of correcting the standard errors will still reject the null hypothesis of no correlation too frequently, as can be seen from the middle panel of Table V. Since the simulated series for y_t is a simple AR(1) process, its residuals constitute a moving average process of infinite order. As the degree of autocorrelation approaches that of a non-stationary series with a unit root, the size of the moving average components declines very slowly. In that case, the Newey-West correction with even as many as 24 moving average terms still leaves the rejection rate too high.

Rather than seeking an appropriate correction formula, a simpler and more direct way of dealing with the high autocorrelation of the regression residuals in Table IV Column A is to run the regression in first differences.[10] The results are given in Table IV Column B. Now we find that margins and volatility are positively rather than negatively correlated, although the margins coefficient is not reliably different from zero. The residuals are no longer autocorrelated (except at the twelfth lag, in consequence of the twelve month averaging of the margins and standard deviations of stock returns), so that the standard inference methods can be applied. The first differencing procedure can be illustrated graphically in Figure 4, which plots $\Delta\sigma_{y,t}$ versus $\Delta\bar{M}_t$. There is no sign of any relation between changes in margins and changes in volatility. The contrast with Figure 3 is striking.[11]

II.C Granger-Causality Tests

Since volatility is highly autocorrelated and since margin requirements are slow to change, the question of whether one affects the other also can be framed in terms of possible lead-lag relations. We can say that margins affect or "Granger-cause" volatility if they lead volatility. (See Granger (1969) and Sims (1972).) Similarly, volatility is said to Granger-cause margins if it leads margins, as might be the case if Federal Reserve policy had been to change margins in response to changes in stock market volatility, which is essentially the way futures exchanges change their margins. It is possible that margins and volatility can Granger-cause each other; it is also possible that neither Granger-causes the other.

To test whether margins Granger-cause volatility, we regress volatility on its own lags and lags of margins. If the coefficients of the lags of margins are reliably different from zero, then margins Granger-cause volatility. To test whether volatility Granger-causes margins, we regress margins on its own lags and lags of volatility. If the coefficients of the lags of volatility are reliably different from zero, then volatility Granger-causes margins.

We begin each regression with 12 lags of both variables, and we increase the lags of the dependent variable until we have removed the serial correlation in the residuals, including, of course, any induced by the overlapping observations in the moving average proxy $\sigma_{y,t}$. The results of the tests of Granger-causality are in Table VI. Note that the coefficients of margins in the volatility regression are not reliably different from zero, either individually or jointly, indicating that margins do not lead volatility. We do, however, see evidence that volatility leads margins, confirming the finding in Schwert (1988).[12] Given the high autocorrelation of both variables, a lead relation of this kind, if strong enough, might well, as noted earlier, account for the negative sign of the coefficient we find in some regressions of volatility on contemporaneous margins. (See, e.g., footnotes 6, 9, and 11.)

II.D Multiple Regression of Volatility on Margins and Other Variables

For his test of whether margin requirements affect stock market volatility, Hardouvelis (1988b) runs the following multiple regression:

$$\sigma_{y,t} = \beta_0 + \beta_1\overline{M}_t + \beta_2\overline{R}_t + \beta_3\overline{MCR}_t + \beta_4\sigma(Y_{y,t}) + \beta_5\overline{Y}_t + \beta_6\overline{\pi}_t + \beta_7\sigma_{y,t-12} + u_t. \quad (8)$$

We use the same notation as in Hardouvelis (1988b):

$$\overline{R}_t = (1/12)\ \Sigma_{j=0}^{11}\ R_{t-j}, \quad (9)$$

where R_t is the real return on stocks in period t.

$$\overline{MCR}_t = (1/12)\ \Sigma_{j=0}^{11}\ MCR_{t-j}, \quad (10)$$

where MCR_t is the rate of change of debt to margin accounts divided by the value of the stocks listed on the NYSE.

$$\overline{Y}_t = (1/12)\ \Sigma_{j=0}^{11}\ Y_{t-j}, \quad (11)$$

where Y_t is the rate of change of industrial production in period t.

$$\sigma(Y_{y,t}) = \text{the volatility of industrial production}, \quad (12)$$

computed in a manner similar to $\sigma_{y,t}$.

$$\bar{\pi}_t = (1/12) \Sigma_{j=0}^{11} \pi_{t-j}, \qquad (13)$$

where π_t is the CPI inflation rate in period t. The margins coefficient, β_1, now measures the partial correlation of margins with volatility above and beyond the correlation between volatility and the other variables.

The numerical results are presented in Table VII Columns A and B for two specifications, one with and one without the twelfth lag of the dependent variable. The twelfth lag is added by Hardouvelis presumably to reduce the autocorrelation of the residuals, though why he adds only the twelfth lag is not clear. A twelfth lag is often added to eliminate an annual seasonal, but no such seasonal component is present in the data. Hardouvelis also uses the Newey-West moving average correction with 12 lags described earlier (p. 17). Note that even after these corrections, the negative margin coefficients are still 4 to 5 times their standard errors and would thus surely seem to qualify as "significant" by conventional standards.

At least two major grounds exist, however, for rejecting such a conclusion. For one thing, the warnings with respect to spurious regression, noted earlier for the bivariate form of the tests, apply here with equal force. The addition of a twelfth lag of the dependent variable has not removed the high serial correlation of the residuals, as indicated by the very low values of the Durbin-Watson statistic. When the degree of autocorrelation is so close to that of a unit root, a Newey-West correction with 12 lags is not likely to be appropriate for calculating the coefficient standard errors, as our simulations in Table V suggest.

As noted earlier, however, the simplest method for correcting a regression whose residuals are very highly autocorrelated is to rerun the regression in first difference form, in this case as [13]

$$\Delta\sigma_{y,t} = \beta_0 + \beta_1\Delta\overline{M}_t + \beta_2\Delta\overline{R}_t + \beta_3\Delta\overline{MCR}_t + \beta_4\Delta\sigma(Y_{y,t}) + \beta_5\Delta\overline{Y}_t + \beta_6\Delta\overline{\pi}_t + u_t. \quad (14)$$

Table VII Column C reports the results. Note that we have dropped the twelfth lag of the dependent variable as a regressor, since the residuals are no longer autocorrelated.[14] The margins coefficient is smaller, but still negative at -0.036. The standard error, however, has risen to 0.020, and the coefficient can thus no longer be considered reliably different from zero by conventional standards.

Doubts about the reliability of the margin effect are further increased by a second danger signal, to wit, the lack of robustness of the specification. Why does the margins coefficient flip from a positive sign in the bivariate regression (Table IV Column B) to a negative sign in the multiple regression (Table VII Column C)? To test the sensitivity of the regression to changes in specification, suppose we were to drop variables successively, starting with the three variables --- $\Delta\sigma(Y_{y,t})$, $\Delta\overline{Y}_t$, and $\Delta\overline{\pi}_t$ --- that add no explanatory power in Table VII Column C. There would be no change in the remaining coefficients, as can be seen from the first column of Table VIII. So far, so good. Now take out each of the remaining regressors one at a time. In the second column, we remove $\Delta\overline{R}_t$. The margins coefficient drops by a factor of six to -0.0056 and to only one third of its standard error. In the third column, we take out $\Delta\overline{MCR}_t$ and put $\Delta\overline{R}_t$ back in. Now the critical margins coefficient drops by two orders of magnitude to -0.0004 and to only about 2% of its standard error. The coefficient of average return falls to slightly less than half its previous value but remains statistically important. In the fourth column, we omit the presumably critical margin requirement variable altogether. Yet we find no important change in the other two coefficients. Clearly the size of the margins coefficient is not robust with respect to the specification of the regression. Furthermore, there are signs that the two "control" variables, $\Delta\bar{R}_t$ and $\Delta\overline{MCR}_t$, are related to each other and that each is also independently related to volatility.

