# The Asymmetric Relation Between Initial Margin Requirements and Stock Market Volatility Across Bull and Bear Markets

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Higher initial margin requirements are associated with lower subsequent stock market volatility during normal and bull periods, but show no relationship during bear periods. Higher margins are also negatively related to the conditional mean of stock returns, apparently because they reduce systemic risk. We conclude that a prudential rule for setting margins (or other regulatory restrictions) is to lower them in sharply declining markets in order to enhance liquidity and avoid a depyramiding effect in stock prices, but subsequently raise them and keep them at the higher level in order to prevent a future pyramiding effect.

Initial margin requirements are official restrictions on the amount of credit available to investors through brokers and dealers for the purpose of buying stocks. Currently, investors in the U.S. stock market face an initial margin requirement of 50%, which means that at least 50% of the value of the stocks they are buying ought to originate from their own funds. These funds are deposited with the brokers in the form of cash or securities and act as collateral against a sudden drop in prices.[1]

Initial margin requirements were first imposed by Congress with the Securities and Exchange Act of 1934. At that time, Congress reasoned that credit-financed speculation in the stock market may lead to excessive price volatility through a "pyramiding–depyramiding" process [Garbade (1982)]. That is, in

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[1] If the price of the stock rises after the initial purchase, investors can withdraw the differential from their margin account or use it to buy additional stock at the 50% margin. If the price declines after the initial purchase, investors are required to add additional funds to their account only after the price drop erodes their equity position to the level of 25% of the current price of the stock. This is the so-called maintenance margin. See Sofianos (1988) for a detailed description of margin regulation in the United States and Hardouvelis and Peristiani (1992) for the same in Japan.

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the absence of broker-enforced margins, optimistic investors could borrow large amounts of funds and bring stock prices up to levels unjustified by economic fundamentals. This price rise could subsequently feed on itself if speculators were to use their increased wealth to buy more stocks on margin, creating a pyramiding effect. Prices, however, could unravel very fast, creating a depyramiding effect if, in the case of some adverse news, brokers were to ask for additional collateral. If some speculators lacked the requested margin funds, brokers would sell their stocks driving prices down further. This outcome would generate further calls for collateral, more liquidations, and additional price declines.

From 1934 to 1974, the Federal Reserve, which has jurisdiction over the appropriate level of margin requirements, changed the initial margin requirement 22 times. The Federal Reserve's rationale for changing margins can be found by tracing its decisions through official documents and/or by estimating a reaction function [Hardouvelis (1990)]. The Federal Reserve raised margins when it saw signs of "excessive" speculative activity, such as rising stock prices and rising margin credit that appeared unusual. It decreased margins when it thought that the factors which led it earlier to increase margins ceased to exist. Since 1974, however, the Federal Reserve has kept the initial margin requirement constant. This inaction may reflect the belief that the most important role of margins is preventive, i.e., that the existence of margins alone is sufficient to deter destabilizing speculation and, thus, changing the margin level would have only a minor impact. The inaction, of course, may also reflect an increased awareness by the Federal Reserve and the economics profession in general that the primary responsibility of a central bank is the stability of the overall price level, and such stability is accomplished by targeting the overall quantity of credit, not by intervening in the allocation of credit between the stock market and alternative users of funds.

Since 1974, interest in the active use of margin requirements has been renewed twice, once following the stock market crash of October 1987, and a second time in the mid and late 1990s, concurrently with the rapid rise in the U.S. stock market; recall, for example, Alan Greenspan's infamous 1996 reference "irrational exuberance." The crash of 1987 reminded economists of the crash of 1929. Both episodes took place at times during which investors could borrow large amounts of funds with little official restriction. In 1929, there was no margin regulation. In 1980s and 1990s, the cash margin regulation was circumvented by the existence of futures and options contracts on the S&P 500 that allowed investors to leverage themselves owning very little capital of their own. At the time of the crash, these futures contracts had a margin requirement which was approximately 5% of their value. The sixty-year-old question naturally arose once again: To what extent do low margins increase systemic risk, that is, lead stock prices to levels not justified by economic fundamentals and hence make the stock market vulnerable to crashes?

The question of market vulnerability to crashes and the role of margins is a difficult one because of the lack of a precise measure of vulnerability. Ex post measures of realized market "turbulence" cannot match exactly the ex ante concept of vulnerability or fragility, which depends on the probability of market disruptions rather than the actual occurrence of disruptions. Hardouvelis (1990) examined three alternative measures aimed at capturing market vulnerability: volatility at the annual and monthly frequency whose purpose was to capture wide swings in stock prices, excess volatility at horizons ranging from one month to five years, and mean reversion of stock prices at horizons ranging again from one month to five years. He found a negative relation between margins and all three alternative measures of market vulnerability, and concluded that the imposition of margin regulation turned out to be a prudent measure.

The conclusion that official margins reduce systemic risk proved controversial in the post-crash discussions on the appropriate level of futures margins. It was immediately put under scrutiny by other authors [e.g., Kupiec (1989), Schwert (1989), Salinger (1989), and Hsieh and Miller (1990)]. These authors concentrated exclusively on only one of the three measures of market vulnerability examined by Hardouvelis, namely that of monthly volatility. Hence, the original question of the role of margins in reducing the fragility of the market was narrowed down to the role of margins in reducing actual market volatility.

If volatility per se is an item of regulatory concern, it would be desirable to use more satisfactory statistical models of volatility together with the full set of available data. Previous authors used end-of-month stock prices to construct volatility estimates, whereas daily prices are readily available. Moreover, with the exception of Salinger (1989), they tested for the effect of margins on volatility using regressions in first-difference form and came up with substantially different conclusions than those in Hardouvelis (1990), whose analysis was performed in levels. As shown in this paper, when the correct model specification is in levels, model estimation based on first differences without proper adjustments would lead to misspecified models and erroneous results.

The first motivation for the present paper is to elaborate on the correct model specification for margins and volatility and explain why the first difference specification leads to model misspecification. A second motivation is to create and utilize more precise measures of the volatility process, by allowing for a general nonlinear specification and by using more frequent data on stock prices. A third motivation stems from the possibility of an asymmetry in the relation of initial margins with volatility, which can originate from the different roles margins could play during bull, normal, and bear periods.

This potential asymmetry is an item never investigated in the literature. Yet while higher margins serve a preventive role during normal times, they could become counterproductive once a major disruption takes place because they reduce liquidity and can exacerbate the ongoing turmoil. Moreover, the pyramiding–depyramiding process that Congress had in mind when it instituted margin regulation some seventy years ago was an asymmetric process: prudential margin regulation was thought to be a tool of avoiding the excesses of a bull market, thus minimizing the probability of disruptions. Higher margin requirements were not thought to be a tool of smoothing the effects of disruptions.

The different role of margins during bear and bull markets must also have underlined the historical decisions of the Federal Reserve to change the level of margin requirements. Federal Reserve records indicate, for example, that while the Federal Reserve raised margins to prevent the excesses of an ongoing bull market, it lowered margins with the intention of simply counteracting the earlier increase once it believed that the excesses of the earlier bull market were over [Hardouvelis (1990)].