The persistent negative sign of the margins coefficient in Table VIII must thus trace to the inclusion of either $\Delta\bar{R}_t$, or $\Delta\overline{MCR}_t$, or both, as regressors in the multiple regression. Since $\Delta\overline{MCR}_t$ is the change in the growth rate of the ratio of margin credit to the market value of stocks on the NYSE, it can be decomposed into the difference between the change in the growth rate of margin credit deflated by the CPI (denoted as $\Delta\overline{CRED}_t$) and the change in the real rate of return on stocks on the NYSE (denoted as $\Delta\overline{NYSE}_t$).[15] The latter variable in turn is highly correlated with $\Delta\bar{R}_t$, the change in the real return on the S&P 500 portfolio.[16] To disentangle the separate contributions of $\Delta\bar{R}_t$ and $\Delta\overline{MCR}_t$, therefore, we can rerun the first differenced regressions using $\Delta\overline{CRED}_t$ in place of $\Delta\overline{MCR}_t$. The results are reported in Table IX. Note that $\Delta\bar{R}_t$ is no longer statistically important, and that when we remove $\Delta\bar{R}_t$, there is little change in the other coefficients. We know therefore that the negative sign of the margin requirements coefficient is due primarily to the presence of margin credit as a regressor. In fact, margin credit is the key variable in the volatility regression. By itself, margin credit is negatively correlated with volatility and is statistically important. Without margin credit, the margin requirements variable is positively correlated with volatility (Table IV Column B).

We now have two ways to estimate the correlation between margin requirements and volatility: the bivariate regression in Table IV Column B, and the multiple regression when margin credit is added, as in the second column of Table IX. Which is the correct specification? The data cannot tell us, but simple common sense suggests that it cannot be meaningful to include both margin requirements and margin credit as regressors (whether or not there are other variables). If we include both, the margin requirements coefficient tells the partial correlation between margin requirements and volatility, that is, the correlation between margin requirements and volatility holding margin credit <u>constant</u>. But such a partial correlation is meaningless. Margin requirements can only affect volatility by inducing <u>changes</u> in margin credit! Thus we can rule out the multiple regressions which include both margin requirements and margin credit. The correct specification is the simple bivariate regression of Table IV Column B.

Still another reason lends us to believe that the correct specification for present purpose is that in Table IV Column B. Recall that the real concern with the whole margin requirements issue is its policy implications. Can the Federal Reserve System really hope to reduce stock market volatility by raising initial margin requirements? When it faces these questions at any date, the System does not have the luxury of being able to hold everything else constant. It is not running controlled experiments. It is not concerned at that point with discovering the "true" structure connecting margin requirements to volatility via all other mediating variables. It wants to know simply what the net effect of its action will be; and for that purpose, the "reduced form" equation in Table IV Column B is clearly the relevant one.

To say that margin requirements have no net effect on volatility is not to say that they have no effects at all. They do affect total margin credit, and exactly in the way one would expect as can be seen from the last column of Table X. That effect, moreover, is robust with respect to the inclusion or exclusion of the other variables. Changes in total margin credit, in turn, do appear to be related both to changes in market returns and to changes in volatility, though we cannot be sure which way the causation runs.[17]

To provide more detail on the relative importance of these interactions, we present in Table XI the final regressions rerun in logarithmic difference form. In terms of elasticities, the results indicate that a 1% increase in margin requirements is associated with a 0.08% decline in margin credit, and that a 1% decrease in margin credit is associated with a 5.08% increase in volatility. On net balance, a 1% increase in margin requirements is associated with a 0.04% increase in volatility. Very small potatoes indeed.

III. Conclusion

We have examined daily and monthly stock returns and initial margin requirements set by the Federal Reserve since October 1934. Using daily returns of the S&P 500 index, we find no short-term negative relation between changes in margins and changes in volatility. Using monthly real returns of the S&P 500 Index, we again find no contemporaneous negative relation between margins and volatility. We do, however, see some indications that volatility leads margins, as would be expected if the Federal Reserve System tended to lower (raise) margins when the market fell (rose) and volatility rose (fell). Our findings are thus consistent with those of Moore (1966), Officer (1973), and Schwert (1988), but not those of Hardouvelis (1988a, 1988b). We show that the form of estimating equation used by Hardouvelis (1988a, 1988b) is biased toward finding "significant" effects even when the variables are unrelated. When we correct for the bias by rerunning his regressions in first differenced form, we find a relation between margins and volatility that is extremely weak, and that appears reliably negative only because Hardouvelis includes the value of total margin credit outstanding among his regressors. Margin requirements, however, cannot have independent effects on volatility apart from margin credit, so including them both is a misspecification. Analyzing the variables separately, we find that stock market volatility is negatively associated with margin credit, which, in turn, is negatively associated with margin requirements. On net, volatility appears to be only weakly associated with margin requirements. The data thus offer no support for the view that Federal Reserve margin requirements have been an effective tool for dampening stock market volatility.

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Footnotes

1. Schwert (1988) using an even longer time series confirmed Officer's findings. By contrast, in an earlier time-series cross-section study of individual stocks on the NYSE from 1926 to 1960, George Douglas (1969) concluded that his "data do yield a coefficient which suggests that margin requirement tend to reduce price volatility" (p. 37). These findings, however, were tentative at best, and peripheral to Douglas's main concerns in his paper.

2. Largay and West (1973) conclude that "at most, the announcements of margin increases have a fairly trivial depressing effect on stock price movements, as measured by the daily changes in the S&P Index." (p. 338) They detect no evidence of any relation between margin decreases and stock returns. Grube, Joy, and Panton (1973) come to the opposite conclusion. They find that "Returns were significantly positive both prior to and on the day of the announcement" of margin decreases (p. 672), but that "No significant return residuals were observed in any of the three periods surrounding margin increases." (p. 673)

3. Brown and Forsythe (1974) show that the F statistic rejects the (true) null hypothesis of equal variances at a rate of 24.1% using a 5% significance level for a Student-t distribution with 4 degrees of freedom, and at a rate of 18.4% for a chi-square distribution with 4 degrees of freedom. [Note that Blattberg and Gonedes (1974) find that 15 of 30 daily stock returns are well described by Student-t distributions with 3 to 5 degrees of freedom.] Brown and Forsythe

(1974) suggest using the modified Levene statistic, which is calculated as follows. Suppose we have G groups of data, indexed i=1,...,G. Each group contains n_i observations. Suppose $\sigma 2$ is the variance of the i-th group. The null hypothesis is that $\sigma_1^2=\sigma_2^2=\ldots=\sigma_I^2$. Let x_{ij} be the j-th observation in the i-th group. The Levene (1960) statistic is computed as follows:

$$z_{ij} = |x_{ij} - \bar{x}_{i.}|, \text{ where } \bar{x}_{i.} = \Sigma_j x_{ij}/n_i$$

$$W = [\ \Sigma_i n_i (z_{i.} - z_{..})^2/(G-1)\ ]/ [\ \Sigma_i \Sigma_j (z_{ij}-z_{i.})^2/\Sigma_i(n_i-1)\ ]$$

where $z_{i.} = \Sigma_j z_{ij}/n_i$ and $z_{..} = \Sigma_i \Sigma_j z_{ij} /\Sigma_k n_k$.