The rest of the paper is organized as follows. Section 1 presents the empirical analysis using a linear regression framework. Besides exploring the existence of asymmetries, the section discusses in detail the stationarity issues that were central to the earlier debate on margin requirements and elaborates on the correct specification of margins and volatility. Section 2 presents the nonlinear econometric framework, which is based on Nelson's (1991) exponential GARCH-in-mean (EGARCH-M) model. This model is a natural candidate for exploring the possible presence of asymmetries. Section 3 discusses the results of the nonlinear model, when it is estimated over three alternative horizons: one day, one week, and one month. Section 4 explores possible hypotheses that can explain the findings. Section 5 summarizes the empirical findings and presents the main policy conclusion.

## 1. The Asymmetric Role of Margins: Linear Regression Analysis

### 1.1 Data and stationarity issues

The daily sample begins on October 15, 1934, when official margin requirements were introduced for the first time, and ends on September 9, 1994. It contains 15,810 daily observations. The weekly sample contains 3,125 observations (week ending on October 20, 1934, through week ending on September 2, 1994), and the monthly sample contains 719 observations (October 1934 through August 1994). Stock returns are constructed from the S&P 500 stock index, $SP_t$, using the formula $R_t = 100^* \ln(SP_t/SP_{t-1})$. Note that returns are expressed in a continuously compounded percentage form and do not include dividends.

The data on initial margin requirements, $M_t$, are taken from Hardouvelis (1990). They are expressed in decimals and, thus, can vary from zero to one.

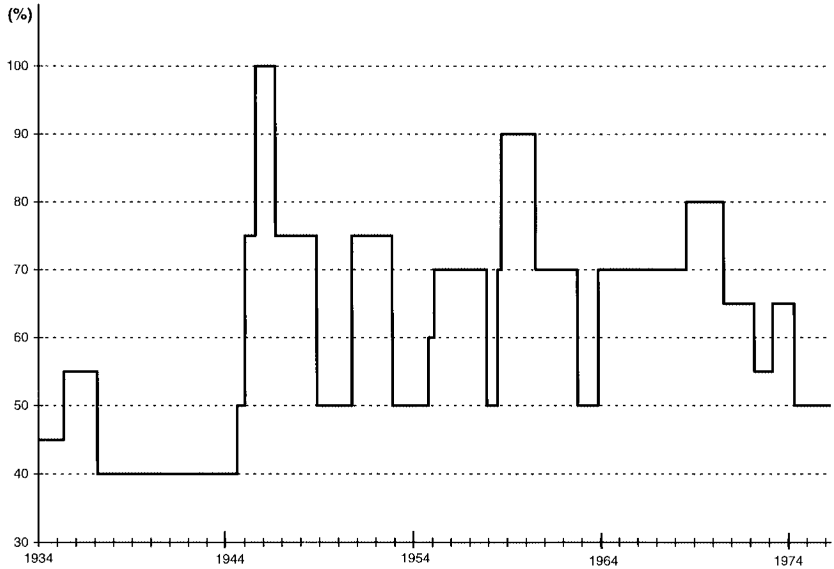


**Figure 1**
**Initial margin requirements in the U.S. stock market**

Figure 1 presents a plot of $M_t$. Over the sampling period, official initial margin requirements were adjusted 22 times. The first official level of margin requirements in October 1934 was set at 45% ($M_t = 0.45$). The current official level is 50% and has been in effect since January 1974. The highest level occurred between January 1946 and January 1947. At that time, the margin was set at 100%, that is, no broker borrowing was allowed. The lowest level ever was 40% and was in effect from November 1937 until February 1945.

Being a discrete policy variable, which is constrained to take values from zero to one, the level of margin requirements cannot be treated as a random walk process, i.e., a process with a unit root, because it has a finite variance. Moreover, from a practical point of view, differencing the margin series results in a new series full of zeroes, except for 22 instances when the value is nonzero. Using such a variable as an explanatory variable of the conditional volatility series is equivalent to testing for temporary blips in volatility at each instance margins were changed and would make it difficult to uncover the long-run relationship between level of margin requirements and volatility.

Although the policy bounds on the level of margin requirements preclude the presence of a unit root in the margin series, in a finite sample its infrequent changes could produce an autocorrelation function similar to one originating from a stochastic series with a unit root. To check this out, we apply a simple Dickey-Fuller (1979) test on the margin series. Let $M_t$ denote the level of margin requirements at the end of month $t$ and $\Delta$ the first-difference operator. We estimate the $k$th-order autoregressive model:

$$\Delta M_t = a_0 + b_1 M_{t-1} + a_1 \Delta M_{t-1} + \cdots + a_k \Delta M_{t-k} + e_{m,t}, \tag{1}$$

where the lag $k(=6)$ is chosen in order to eliminate any serial correlation in the residuals, and test the null hypothesis that $b_1 = 0$. As expected, the infrequent changes in margin requirements make the coefficient $b_1$ close to zero. The estimate of $b_1$ is $-0.0366$ and its $t$-statistic of $-3.81$ is greater than the 5% critical value of $-2.86$.[2] Similar results are obtained when applying the Phillips-Perron (1988) test. We conclude that the unit root hypothesis is rejected both conceptually and empirically.

Turning to the volatility series, we run Dickey-Fuller (1979) tests at the monthly frequency, using the standard deviation of daily returns during month $t$, $\sigma_{d,t}$. The regression model is as follows:

$$\Delta\sigma_{d,t} = a_0 + b_1 \sigma_{d,t-1} + a_1 \Delta\sigma_{d,t-1} + \cdots + a_k \Delta\sigma_{d,t-k} + e_{s,t}, \tag{2}$$

where $k = 2, 6$, or 12. The estimated coefficients $b_1$ with their $t$-statistics in parentheses are $-0.32$ ($-6.32$) for $k = 2$, $-0.23$ ($-4.29$) for $k = 6$, and $-0.21$ ($-3.71$) for $k = 12$. The unit root hypothesis is rejected decisively. Phillips-Perron (1988) tests provide similar rejections. Later, in section 4, we test again for the presence of unit root in conditional volatility using the EGARCH-M model at all three frequencies and reach similar conclusions.

The lack of a unit root in both the margin series and the volatility series suggests that the specification of a model that relates the two variables in levels is a proper one. Nevertheless, the near-unit-root behavior of the margin series together with the high serial correlation in the volatility series could produce a "spurious regression" phenomenon between the levels of the two series, i.e., biased coefficient estimates [Granger and Newbold (1974)]. The possibility of such spurious results has led previous authors to examine the relation between volatility and margin requirements in first-difference form.[3] In subsection 1.3, we examine this issue in greater detail. To anticipate some of the results, we find that in the regressions in levels, the spurious regression phenomenon does not affect our estimates and that estimating the relationship in first-differences can lead to incorrect interpretations of the estimated coefficients.

[2] We have repeated the tests at the daily and weekly frequencies to check the robustness of the rejections. In the daily sample, $k = 23$ and $b_1 = -0.0012$ with a $t$-statistic of $-3.13$. In the weekly sample, $k = 13$ and $b_1 = -0.0069$ with a $t$-statistic of $-3.38$. All Dickey-Fuller tests also reject when $k = 1$.