Under the null hypothesis that x_{ij} is independently and identically distributed, W is asymptotically an $F(G-1,\Sigma_i(n_i-1))$ distribution. Brown and Forsythe (1974) suggest the modified Levene statistic by replacing the mean $\bar{x}_{i.}$ with a trimmed mean. In this paper, we use a 10% trimmed mean, which is recommended in Brown and Forsythe (1974).

4. This is not exactly the same as that in Efron (1982). Using his procedure, we will resample both margin requirement and stock market returns. This will break the conditional heteroskedasticity in the latter series. In our procedure, we resample only the path of margin requirements, thus preserving the conditional heteroskedasticity in the stock market returns.

5. There are 23!=1×2×3×...×23 possible rearrangements. We ignore permutations which lead to the same margin requirement in any adjacent periods.

6. A regression of these standard deviations on a constant term and margin requirements yields a slope coefficient of -0.000117, with a standard error of 0.000196, giving no evidence that the level of margin requirements reliably affect stock market volatility.

7. Still another approach to developing a time series on volatility is that of Kupiec (1989), who has estimated monthly volatilities using the generalized autoregressive conditional heteroskedasticity model (GARCH) in Bollerslev (1986). When he tests his measure of volatility against margin requirements, he finds no relation between them. We obtain similar results using Nelson's (1988) exponential GARCH model.

8. The results using M_t are similar, and are therefore not reported.

9. How critical this assumption of independence is to the interpretation of the regression results can be seen from the following calculation. Suppose we were to treat the sample size in Table 6 not as 627 independent observations, but only 23, one for each separate margin regime. Then the t-ratio of the margins coefficient would drop from an impressive 8 to a ho-hum 1.5! And even that might well be substantially too high for any of the additional reasons to be considered below.

10. Salinger (1989) takes issue with the first differenced regression, because "in first differences, more weight is given to the period when margin debt was so low that margin buying could not possibly have affected volatility significantly." (p. 12) But this misses our point. When the results of the levels regression and the first differenced regression differ substantially, the correct specification depends on

the nature of the residuals. In the present context, the levels regression has substantial autocorrelation in residuals, while the first differenced regression does not. Thus the latter is the correct specification, regardless of the difference in weights between the two regressions. The weights in the first differenced regression can be presumed correct, since they produce a properly specified regression.

11. As a further check, we have rerun the bivariate regressions using a proxy for monthly volatility that does not use overlapping data. Specifically, we take the standard deviation of the daily stock returns of the S&P 500 Index within each month. The serial correlation of that volatility series is smaller than the Hardouvelis moving average proxy, as would be expected; but the correlation of the regression residuals is still high enough to require correction by adding several lags of the dependent variable. The coefficients of M_t or $\bar{M}_t$ turn out to have negative signs, but remain very small relative to their standard errors (with t-ratios around 0.2) and hence again cannot be considered reliably different from zero.

12. The covariance matrix of the coefficients allows for heteroskedastic residuals. In an earlier draft, we assumed homoskedastic residuals, and found no lead-lag relation between margins and volatility. We thank William Schwert for calling this to our attention.

13. An alternative way is to start with the first lag of the dependent variable, and continue to add lags until the autocorrelation of the residuals has been removed. For this equation, thirteen lags are

needed. It turns out, however, that margin requirements change so infrequently that the margins variable appears to have a unit root. When that is the case, the problem of estimating the correct standard errors becomes extremely complex.

14. The large twelfth autocorrelation coefficient of the residuals is caused by the twelve month window in calculating $\sigma_{y,t}$.

15. The regression of $\Delta\overline{MCR}_t$ on $\Delta\overline{CRED}_t$ and $\Delta\overline{NYSE}_t$ is:

$$\Delta\overline{MCR}_t = \underset{(1.39\times10^{-4})}{5.58\times10^{-6}} + \underset{(0.0032)}{0.984}\ \Delta\overline{CRED}_t - \underset{(0.0030)}{0.980}\ \Delta\overline{NYSE}_t .$$

$R^2 = 0.995$, D.W. = 2.08.

16. The regression of $\Delta\overline{NYSE}_t$ on $\Delta\overline{R}_t$ is:

$$\Delta\overline{NYSE}_t = \underset{(2.96\times10^{-4})}{1.68\times10^{-6}} + \underset{(0.0054)}{0.948}\ \Delta\overline{R}_t$$

$R^2 = 0.980$, D.W. = 2.12.

17. The observed negative correlation between margin credit and volatility could mean, for example, either that brokers were restricting margin accounts because volatility had increased; or that investors were reducing their margin accounts because the market had fallen (which also typically happens to involve a rise in volatility). The direction of these and other interactions among the variables cannot be settled short of a full, simultaneous equation analysis of a kind far beyond the scope of this paper.

Table I
Margins and Volatility of Daily Stock Returns
25-Day Window Around Margin Changes

The modified Levene statistic tests the equality of the standard deviations of stock returns for the 25 trading days before and after each of the 22 margin changes. Bootstrap marginal significance levels are obtained by randomly selecting 1000 days from 14118 daily stock returns and calculating the corresponding 1000 modified Levene statistics for the 25 trading days before and after.

Dates of Margin Change	Margins		Daily Standard Deviations		Modified Levene Statistic	Bootstrap Marginal Significance Level
	Before	After	25 days Before	25 days After		
2/ 1/36	45.00	55.00	0.00832	0.00980	0.2620	0.6860
11/ 1/37	55.00	40.00	0.03607	0.02885	0.4546	0.6040
2/ 5/45	40.00	50.00	0.00560	0.00763	0.1916	0.7200
7/ 5/45	50.00	75.00	0.00570	0.00913	4.2529	0.1290
1/21/46	75.00	100.00	0.00783	0.01346	3.0721	0.1850
2/ 1/47	100.00	75.00	0.00905	0.00785	0.5222	0.5760
3/30/49	75.00	50.00	0.00606	0.00460	1.1176	0.4310
1/17/51	50.00	75.00	0.00799	0.00583	1.5768	0.3440
2/20/53	75.00	50.00	0.00472	0.00547	0.1167	0.7800
1/ 4/55	50.00	60.00	0.00721	0.00869	0.5342	0.5710
4/23/55	60.00	70.00	0.00537	0.00619	1.1054	0.4310
1/16/58	70.00	50.00	0.00818	0.00569	2.8739	0.2060
8/ 5/58	50.00	70.00	0.00516	0.00466	0.0112	0.9260
10/16/58	70.00	90.00	0.00546	0.00755	0.4314	0.6170
7/28/60	90.00	70.00	0.00505	0.00511	0.1439	0.7550
7/10/62	70.00	50.00	0.01667	0.00708	11.2051*	0.0110
11/ 6/63	50.00	70.00	0.00462	0.01128	2.6869	0.2270
6/ 8/68	70.00	80.00	0.00504	0.00594	0.0246	0.8940
5/ 6/70	80.00	65.00	0.00840	0.01836	9.8626*	0.0240
12/ 6/71	65.00	55.00	0.01057	0.00526	8.3417*	0.0370
11/24/72	55.00	65.00	0.00477	0.00500	0.0016	0.9800
1/ 3/74	65.00	50.00	0.01584	0.01199	2.4241	0.2410

* Significant at the 5% level.