[3] An exception is Salinger (1989), who performs the analysis in levels.

### 1.2 Regression analysis in levels

This subsection presents a linear regression analysis of the relation between volatility and margin requirements in level form. The sampling period ends in December 1987, instead of September 1994, to facilitate a comparison of the present results to those of Salinger (1989), Hardouvelis (1989, 1990), Hsieh and Miller (1990), and others. Nevertheless, the results for the whole sample are similar. One major difference between the present analysis and the aforementioned studies relates to the empirical proxy of volatility. Our proxy of volatility is the standard deviation of daily returns during each month, $\sigma_{d,t}$. This is, indeed, a daily volatility measure, sampled every month with no data overlapping in its construction. By contrast, the above-mentioned studies use end-of-month stock prices to construct monthly stock returns. Subsequently, either the absolute value of the monthly return in month $t$ is used as a proxy for the volatility of month $t$ or a rolling window of $N$ months, say from $t-N+1$ through $t$, is utilized in order to construct a standard deviation which is taken to measure the volatility of month $t$. The data overlapping in the latter construction generates artificial serial correlation up to order $N-1$ in the volatility estimate.

Table 1 presents the results of five different regressions in which the dependent variable is the level of volatility, $\sigma_{d,t}$. The general form of the model is as follows:

$$\begin{aligned}\sigma_{d,t} = {} & \gamma_0 + \gamma_1\sigma_{d,t-1} + \gamma_2\sigma_{d,t-2} + \theta_R|R_{d,t-1}| \\ & + \delta_R R_{d,t-1} + \alpha_{M,1}M_{t-1} + \delta_{RM}R_{d,t-1}M_{t-1} + \varepsilon_t. \end{aligned} \tag{3}$$

The independent variables are: (i) the past monthly values of daily volatility $\sigma_{d,t-1}$ and $\sigma_{d,t-2}$; (ii) the past volatility shock, measured by the absolute value of the average daily return within the month $|R_{d,t-1}|$; (iii) the average daily stock return of the previous month $R_{d,t-1}$, intended to control for the so-called "leverage" effect on volatility; (iv) the past level of margin requirements, $M_{t-1}$; and (v) the cross product $R_{d,t-1}M_{t-1}$, intended to capture a possible asymmetric relation between margin requirements and volatility.

Estimation is performed using the ordinary least squares (OLS) method. The 95% confidence intervals for the parameters of each regression model, presented in brackets, [.], are constructed using 10,000 bootstrap samples, each generated randomly from the empirical distribution of the OLS residuals of the model. The estimated confidence intervals avoid the pitfalls of the zero autocorrelation assumption, which is implicit in the construction of the usual OLS standard errors. Autocorrelation is particularly problematic in model 1 [observe the Durbin-Watson (DW) and the Ljung-Box (LB) statistics], which does not include any lags of the dependent variable. At the bottom of Table 1, all unit root test statistics reject the null hypothesis of unit root in the residuals. Given the earlier evidence that volatility is stationary, it is not surprising that all these statistics overwhelmingly reject the null hypothesis.

In all five models, a second set of statistics is presented, which are constructed under the null hypothesis that the independent variables $M_{t-1}$, $R_{d,t-1}$, and $R_{d,t-1}M_{t-1}$ are unrelated to volatility $\sigma_{d,t}$. The main purpose of the exercise is to ascertain whether or not there is a bias in the estimated coefficients of these variables, originating from the Granger-Newbold spurious regression

**Table 1**

| Estimates | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Panel A. Regressions of daily volatility on margin requirements | | | | | |
| $\gamma_0$ | 1.1467 | 0.3980 | 0.4590 | 0.4578 | 0.4595 |
| | (14.9)* | (5.13)* | (5.89)* | (5.88)* | (5.90)* |
| | [1.00, 1.30] | [0.25, 0.55] | [0.30, 0.61] | [0.30, 0.61] | [0.31, 0.61] |
| $\gamma_1$ | | 0.4048 | 0.3343 | 0.3323 | 0.3318 |
| | | (9.27)* | (7.23)* | (7.16)* | (7.15)* |
| | | [0.32, 0.49] | [0.25, 0.43] | [0.25, 0.42] | [0.25, 0.43] |
| $\gamma_2$ | | 0.1772 | 0.2024 | 0.2041 | 0.2039 |
| | | (4.50)* | (5.15)* | (5.19)* | (5.18)* |
| | | [0.11, 0.26] | [0.13, 0.28] | [0.14, 0.29] | [0.14, 0.28] |
| $\theta_R$ | | 0.3220 | 0.3748 | 0.3722 | 0.3744 |
| | | (2.56)* | (3.00)* | (2.98)* | (2.99)* |
| | | [0.09, 0.58] | [0.13, 0.63] | [0.14, 0.62] | [0.14, 0.63] |
| $\delta_R$ | | | −0.3250 | | −0.1487 |
| | | | (−4.21)* | | (−0.53) |
| | | | [−0.47, −0.17] | | [−0.71, 0.39] |
| bias($\delta_R$) | | | 0.0002 | | 0.0017 |
| | | | (0.00) | | (0.01) |
| | | | {−2.02} | | {−2.04} |
| $\alpha_{M,1}$ | −0.5630 | −0.1823 | −0.2252 | −0.2229 | −0.2247 |
| | (−4.42)$^\flat$ | (−1.70)$^\flat$ | (−2.11)* | (−2.09)* | (−2.11)* |
| | [−0.81, −0.30] | [−0.39, 0.03] | [−0.43, −0.01] | [−0.43, −0.01] | [−0.43, −0.02] |
| bias($\alpha_{M,1}$) | −0.0849 | −0.0022 | −0.0022 | −0.0022 | −0.0022 |
| | (−0.34) | (−0.02) | (−0.02) | (−0.02) | (−0.02) |
| | {−4.60} | {−1.95} | {−1.95} | {−1.95} | {−1.95} |
| $\delta_{RM}$ | | | | −0.5739 | −0.3224 |
| | | | | (−4.22)* | (−0.65) |
| | | | | [−0.85, −0.30] | [−1.30, 0.65] |
| bias($\delta_{RM}$) | | | | 0.0002 | −0.0027 |
| | | | | (0.00) | (−0.01) |
| | | | | {−2.02} | {−2.08} |
| $R^2$ | 0.0299 | 0.3454 | 0.3633 | 0.3635 | 0.3638 |
| $F$-value | 19.55* | 83.2* | 71.9* | 72.0* | 59.9* |
| DW | 0.91 | 2.02 | 2.00 | 2.00 | 2.01 |
| LB(60) | 831.7* | 51.7 | 60.7 | 61.2 | 61.2 |
| Panel B. Unit-root test statistics for the residuals of the models | | | | | |
| Model with a drift: $\varepsilon_t = m + b\varepsilon_{t-1} + v_t$ | | | | | |
| P-P Statistic for $H_0$ $b = 1$ (Cr. value = −2.86) | −14.66* | −25.49* | −25.31* | −25.39* | −25.35* |
| D-F Statistic for $H_0$ $b = 1$ (Cr. value = −2.86) | −13.60* | −25.43* | −25.16* | −25.25* | −25.21* |