Table II
Power of the Bootstrap Modified Levene Test

We perform the following simulation experiment to demonstate that the bootstrap modified Levene test can detect a strong relation between margins and volatility. There are 23 margin periods, each having the same number of months as the original data (totaling 639 observations), as illustrated in Figure 1. In each replication, the simulated stock return in each month is Normally distributed*, with zero mean and standard deviation:

$$\sigma = \alpha - \beta \text{ Margin}.$$

We calibrate the values of α and β to match the following aspects of our data: the highest margin requirement (100%) is matched with the lowest standard deviation (0.0114 per month), and the lowest margin requirement (40%) with the highest standard deviation (0.0668 per month). This gives values of α=.1037 and β=0.0009233, representing a strong negative relation between margins and volatility.

In each replication, we apply the bootstrap modified Levene test to determine the significance level of the rejection using 100 permutations of the margin variable. We perform 1000 replications, and tabulate the percentage of rejection at various significance levels. The results, given below, show that the bootstrap modified Levene test has enough power to detect a strong negative relation between margins and volatility.

Significance Level of the Test	Percentage of Replications Rejected
50%	100.0%
25%	99.8%
10%	97.7%
5%	93.2%
1%	79.7%

* Since the modified Levene statistic is not sensitive to the distributional assumption, we can use the Normal distribution.

Table III
Summary Statistics of Margin and Volatility
October 1934 - December 1987

Summary statistics are given for monthly volatility, $\sigma_{y,t}$, defined as:

$$\sigma_{y,t} = [\ (1/11)\ \Sigma_{j=0}^{11}\ \{ r_{t-j} - (1/12)\ \Sigma_{i=0}^{11} r_{t-i}\ \}^2\ ]^{½}$$

where r_t is the stock return in month t; and for margin requirement in month t, M_t, and average margin requirement in month t, $\overline{M}_t$, defined as:

$$\overline{M}_t = (1/12)\ [\ \Sigma_{j=0}^{11} M_{t-j}\ ].$$

There are 639 observations for $\sigma_{y,t}$ and M_t, and 627 observations for $\overline{M}_t$.

	$\sigma_{y,t}$	M_t	$\overline{M}_t$ [1]
Mean	0.0427	0.5876	0.5898
Median	0.0388	0.5000	0.5500
Standard Deviation	0.0182	0.1460	0.1373
Skewness	2.05	0.71	0.57
Kurtosis	8.93	2.79	2.59
Autocorrelation coefficients:			
Lag 1	0.9570	0.9729	0.9973
2	0.9118	0.9457	0.9889
3	0.8630	0.9155	0.9751
4	0.8200	0.8844	0.9566
5	0.7752	0.8532	0.9338
6	0.7293	0.8201	0.9075
7	0.6795	0.7822	0.8782
8	0.6317	0.7472	0.8466
9	0.5785	0.7121	0.8133
10	0.5241	0.6798	0.7790
11	0.4696	0.6475	0.7443
12	0.4179	0.6139	0.7098
Autocorrelation coefficients of the first differences:			
Lag 1	0.0370	0.0000	0.9298
2	0.0550	0.0533	0.8549
3	0.0420	0.0133	0.7706
4	-0.0050	0.0000	0.6803
5	0.0081	0.0335	0.5859
6	0.0241	0.0838	0.4825
7	-0.0271	-0.0538	0.3727
8	0.0591	0.0000	0.2682
9	0.0281	-0.0539	0.1633
10	-0.0032	0.0000	0.0615
11	-0.0425	0.0203	-0.0429
12	-0.3166	0.0000	-0.1583

1/ October 1935 to December 1987.

Table IV
Regression of Volatility on Margins
October 1935 - December 1987

The regression of volatility $\sigma_{y,t}$ on margins $\bar{M}_t$ is performed in levels:

$$\sigma_{y,t} = \beta_0 + \beta_1 \bar{M}_t + u_t,$$

and in first differences:

$$\Delta\sigma_{y,t} = \beta_0 + \beta_1 \Delta\bar{M}_t + u_t.$$

	(A)	(B)
Method	Levels	First Differences
β_0	0.0674 (0.0030)	0.000053 (0.00022)
β_1	-0.0425 (0.0050)	0.0050 (0.0166)
R^2	0.10	0.0001
D.W.	0.09	1.92

Autocorrelation coefficients of residuals:

Lag	(A) Levels	(B) First Differences
1	0.9518	0.0394
2	0.9002	0.0511
3	0.8445	0.0495
4	0.7927	-0.0080
5	0.7396	0.0102
6	0.6850	0.0147
7	0.6273	-0.0224
8	0.5714	0.0544
9	0.5103	0.0407
10	0.4456	-0.0061
11	0.3812	-0.0371
12	0.3195	-0.3273

Table V
Simulation Experiment Involving Spurious Regression

To simulate the distribution of regression coefficients of volatility on margins, we generate y_t by:

$$y_t = \rho\, y_{t-1} + e_t.$$

We then regress y_t on $\overline{M}_t$:

$$y_t = \alpha + \beta\, \overline{M}_t + u_t.$$

There are 627 observations. We replicate this 10000 times and tabulate the percentage of times the null hypothesis β=0 was rejected, first employing the usual covariance matrix, and then the Newey-West covariance matrix for 12 and 24 lags.

Percent of Replication Rejecting the Null Hypothesis that β=0

	Nominal Size Left tail			Nominal Size Right tail		
ρ	1%	2.5%	5%	5%	2.5%	1%
Least Squares with usual covariance						
0.00	1.07	2.58	5.03	5.38	2.58	1.12
0.50	8.73	12.54	16.64	17.35	13.23	9.16
0.95	32.47	34.82	37.25	38.32	36.02	33.42
1.00	38.93	40.74	42.37	41.32	39.82	37.88
Least Squares with Newey-West covariance (12 lags)						
0.00	1.51	3.34	5.99	6.36	3.55	1.57
0.50	2.12	4.23	7.03	7.38	4.59	2.29
0.95	9.26	12.88	17.08	18.21	13.86	10.07
1.00	17.22	20.94	24.69	23.81	20.06	16.47
Least Squares with Newey-West covariance (24 lags)						
0.00	1.94	3.97	6.66	6.99	4.06	2.00
0.50	2.27	4.40	7.21	7.74	4.69	2.39
0.95	5.94	9.34	13.24	14.06	10.28	6.77
1.00	11.90	15.51	19.55	18.65	15.12	11.75

Table VI
Granger-Causality Tests of Margin and Volatility
October 1935 - December 1987

To test whether the time series x_t Granger-causes the time series y_t, we run the regression:

$$y_t = \alpha_0 + \Sigma_{i=1}^{p} \alpha_i y_{t-i} + \Sigma_{j=1}^{q} \beta_j x_{t-j} + e_t$$

If at least one of the β coefficients is different from zero, then x_t Granger-causes y_t. The lag length p is selected so that the residual e_t is white noise. The lag length q is arbitrary, and was set at 12. Heteroskedasticity-consistent standard errors are in parentheses. Marginal significance levels are in brackets.

x_t	$\bar{M}_t$	$\sigma_{y,t}$
	Granger-causes	Granger-causes
y_t	$\sigma_{y,t}$	$\bar{M}_t$
p	13	38
q	12	12
β_1	0.0022	-0.0459*
	(0.0361)	(0.0183)
β_2	-0.0207	0.0193
	(0.0786)	(0.0256)
β_3	0.0677	0.0049
	(0.0864)	(0.0313)
β_4	-0.1858	-0.0008
	(0.0924)	(0.0250)
β_5	0.2075	-0.0238
	(0.1048)	(0.0274)
β_6	-0.0266	0.0089
	(0.0852)	(0.0306)
β_7	-0.0908	0.0401
	(0.0839)	(0.0304)
β_8	0.1471	-0.0366

	(0.1084)	(0.0312)
β_9	-0.1689	0.0233
	(0.0991)	(0.0306)
β_{10}	0.0851	0.0028
	(0.1035)	(0.0267)
β_{11}	-0.0370	0.0223
	(0.0781)	(0.0244)
β_{12}	0.0195	-0.0438
	(0.0323)	(0.0212)
R^2	0.937	0.9995
D.W.	1.98	1.97
χ^2-test	11.24	21.40
$\beta_1=\beta_2=...=\beta_{12}=0$	[.5085]	[.0448]

* Statistically significant at the 1% level (two-tailed test).

Table VII
Multiple Regression of Volatility on Margin and Other Economic Variables
October 1935 - December 1987

Volatility $\sigma_{y,t}$ is regressed on margin requirement $\overline{M}_t$, returns $\overline{R}_t$, margin credit $\overline{MCR}_t$, industrial production $\overline{Y}_t$, inflation $\overline{\pi}_t$, volatility of industrial production $\sigma(Y_{y,t})$ and the twelfth lag of volatility $\sigma_{y,t-12}$ in levels:

$$\sigma_{y,t} = \beta_0+\beta_1\overline{M}_t+\beta_2\overline{R}_t+\beta_3\overline{MCR}_t+\beta_4\sigma(Y_{y,t})+\beta_5\overline{Y}_t+\beta_6\overline{\pi}_t+\beta_7\sigma_{y,t-12}+u_t.$$

and in first differences:

$$\Delta\sigma_{y,t} = \beta_0+\beta_1\Delta\overline{M}_t+\beta_2\Delta\overline{R}_t+\beta_3\Delta\overline{MCR}_t+\beta_4\Delta\sigma(Y_{y,t})+\beta_5\Delta\overline{Y}_t+\beta_6\Delta\overline{\pi}_t+\beta_7\Delta\sigma_{y,t-12}+u_t.$$

Standard errors, estimated by the Newey-West method with 12 lags, are in parentheses.

Method	(A) Levels	(B) Levels	(C) First Differences
β_1	-0.066	-0.049	-0.036
	(0.014)	(0.012)	(0.020)
β_2	-0.421	-0.374	-0.247
	(0.100)	(0.093)	(0.047)
β_3	-0.384	-0.365	-0.267
	(0.108)	(0.092)	(0.051)
β_4	-0.139	-0.343	-0.015
	(0.213)	(0.191)	(0.093)
β_5	-0.948	-0.824	0.052
	(0.649)	(0.558)	(0.385)
β_6	0.566	0.423	-0.182
	(0.218)	(0.202)	(0.091)
β_7		0.285	
		(0.056)	
R^2	0.46	0.51	0.055
D.W.	0.15	0.20	2.05

Autocorrelation coefficients of residuals:

Lag	(A)	(B)	(C)
1	0.9203	0.8950	-0.0224
2	0.8460	0.7946	0.0509
3	0.7661	0.6860	0.0396
4	0.7008	0.5972	0.0008
5	0.6379	0.5174	-0.0088
6	0.5828	0.4482	0.0005
7	0.5281	0.3829	-0.0156

8	0.4718	0.3157	0.0733
9	0.4020	0.2287	0.0229
10	0.3215	0.1279	-0.0467
11	0.2480	0.0359	-0.0120
12	0.1712	-0.0565	-0.3521

Table VIII
Sensitivity of the Volatility Regression
November 1935 - December 1987

The sensitivity of the first differenced regression of volatility $\sigma_{y,t}$ on margin requirement $\bar{M}_t$, returns $\bar{R}_t$, and margin credit $\overline{MCR}_t$ is shown by omitting the regressors one at a time. Standard errors are in parentheses.

	Dependent Variable			
Independent Variables	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$
$\Delta\bar{M}_t$	-0.036	-0.0056	-0.0004	
	(0.020)	(0.019)	(0.019)	
$\Delta\bar{R}_t$	-0.248*		-0.098*	-0.224*
	(0.046)		(0.037)	(0.044)
$\Delta\overline{MCR}_t$	-0.268*	-0.103*		-0.236*
	(0.050)	(0.041)		(0.047)
R^2	0.055	0.010	0.011	0.049
D.W.	2.05	1.95	1.95	2.03
Autocorrelation coefficients of residuals:				
Lag 1	-0.0224	0.0256	-0.0248	-0.0120
2	0.0503	0.0338	0.0685	0.0558
3	0.0388	0.0535	0.0513	0.0442
4	0.0000	-0.0194	-0.0004	0.0029
5	-0.0105	-0.0036	0.0116	-0.0066
6	0.0001	-0.0079	-0.0062	0.0013
7	-0.0149	-0.0364	-0.0428	-0.0180
8	0.0732	0.0606	0.0516	0.0702
9	0.0241	0.0115	0.0102	0.0221
10	-0.0467	-0.0132	-0.0225	-0.0434
11	-0.0110	-0.0456	-0.0436	-0.0166
12	-0.3526	-0.3398	-0.3613	-0.3517

* Significant at the 5% one-tailed test.

Table IX
Decomposing the Margin Credit Variable
November 1935 - December 1987

We rerun the regressions in Table VIII, replacing the growth rate of the ratio of margin credit to the market value of stocks on the New York Stock Exchange $\Delta\overline{MCR}_t$ by the change in the growth rate of margin credit deflated by the Consumer Price Index $\Delta\overline{CRED}_t$, since $\Delta\overline{MCR}_t = \Delta\overline{CRED}_t + \Delta\overline{NYSE}_t$, where $\Delta\overline{NYSE}_t$ is the growth rate of the market value of stocks on the New York Stock Exchange. Note that $\Delta\overline{NYSE}_t$ is omitted from the regression, because it is highly correlated with the change in the real return on the Standard and Poors 500 portfolio $\Delta\bar{R}_t$. Standard errors are in parentheses.