**Table 1**
**(continued)**

| Estimates | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Extended Dickey-Fuller drift and time-trend model: $\Delta\varepsilon_t = m + a(t - T/2) + (b-1)\varepsilon_{t-1} + \sum \Delta\varepsilon_{t-s} + v_t$ | | | | | |
| F-statistic for $H_0$ $(m, a, b) = (0, 0, 1)$ (Cr. value $= 4.68$) | 9.154* | 29.69* | 28.84* | 28.29* | 28.51* |
| F-statistic for $H_0$ $(m, a, b) = (m, 0, 1)$ (Cr. value $= 6.25$) | 13.68* | 44.52* | 43.25* | 42.42 | 42.75* |

The estimated model is

$$\sigma_{d,t} = \gamma_0 + \gamma_1 \sigma_{d,t-1} + \gamma_2 \sigma_{d,t-2} + \theta_R |R_{d,t-1}| + \delta_R R_{d,t-1} + \alpha_{M,1} M_{t-1} + \delta_{RM}(R_{d,t-1} M_{t-1}) + \varepsilon_t.$$

The sample covers the period October 1934 to December 1987 and includes 636 observations. The dependent variable $\sigma_{d,t}$ is the daily volatility during month $t$, computed using the standard deviation of daily returns during month $t$. Its sample mean is 0.8161% and its standard deviation 0.4753%. $R_{d,t}$ is the average daily return for month $t$ expressed in percent. It has a sample mean of 0.0232% and a standard deviation of 0.2114%. || is the absolute value operator and $|R_{d,t}|$ has a sample mean of 0.1594%. $M_t$ is the level of margin requirements at the end of month $t$, expressed in decimals and has a sample mean of 0.5873. Parentheses, (.), include $t$-values and brackets, [.], include 95% confidence intervals constructed from 10,000 bootstrap simulations. Bias (.) denotes the average coefficient constructed from separate 10,000 bootstrap simulations under the null hypothesis of no relation between the dependent variable $\sigma_{d,t}$ with the relevant independent variable. Curved brackets, {.}, below the bias statistics include the 2.5% lower cutoff point in the distribution of 10,000 $t$-statistics generated from the simulations under the null. Asterisk, *, denotes statistical significance at the 5% level and the symbol $^b$ at the 10% level in a two-tailed test. $R^2$ is the regression R-square, D/W is the Durbin-Watson statistic, and LB(60) is the Ljung-Box $\chi^2$ statistic with 60-$k$ degrees of freedom, where 60 is the number of lags in the serial correlation test and $k$ is the number of explanatory variables in each model. P-P and D-F are the Phillips-Perron and Dickey-Fuller statistics for testing the hypothesis of a unit root in the residuals of each model.

phenomenon. A description of the bootstrap simulations is contained in the appendix.

Model 1 presents the simple univariate regression of daily volatility on the level of margin requirements. Consistent with the earlier literature, the margin coefficient is negative and statistically significant, indicating that higher initial margins are associated with lower subsequent volatility. The coefficient of $-0.563$ indicates that an increase of margin requirements from 0.5 to 0.6 is associated with a decline of volatility by 0.0563, or 5.63 basis points. There is substantial serial correlation in model 1, however. This is evidenced by both the DW and LB statistics.[4]

The simulations in model 1, which are run under the null hypothesis that volatility and margins are unrelated, result in an average coefficient estimate of $-0.0849$, denoted in the table as bias $(\alpha_{M,1})$. This estimate is approximately seven times smaller than the OLS coefficient of $-0.563$ and has a very small $t$-value. Thus, the bias is neither statistically nor economically significant. Nevertheless, the simulations also show that inferences from the OLS $t$-statistics are misleading. A $t$-statistic of $-4.42$, as the one of coefficient $\alpha_{M,1}$, would ordinarily indicate strong statistical significance. Yet our simulations under the null show that the 2.5% lower cutoff point of the

[4] The Ljung-Box statistic for $N$ lags is a $\chi^2$ statistic and is calculated using the formula $\mathrm{LB}(N) = T(T+2)\sum_{j=1}^{N} r_j^2/(T-j)$, where $r_j$ is the $j$th-order sample autocorrelation of the series and $T$ is the sample size, see Ljung and Box (1978).

distribution of $t$-statistics is $-4.60$, instead of the expected level of $-1.96$. Thus the estimate of $\alpha_{M,1}$ in model 1 is not statistically significant at the 5% level (in a two-tailed test). It is only statistically significant at the 10% level because the lowest 5% cutoff point of the distribution of $t$-statistics, not reported in Table 1, is $-3.97$. We conclude that model 1 does not have a serious bias problem, but it does have an inference problem, attributed to serial correlation in the residuals or any other model misspecification.

Model 2 enhances model 1 by adding two lags of volatility and one lag of the volatility shock, proxied by $|R_{d,t-1}|$. These variables absorb the serial correlation in the residuals of model 1, as evidenced by both the DW and the LB statistics, which are now statistically insignificant. The margin coefficient in model 2 continues to be negative, but decreases in size from $-0.563$ to $-0.1823$. However, the presence of positive autoregressive terms imply that, following a permanent change in margins, the cumulative long-run association between margins and volatility remains approximately the same. This long-run association is $\alpha_{M,1}/(1-\gamma_1-\gamma_2) = -0.1823/(1-0.4048-0.1772) = -0.4361$, a number not far from the estimated coefficient of $-0.563$ in model 1.

The bootstrap simulations for model 2, run under the null hypothesis that volatility and margins are unrelated, result in an average coefficient estimate for the bias of $-0.0022$, which is orders of magnitude smaller than the OLS coefficient of $-0.1823$. Hence, there is no evidence that the Granger-Newbold spurious regression problem affects the OLS coefficient estimate. The same conclusion is reached in the remaining models 3, 4, and 5, not only for the coefficient $\alpha_{M,1}$, but also for the coefficients $\delta_R$ and $\delta_{RM}$. Their bias is infinitesimal and, of course, statistically insignificant.[5] Moreover, the lowest 2.5% cutoff point in the distribution of $t$-statistics under the null is $-1.95$ for $\alpha_{M,1}$ and slightly below $-2.0$ for $\delta_R$ and $\delta_{RM}$. Hence, inference from the OLS $t$-statistics is not affected by the Granger-Newbold problem.

The weak statistical significance of the margin coefficient in model 2 could be attributed to the lack of appropriate control variables in the regressions [Hardouvelis (1990)]. Variables like margin credit or the recent movement in stock prices influence the Federal Reserve's decision to alter margin requirements and could also be correlated with volatility, biasing the estimate of coefficient $\alpha_{M,1}$. Similarly, the relationship between margin requirements and volatility may be asymmetric. Such an asymmetry would imply that models 1 and 2 would be misspecified even if they were enhanced by other control variables.