		Dependent	Variable	
Independent Variables	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$	$\Delta\sigma_{y,t}$
$\Delta\bar{M}_t$	-0.046*	-0.045*		
	(0.019)	(0.019)		
$\Delta\bar{R}_t$	0.030		0.025	
	(0.040)		(0.400)	
$\Delta\overline{CRED}_t$	-0.343*	-0.328*	-0.306*	-0.294*
	(0.047)	(0.042)	(0.045)	(0.078)
R^2	0.089	0.088	0.081	0.080
D.W.	2.08	2.08	2.05	2.05
Autocorrelation coefficients of residuals:				
Lag 1	-0.0373	-0.0369	-0.0220	-0.0220
2	0.0458	0.0517	0.0534	0.0582
3	0.0336	0.0330	0.0413	0.0408
4	0.0000	0.0037	0.0046	0.0076
5	-0.0138	-0.0114	-0.0088	-0.0068
6	0.0039	0.0044	0.0059	0.0063
7	-0.0018	-0.0038	-0.0055	-0.0070
8	0.0813	0.0791	0.0779	0.0761
9	0.0221	0.0228	0.0209	0.0213
10	-0.0557	-0.0577	-0.0513	-0.0530
11	0.0015	0.0008	-0.0071	-0.0060
12	-0.3457	-0.3495	-0.3446	-0.3478

* Significant at the 5% one-tailed test.

Table X
Robustness of the Effect of Margin Requirement on Margin Credit
November 1935 - December 1987

To measure the effect of margins on margin credit, we regress $\Delta\overline{CRED}_t$ on $\Delta\bar{M}_t$. The association is robust with respect to inclusion or exclusion of other variables, such as returns $\Delta\bar{R}_t$ and volatility $\Delta\sigma_{y,t}$. The iterative Cochrane-Orcutt procedure is used to remove the first order serial dependence in the regression residuals. Standard errors are in parentheses.

Independent Variables	Dependent Variable $\Delta\overline{CRED}_t$	$\Delta\overline{CRED}_t$	$\Delta\overline{CRED}_t$
$\Delta\bar{M}_t$	-0.135*	-0.136*	-0.153*
	(0.018)	(0.019)	(0.023)
$\Delta\bar{R}_t$	0.310*	0.310*	
	(0.028)	(0.029)	
$\Delta\sigma_{y,t}$	-0.190*		
	(0.031)		
R^2	0.284	0.225	0.069
D.W.	2.04	2.06	2.08
ρ [Cochrane-Orcutt]	0.19	0.25	0.32
Autocorrelation coefficients of residuals:			
Lag 1	-0.0298	-0.0399	-0.0546
2	0.1188	0.1071	0.0988
3	0.0710	0.0719	0.0366
4	0.0567	0.0355	0.0648
5	0.0968	0.1175	0.1028
6	0.0063	-0.0110	0.0170
7	0.0656	0.0361	0.0153
8	-0.0059	-0.0233	-0.0659
9	-0.0459	-0.0530	0.0050
10	-0.0315	0.0129	-0.0273
11	0.0494	0.0313	0.0852
12	-0.4054	-0.4168	-0.4328

* Significant at the 5% one-tailed test.

Table XI
Association of Volatility, Margin Requirement, and Margin Credit in Terms of Elasticities
November 1935 - December 1987

Key regressions from Tables IX and X are rerun in logarithms to show elasticities. Note that $\ell\sigma_{y,t}$=log($\sigma_{y,t}$), $\ell\bar{M}_t$=log($\bar{M}_t$), $\ell\bar{R}_t$=log(1+$\bar{R}_t$), and $\ell\overline{CRED}_t$=log(1+$\overline{CRED}_t$). The iterative Cochrane-Orcutt procedure is used to remove the first order serial dependence in the regression residuals, when applicable. Standard errors are in parentheses.

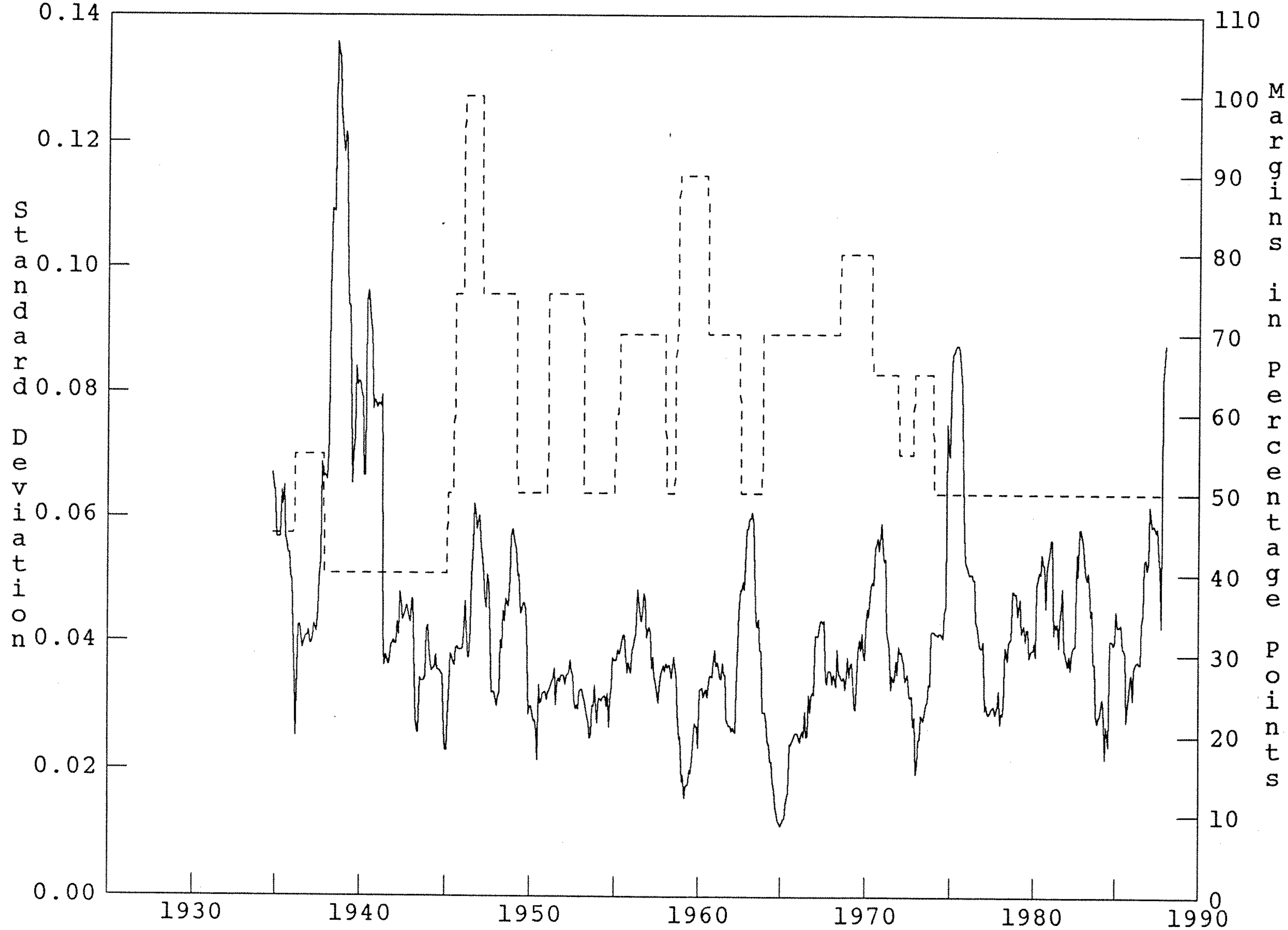
Independent Variables	Dependent Variable: $\Delta\ell\sigma_{y,t}$	$\Delta\ell\overline{CRED}_t$	$\Delta\ell\sigma_{y,t}$
$\Delta\ell\bar{M}_t$		-0.084*	0.044
		(0.012)	(0.266)
$\Delta\ell\bar{R}_t$	-0.337	0.310*	
	(0.894)	(0.029)	
$\Delta\ell\overline{CRED}_t$	-5.075*		
	(0.993)		
$\Delta\ell\sigma_{y,t}$		-0.006*	
		(0.0014)	
R^2	0.053	0.249	0.00004
D.W.	2.15	2.05	2.02
ρ [Cochrane-Orcutt]		0.21	
Autocorrelation coefficients of residuals:			
Lag 1	-0.0710	-0.0350	-0.0083
2	0.0741	0.1203	0.0724
3	0.0325	0.0790	0.0439
4	-0.0306	0.0414	-0.0339
5	0.0559	0.1058	0.0606
6	0.0200	0.0000	0.0080
7	-0.0488	0.0479	-0.0681
8	0.0636	-0.0137	0.0427
9	-0.0086	-0.0595	-0.0158
10	-0.0549	-0.0195	-0.0235
11	0.0431	0.0338	0.0048
12	-0.3033	-0.4109	-0.3049

* Significant at the 5% one-tailed test.

Figure 1. Monthly Volatility and Initial Margin Requirement. The solid line is the monthly volatility, as measured by $\sigma_{y,t}$, defined as:

$$\sigma_{y,t} = [(1/11) \Sigma_{j=0}^{11} \{ r_{t-j} - (1/12) \Sigma_{i=0}^{11} r_{t-i} \}^2]^{1/2}$$

where r_t is the stock return in month t. The dashed line is the margin requirement at the end of month t, M_t.



Standard Deviation
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
1930
1940
1950
1960
1970
1980
1990
Margins in Percentage Points
110
100
90
80
70
60
50
40
30
20
10
0

Figure 2. Average Volatility During the Margin Periods. This is a scatter plot of the average monthly volatility versus the margin requirement during the 22 margin periods.

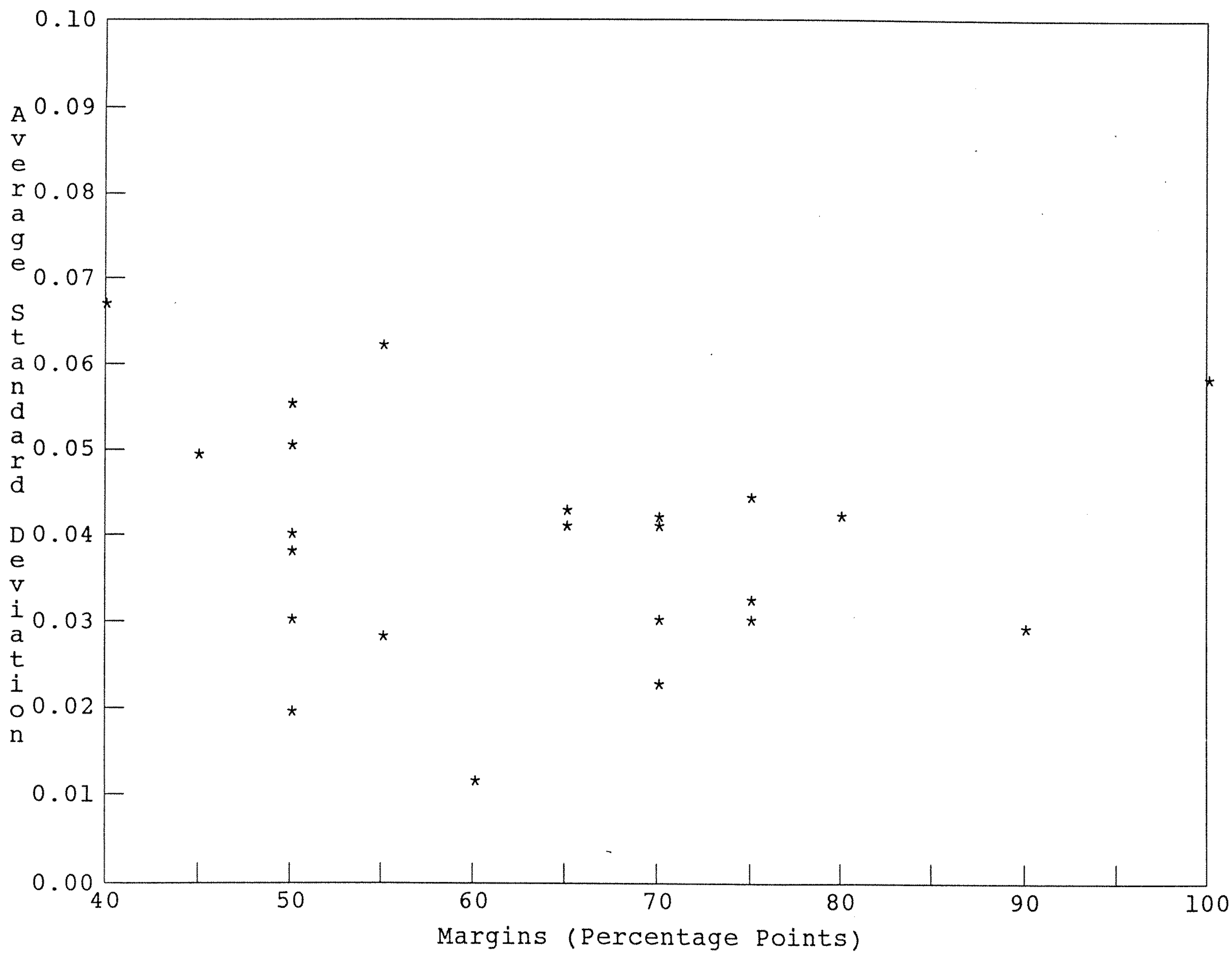
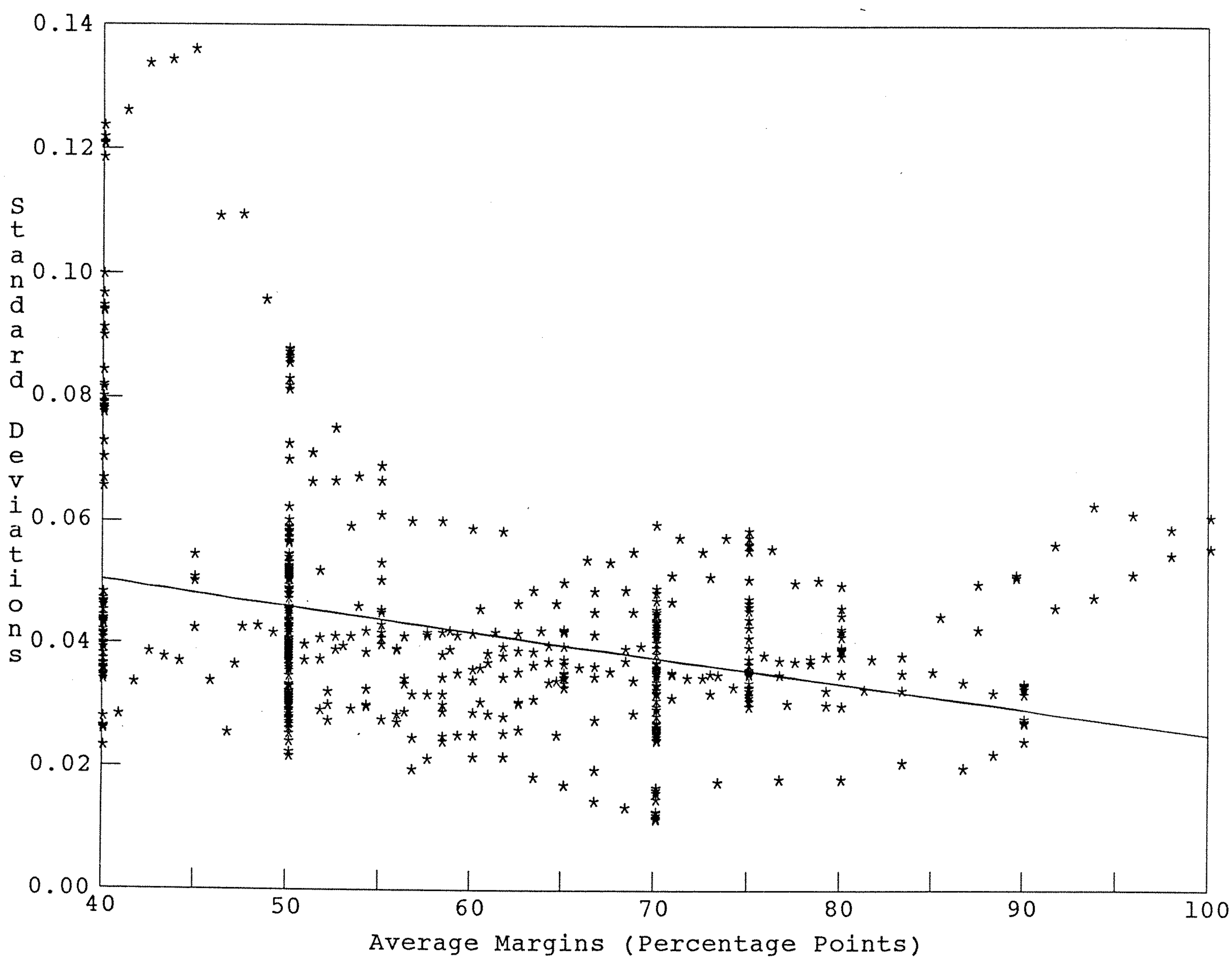