Although the focus of the paper is on a possible asymmetric relation between margins and volatility, in model 3 we control for one of the variables

[5] This result is not surprising. In discussing possible remedies for the spurious regression bias, Granger and Newbold propose including in the regression equation the lagged dependent variable, which is exactly what models 2–5 do.

to which the Federal Reserve reacted, the average daily stock return of the previous month, $R_{d,t-1}$. A well-known result in the finance literature is that lagged stock returns are also associated with current volatility and the correlation is negative. This result is confirmed in model 3 of Table 1, where the coefficient $\delta_R$ is negative and statistically significant. Black (1976) argues that lower returns increase financial leverage and, hence, future volatility rises. Christie (1982) finds evidence consistent with the leverage explanation. Another interpretation is that the expectation of higher future volatility increases the risk premium driving down current stock prices [see Campbell and Hentschel (1992) for empirical support]. Duffee (1995) claims the association is a reflection of the skewness of returns, while Gallant, Rossi, and Tauchen (1992) show that the negative association is a tail phenomenon—namely, it is particularly evident following large price changes.

The inclusion of $R_{d,t-1}$ in the regression of model 3 boosts slightly the coefficient $\alpha_{M,1}$ of margin requirements, making it statistically significant. The long-run association between margins and volatility is now $\alpha_{M,1}/(1-\gamma_1-\gamma_2) = -0.2252/(1-0.3343-0.2024) = -0.4861$, implying that the long-run elasticity of volatility with respect to changes in initial margin requirements, that is, the percentage change in volatility with respect to a percentage change in margin requirements, is approximately $-0.35 = -0.4861$ $(0.5873/0.8161)$, where 0.5873 is the average margin requirement in the sample and 0.8161 is the average daily volatility.

Model 4 tests for the presence of an asymmetry according to the sign and size of the previous month's price change. It enhances model 2 through the inclusion of the cross product $R_{d,t-1}M_{t-1}$, instead of $R_{d,t-1}$. The association between margins and volatility is now reflected in the composite coefficient $\alpha_{M,1}+\delta_{RM}R_{d,t-1}$ and, thus, is allowed to vary according to both the sign and the size of the earlier stock price change. Observe that both coefficients $\alpha_{M,1}$ and $\delta_{RM}$ are negative and statistically significant. The statistical significance of $\delta_{RM}$ establishes that the relation of margins to volatility is nonlinear, a result inline with the later EGARCH-M results. The negative sign of $\delta_{RM}$ implies that the negative sensitivity of volatility to margins gets larger in absolute terms, the higher (the more positive) the previous periods return.[6] As a matter of fact, during major stock market downturns, the relationship of initial margins to volatility could even be positive. For margin requirements equal to the current level of 0.5 (or 50%), this anomalous behavior can occur for the cases when the average daily return for a month, $R_{d,t-1}$, is less than $-0.3884\%$, so that the coefficient $-0.2229-0.5739R_{d,t-1} > 0$. About 25.4% of the returns in the daily sample are less than $-0.3884\%$, indicating that the margin coefficient could be reversing its sign quite frequently.

[6] In an alternative formulation of the asymmetry, we separated the months with positive and negative $R_{d,t-1}$. When $R_{d,t-1} > 0$, $\alpha_{M,1} = -0.29$, but when $R_{d,t-1} < 0$, $\alpha_{M,1} = -0.10$ and their difference is statistically significant.

Since the variability of margin requirements is small, one may wonder whether the results of asymmetry in model 4 represent simply another manifestation of the "leverage" effect of model 3. It is possible that the information in the cross product $R_{d,t-1}M_{t-1}$ is dominated by the information in $R_{d,t-1}$. After all, models 3 and 4 provide similar fits to the data, as evidenced by the similarity of their respective $R^2$s. To investigate this issue, we include in model 5 both variables $R_{d,t-1}$ and $R_{d,t-1}M_{t-1}$. If the leverage effect dominates the information in $R_{d,t-1}M_{t-1}$, then $\delta_R$ should be significant and $\delta_{RM}$ insignificant. Conversely, if the information in the cross product $R_{d,t-1}M_{t-1}$ represents mainly an asymmetry effect, then $\delta_{RM}$ should continue being significant despite the presence of $R_{d,t-1}$ in the regression. We find that due to multicollinearity, neither $\delta_R$ nor $\delta_{RM}$ is significant, although both continue to be negative as before. We conclude that both the leverage effect and the asymmetry effect are behind the information in $R_{d,t-1}M_t$, but neither can be detected very clearly when the other is present in regression models.

### 1.3 Regressions in levels or first-differences? A comparison

The earlier battery of tests showed that the correct specification of the model is in levels. In addition, the bootstrap simulations showed that the spurious regression phenomenon of Granger and Newbold (1974) does not affect the estimated coefficients, neither does it affect inferences when lagged dependent variables are included in the regressions. Nevertheless, because previous authors utilized the specification in first differences, which gave little evidence of a negative relationship between volatility and margins, it is worthwhile to estimate the relationship in first-difference form in order to compare the two sets of results and isolate the source of their different empirical assessments.

To facilitate the comparison, we pick model 3 of Table 1, which incorporates the leverage effect, and enhance it by adding a superfluous second lag of margin requirements, $M_{t-2}$, as an explanatory variable:

$$\begin{aligned}\sigma_{d,t} = {} & \gamma_0 + \gamma_1\sigma_{d,t-1} + \gamma_2\sigma_{d,t-2} + \theta_R|R_{d,t-1}| \\ & + \delta_R R_{d,t-1} + \alpha_{M,1}M_{t-1} + \alpha_{M,2}M_{t-2} + \varepsilon_t, \end{aligned} \tag{4}$$

where the various symbols are as defined previously. Recall that the $M_t$ series is highly autocorrelated. Its first-order autocorrelation coefficient is 0.9722 in the monthly sample. Hence, severe multicollinearity exists between $M_{t-1}$ and $M_{t-2}$ in the regression Equation (4). The coefficient estimates for the first five terms of Equation (4), with their $t$-statistics in parentheses, are $\gamma_0 = 0.4714$ (5.74), $\gamma_1 = 0.3302$ (7.17), $\gamma_2 = 0.2089$ (5.43), $\theta_R = 0.3757$ (3.20), and $\delta_R = -0.3368$ ($-4.47$). These estimates are very close to those in Table 1, model 3. The estimated coefficients for the lagged values of margins are $\alpha_{M,1} = 0.6764$ (1.56) and $\alpha_{M,2} = -0.9259$ ($-2.16$). Notice that while multicollinearity pushes the two coefficients in opposite directions, their sum

$\alpha_{M,1} + \alpha_{M,2}$, which represents the cumulative short-run association of margins with volatility, is equal to $-0.2495$, a number very close to the $\alpha_{M,1}$ estimate of $-0.2252$ of model 3 in Table 1. Similarly, the long-run association equals $(\alpha_{M,1} + \alpha_{M,2})/(1 - \gamma_1 - \gamma_2) = -0.2495/(1 - 0.3302 - 0.2089) = -0.5413$, a number close to $-0.4861$ of model 3 in Table 1.