Average Standard Deviation
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
40
50
60
70
80
90
100
Margins (Percentage Points)

Figure 3. <u>Monthly Volatility Versus Average Margins</u>. This is a scatter plot of the monthly volatility $\sigma_{y,t}$ versus the average margin requirement $\bar{M}_t$. The solid line is the fitted values of the regression of $\sigma_{y,t}$ on $\bar{M}_t$,

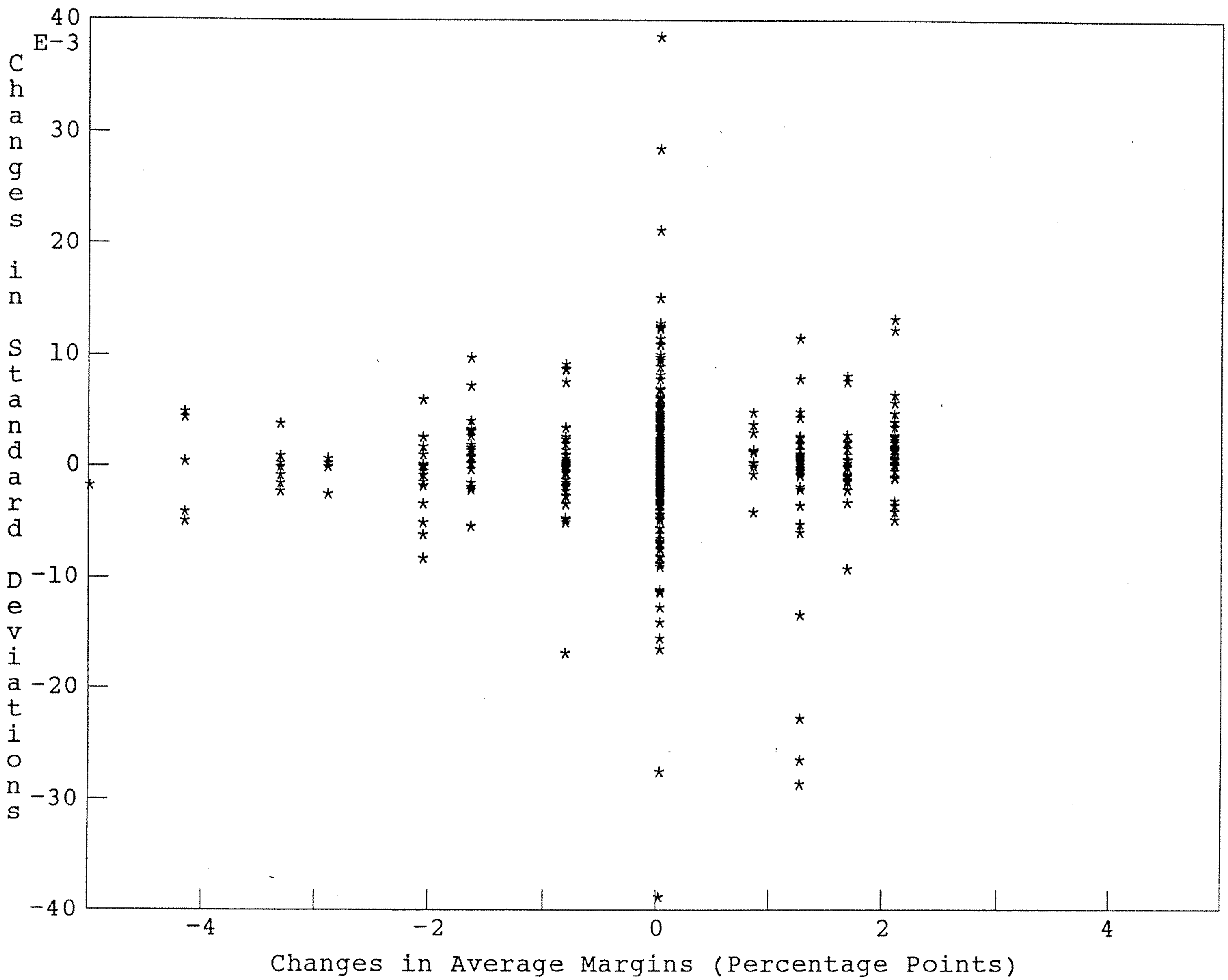
$$\sigma_{y,t} = 0.0674 - .0425\ \bar{M}_t,$$

given in Table IV Column A.



Standard Deviations
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
40
50
60
70
80
90
100
Average Margins (Percentage Points)

Figure 4. <u>Monthly Volatility Changes Versus Margin Changes</u>. This is a scatter plot of the changes in monthly volatility $\Delta\sigma_{y,t}$ versus the changes in average margin requirement $\Delta\bar{M}_t$.



Changes in Standard Deviations
E-3
40
30
20
10
0
-10
-20
-30
-40
-4
-2
0
2
4
Changes in Average Margins (Percentage Points)