Equation (4) can be transformed into a mathematically equivalent formulation, in which the volatility and the margin variables appear in first-differences, as follows:

$$\begin{aligned}\Delta\sigma_{d,t} = {} & \gamma_0 + (\gamma_1 + \gamma_2 - 1)\sigma_{d,t-1} - \gamma_2 \Delta\sigma_{d,t-1} + \theta_R |R_{d,t-1}| + \delta_R R_{d,t-1} \\ & + (\alpha_{M,1} + \alpha_{M,2}) M_{t-1} - \alpha_{M,2} \Delta M_{t-1} + \varepsilon_t, \end{aligned} \tag{5}$$

where $\Delta$ denotes the first difference operator. Observe that in addition to the lagged first differences in margin requirements and volatility, Equation (5) includes the lagged levels of both margin requirements and volatility as regressors. When the correct specification is in levels, as it is in our case, but the estimation is performed in first-differences, omitting these lagged levels from the regression would result in misspecification error. Previous authors, who employed first difference specifications to investigate the relationship between margins and volatility, omitted these additional level terms and, hence, estimated misspecified models. Observe that the omitted regressors are reminiscent of the error correction terms of cointegrated systems. Hence, previous authors have a misspecification problem similar to the one faced by investigators who ignore the error correction term in co-integrated systems [Engle and Granger (1987)].

Table 2 presents regression estimates for special cases of Equation (5). Models 1 and 2 resemble those used previously to investigate the relationship between margins and volatility because they exclude the lagged levels of margin requirements and volatility as additional regressors. The LB tests clearly indicate that there is unexplained serial correlation in the residuals—due to the exclusion of $\sigma_{d,t-1}$—which is itself indicative of model misspecification. In these models, the coefficients for $\Delta M_{t-1}$ are positive and, in model 2, statistically significant as well! An investigator who would estimate models 1 and 2 of Table 2 would wrongly conclude that the relationship between margin requirements and volatility is positive, when in fact, according to Equation (5), the estimated coefficient is actually the coefficient $-\alpha_{M,2}$, denoting—even in these misspecified models—a negative association between margins and volatility.

Model 3 of Table 2 includes the lagged levels of margin requirements and volatility and, thus, provides a more appropriate specification of the relationship between margins and volatility. Note that the results are identical to those of Equation (4). The sum of the coefficients of $M_{t-1}$ and $M_{t-2}$, $\alpha_{M,1} + \alpha_{M,2}$, is equal to $-0.2495$, exactly the implied number from the estimates of Equation (4) which, in turn, are close to the results of the more correct specification of model 3 in Table 1, which does not include the superfluous second

**Table 2**
**Regressions of changes in daily volatility on margin requirements: levels vs. first differences**

| Estimates | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| $\gamma_0$ | 0.0011 | 0.0403 | 0.4714 |
| | (0.06) | (1.59) | (6.05)* |
| | [−0.03, 0.04] | [−0.01, 0.09] | [0.32, 0.62] |
| $\gamma_1+\gamma_2-1$ | | | −0.4609 |
| | | | (−10.8)* |
| | | | [−0.54, −0.37] |
| $-\gamma_2$ | | −0.3648 | −0.2089 |
| | | (−9.17)* | (−5.31)* |
| | | [−0.44, −0.29] | [−0.29, −0.14] |
| $\theta_R$ | | −0.2253 | 0.3757 |
| | | (−1.86)$^\flat$ | (3.01)* |
| | | [−0.45, 0.02] | [0.14, 0.63] |
| $\delta_R$ | | −0.1273 | −0.3368 |
| | | (−1.57) | (−4.36)* |
| | | [−0.29, 0.03] | [−0.49, −0.18] |
| $\alpha_{M,1}+\alpha_{M,2}$ | | | −0.2495 |
| | | | (−2.33)* |
| | | | [−0.45, −0.03] |
| $-\alpha_{M,2}$ | 0.7665 | 1.0473 | 0.9259 |
| | (1.49) | (2.19)* | (2.09)* |
| | [−0.24, 1.79] | [0.10, 2.00] | [0.05, 1.77] |
| $R^2$ | 0.0035 | 0.1453 | 0.2800 |
| $F$-value | 2.23 | 26.8* | 40.8* |
| DW | 2.72 | 2.12 | 1.99 |
| LB(60) | 124.2* | 97.1* | 60.2 |

The general regression model is

$$\Delta\sigma_{d,t} = \gamma_0 + (\gamma_1+\gamma_2-1)\sigma_{d,t-1} - \gamma_2\Delta\sigma_{d,t-1} + \theta_R|R_{d,t-1}| + \delta_R R_{d,t-1} + (\alpha_{M,1}+\alpha_{M,2})M_{t-1} - \alpha_{M,2}\Delta M_{t-1} + \varepsilon_t,$$

where $\Delta$ denotes the first difference operator. The above model originates from an algebraic transformation of the following regression equation in levels:

$$\sigma_{d,t} = \gamma_0 + \gamma_1\sigma_{d,t-1} + \gamma_2\sigma_{d,t-2} + \theta_R|R_{d,t-1}| + \delta_R R_{d,t-1} + \alpha_{M,1}M_{t-1} + \alpha_{M,2}M_{t-2} + \varepsilon_t,$$

which adds a superfluous second lag of margin requirements, $M_{t-2}$ , on the regression equation of model 3, Table 1. See the notes of Table 1 for variable definitions and other explanations.

lag in margin requirements. Thus, it is possible to approximately replicate the results of regressions in levels when one runs the models in first differences. However, an investigator who runs regressions in first differences without the benefit of Equation (5) would most likely omit the lagged levels of volatility and margin requirements. Hence, estimating the relationship between margin requirements and volatility in first differences can lead to serious misinterpretations of the estimated coefficients. The true relationship between margin requirements is detected clearly and easily only from regressions in levels.

## 1.4 Is there an asymmetric relation across bull and bear markets?

In this subsection we extend our investigation into the possible existence of an asymmetric relation between margin requirements and stock market volatility by separating out periods of rising stock prices, the so-called "bull" markets, and periods of declining stock prices, i.e., "bear" periods. Our earlier analysis examined the possibility of an asymmetry based on the magnitude and sign of the price change of the previous month. However, a bull or a bear market is a period of consecutive monthly increases or decreases in stock prices whose horizon is perceived to last well beyond one month. Indeed, in our present analysis we examine horizons of three months and longer.

We adopt as a definition of a bull or a bear market the following: a period during which there are at least $N$ consecutive monthly stock returns with the same algebraic sign. Because there is no widely accepted definition of a bull or a bear period, the horizon $N$ of our analysis takes four possible values, $N = 3, 4, 5$, and 6 months. We thus allow the readers to focus on the results that best fit their intuition of a bull or a bear market.

Table 3 presents some descriptive statistics for these periods. In the case of $N = 3$, there are 44 disjoint "bull" periods, i.e., periods containing at least three consecutive positive monthly returns. These periods contain 220 monthly observations, or 34.6% of the sample. The bear periods are 31 and the number of observations falling into these periods is 123, or 19.4% of the sample. The "normal" periods, i.e., periods with at most two consecutive monthly returns with the same algebraic sign, are 293 ($=636 - 220 - 123$), or 45% of the sample. Observe that as the horizon $N$ increases, the number of bull and bear periods (as well as the number of observations in them) decline. At the longest horizon we examine, the horizon of six months, the bull periods are 16 and the bear periods 5 and, together, they cover only 24.7% of the sample.[7]

To check for a possible asymmetry effect across bull and bear periods, we define two dummy variables, $\mathrm{BULL}_t$ and $\mathrm{BEAR}_t$, which take the value of unity during bull and bear periods respectively and the value zero otherwise. Subsequently, we include the cross products $\mathrm{BULL}_t M_{t-1}$ and $\mathrm{BEAR}_t M_{t-1}$ as additional regressors to model 3 of Table 1. Model 3 was chosen because it controls for the leverage effect. The regression equation takes the form:

$$\begin{aligned}\sigma_{d,t} = {} & \gamma_0 + \gamma_1 \sigma_{d,t-1} + \gamma_2 \sigma_{d,t-2} + \theta_R |R_{d,t-1}| + \delta_R R_{d,t-1} \\ & + \alpha_{M,1} M_{t-1} + \alpha_{MBULL} \mathrm{BULL}_t M_{t-1} + \alpha_{MBEAR} \mathrm{BEAR}_t M_{t-1} + \varepsilon_t. \quad (6)\end{aligned}$$

[7] We have also utilized an alternative definition of bull and bear markets based on excess stock returns, defined as deviations of monthly returns from their overall sample mean. For each horizon $N$, this alternative definition provides fewer bull periods and more bear periods. The results are qualitatively similar. We prefer the definition based on total returns, as opposed to excess returns, because excess returns can be defined vis-à-vis a variety of benchmarks. We also checked the sensitivity of the results by replacing the unit values of the first one (case $N = 3$) or two observations (cases $N = 4, 5$, and 6) of the $\mathrm{BEAR}_t$ or $\mathrm{BULL}_t$ dummy variables in each bull and bear segments with zero. This was done in order to isolate periods in which the underlying presence of a bear or bull market were already incorporated into the market expectations. The results are qualitatively similar.

**Table 3**
**Margin requirements and volatility across bull and bear markets**

| | $N=3$ | $N=4$ | $N=5$ | $N=6$ |
|---|---|---|---|---|
| BULL nobs | 220 (34.6%) | 169 (26.6%) | 129 (20.3%) | 124 (19.5%) |
| BULL periods | 44 | 27 | 17 | 16 |
| BEAR nobs | 123 (19.4%) | 72 (11.3%) | 48 (7.6%) | 33 (5.2%) |
| BEAR periods | 31 | 14 | 8 | 5 |
| $\gamma_0$ | 0.4829 | 0.5021 | 0.5056 | 0.4960 |
| | (6.30)* | (6.47)* | (6.46)* | (6.29)* |
| | [0.33, 0.63] | [0.35, 0.65] | [0.35, 0.66] | [0.34, 0.65] |
| $\gamma_1$ | 0.3204 | 0.3201 | 0.3215 | 0.3286 |
| | (7.03)* | (6.98)* | (6.99)* | (7.11)* |
| | [0.24, 0.41] | [0.24, 0.42] | [0.24, 0.41] | [0.24, 0.42] |
| $\gamma_2$ | 0.2043 | 0.1930 | 0.1936 | 0.1955 |
| | (5.29)* | (4.97)* | (4.97)* | (4.98)* |
| | [0.14, 0.28] | [0.12, 0.27] | [0.12, 0.27] | [0.13, 0.28] |
| $\theta_R$ | 0.3991 | 0.4027 | 0.3901 | 0.3916 |
| | (3.25)* | (3.26)* | (3.15)* | (3.14)* |
| | [0.17, 0.65] | [0.17, 0.65] | [0.16, 0.63] | [0.16, 0.65] |
| $\delta_R$ | −0.2278 | −0.2504 | −0.2682 | −0.2876 |
| | (−2.90)* | (−3.18)* | (−3.41)* | (−3.64)* |
| | [−0.38, −0.07] | [−0.41, −0.09] | [−0.42, −0.12] | [−0.44, −0.14] |
| $\alpha_{M,1}$ | −0.2780 | −0.2918 | −0.2949 | −0.2771 |
| | (−2.59)* | (−2.75)* | (−2.76)* | (−2.57)* |
| | [−0.48, −0.06] | [−0.49, −0.08] | [−0.51, −0.08] | [−0.48, −0.06] |
| $\alpha_{MBULL}$ | −0.0992 | −0.0838 | −0.0706 | −0.0765 |
| | (−1.75)$^\flat$ | (−1.37) | (−1.03) | (−1.10) |
| | [−0.21, 0.01] | [−0.20, 0.04] | [−0.20, 0.08] | [−0.21, 0.07] |
| $\alpha_{M,1}+\alpha_{MBULL}$ | −0.3771 | −0.3756 | −0.3655 | −0.3537 |
| | (−3.33)* | (−3.09)* | (−2.82)* | (−2.73)* |
| | [−0.59, −0.14] | [−0.60, −0.13] | [−0.62, −0.11] | [−0.60, −0.09] |
| $\alpha_{MBEAR}$ | 0.2574 | 0.3179 | 0.3495 | 0.2542 |
| | (3.89)* | (4.00)* | (3.77)* | (2.42)* |
| | [0.14, 0.39] | [0.18, 0.49] | [0.19, 0.55] | [0.08, 0.50] |
| $\alpha_{M,1}+\alpha_{MBEAR}$ | −0.0206 | 0.0261 | 0.0546 | −0.0230 |
| | (−0.18) | (0.21) | (0.42) | (−0.18) |
| | [−0.24, 0.21] | [−0.19, 0.28] | [−0.19, 0.32] | [−0.27, 0.27] |
| $R^2$ | 0.3876 | 0.3831 | 0.3792 | 0.3708 |
| F-value | 56.8* | 55.7* | 54.8* | 52.9* |
| DW | 2.02 | 2.01 | 2.01 | 2.00 |
| LB(60) | 58.6 | 53.7 | 61.1 | 59.59 |

The estimated model is

$$\sigma_{d,t} = \gamma_0 + \gamma_1 \sigma_{d,t-1} + \gamma_2 \sigma_{d,t-2} + \theta_R |R_{d,t-1}| + \delta_R R_{d,t-1}$$
$$+ \alpha_{M,1} M_{t-1} + \alpha_{MBULL} \mathrm{BULL}_t M_{t-1} + \alpha_{MBEAR} \mathrm{BEAR}_t M_{t-1} + \varepsilon_t,$$

where BULL (BEAR) is a dummy variable that takes the value of one during those periods when at least $N$ consecutive total monthly returns are positive (negative), and the value zero otherwise. Four cases are examined for $N = 3, 4, 5$, and 6 months. See Table 1 for remaining variable definitions and explanations.

Table 3 presents the regression results for all four definitions of bull and bear periods. The coefficients of interest are $\alpha_{MBULL}$ and $\alpha_{MBEAR}$. The coefficient $\alpha_{MBULL}$ is negative, suggesting that in bull periods the negative association of margins with volatility is slightly stronger. This coefficient, is however, not statistically significant. Only in the horizon $N = 3$, do we find statistical significance at the 10% level. The sum $\alpha_{M,1} + \alpha_{MBULL}$ shows that the total short-run association of volatility with margins during bull periods strengthens marginally relative to normal periods.

Unlike bull periods, the relationship between margin requirements and volatility weakens substantially in bear periods. In all cases, the coefficient $\alpha_{MBEAR}$ is positive and statistically significant. Moreover, the sum $\alpha_{M,1} + \alpha_{MBEAR}$ is close to zero and statistically insignificant. For example, in the case of $N = 3$, coefficient $\alpha_{MBEAR}$ is equal to 0.2574 with a $t$-statistic of 3.89, while the sum $\alpha_{M,1} + \alpha_{MBEAR}$ is equal to $-0.0206$ with a $t$-statistic of only $-0.18$. In the cases of $N = 4$ and 5, the sum $\alpha_{M,1} + \alpha_{MBEAR}$ even turns slightly positive. We conclude that the relation between margins and volatility turns slightly more negative during bull periods, but disappears during bear periods.[8]

## 2. An EGARCH-M Model of the Asymmetry

The previous section investigated the relationship of margin requirements with daily volatility in the U.S. stock market through regression analysis in a monthly sample. This section presents a complementary model, which can be used to investigate the relationship between initial margin requirements and the conditional moments—mean and variance—of daily, weekly, and monthly stock market returns. The model is an expanded version of Nelson's (1991) model.

### 2.1 Conditional mean of returns

Stock market returns are expressed as: $R_t = \mu_t + \varepsilon_t$, where $\mu_t \equiv E(R_t \mid I_{t-1})$ is the conditional mean of returns for period $t$ based on information available up to time $t-1, I_{t-1}$, and $\varepsilon_t$ is an error term used as proxy for market innovations (shocks). The conditional mean is specified as:

$$\mu_t = \beta_0 + \beta_M M_{t-1} + \sum_{s=1}^{k} \beta_s R_{t-s} + \lambda \sigma_t^2, \tag{7}$$

where $M_t$ denotes the level of initial margin requirement at time $t-s$ fraction from zero to one, as defined previously, $R_{t-s}$ are past returns, and $\sigma_t^2 \equiv \mathrm{var}(R_t \mid I_{t-1})$ is the conditional variance of $R_t$ based on $I_{t-1}$.

The specification of the conditional mean in Equation (7) is standard. Lagged returns are included to absorb serial correlation whenever it exists. The $\sigma_t^2$ term is intended to capture a possible linkage between the first and second conditional moments of the distribution of returns. This specification is consistent with the static capital asset pricing model (CAPM) that assumes a positive linear relationship between $\mu$ and $\sigma^2$.[9] Finally, the variable $M_{t-1}$

[8] The sample period in Table 3 stops at December 1987 in order to facilitate the comparison with Tables 1 and 2. The results are qualitatively the same when the sample is extended to August 1994. We have also explored other differences during bull and bear periods. For example, both the nonlinearity and the leverage effect are stronger during bear periods, and the former seems to dominate the latter.

[9] The empirical evidence on the presumed positive theoretical association for the U.S. is mixed; see French, Schwert, and Stambaugh (1987), Baillie and DeGennaro (1990), Glosten, Jagannathan, and Runkle (1993), and Theodossiou and Lee (1995).

is included in order to capture a possible direct influence of margin requirements on the risk premium beyond its indirect influence through its possible association with volatility. Indeed, if higher margin requirements reduce uncertainty about future unwarranted stock price movements, that is, uncertainty originating from bubbles, fads, the pyramiding–depyramiding process, etc., that is not fully captured by our measures of volatility, they may well reduce the return investors require in order to invest in the stock market.

## 2.2 Conditional variance of returns

The specification of short-term market volatility in terms of the natural logarithm of the conditional variance of returns, follows the work of Nelson (1991) with some modifications, which allow for a possible nonlinear and asymmetric association between margin requirements and conditional volatility:

$$\ln(\sigma_t^2) = \alpha_t + \alpha_M M_{t-1} + \alpha_{MBEAR}\mathrm{BEAR}_t M_{t-1} + \alpha_{MBULL}\mathrm{BULL}_t M_{t-1} + \sum_{s=1}^{p}\theta_s g(z_{t-s}) + \gamma \ln(\sigma_{t-1}^2). \tag{8}$$

For daily returns, the constant term $\alpha_t = \alpha_0 + \ln(1+\alpha_N N_t)$, where $N_t$ is the number of nontrading days between two successive trading days [Nelson (1991)]. For weekly and monthly returns, $\alpha_t = \alpha_0$. The component $\alpha_M M_{t-1}$ captures the influence of an once-and-for-all change in margin requirements during normal periods. The components $\alpha_{MBEAR}$ $\mathrm{BEAR}_t M_{t-1}$ and $\alpha_{MBULL}$ $\mathrm{BULL}_t M_{t-1}$ allow for a different relationship between margin requirements and volatility during bull and bear periods. Recall that $\mathrm{BEAR}_t$ ($\mathrm{BULL}_t$) is a dummy variable that takes the value of one during bear (bull) periods and zero otherwise. Bear and bull periods are defined as in Table 3, column 2, i.e., they represent periods of at least four consecutive ($N = 4$) total monthly returns of the same algebraic sign.

The variables $z_{t-s} \equiv \varepsilon_{t-s}/\sigma_{t-s}$, for $s = 1, \ldots, p$, are Nelson's (1991) standardized innovations, and the function $g(z_{t-s})$ is an asymmetric nonlinear function of $z_{t-s}$ given by:

$$g(z_{t-s}) = |z_{t-s}| - E|z_{t-s}| + \delta_{t-s}z_{t-s}, \quad \delta_{t-s} = \delta_0 + \delta_M M_{t-s}, \tag{9}$$

where || is the absolute value operator and $E$ denotes the unconditional expected value operator. Nelson's (1991) formulation is the special case of Equation (9), when $\delta_M = 0$. The function $g(z_{t-s})$ can be viewed as a proxy function for past volatility shocks. By construction, the unconditional mean of $g(z_{t-s})$ is zero, $E(g(z_{t-s})) = 0$. Therefore, under stationarity of the conditional variance, $g(z_{t-s})$ has a transitory impact on current conditional volatility and no impact on unconditional volatility. In general, a positive "overall" relationship is expected between past volatility shocks and current volatility, that is, $\sum_{s=1}^{p} \theta_s > 0$.

The function $g(z_{t-s})$ is composed of both a symmetric component of past innovations, $|z_{t-s}| - E|z_{t-s}|$, and an asymmetric component, $\delta_{t-s} z_{t-s}$. As such, it allows for a differential impact of past volatility shocks on current conditional volatility, depending on whether these shocks are based on negative or positive innovations. For example, if the asymmetry coefficient is negative ($\delta_{t-s} < 0$), then negative past innovations ($z_{t-s} < 0$) would have a greater impact on current volatility than positive innovations of the same magnitude.[10] This can be verified by the fact that, for $\delta_{t-s} < 0$, the partial derivative of $g(z_{t-s})$ with respect to $z_{t-s}$ is larger for negative innovations than for positive innovations. That is, when $\delta_{t-s} < 0$,

$$\partial g(z_{t-s})/\partial z_{t-s} = -1 + \delta_{t-s} \quad \text{for } z_{t-s} < 0 \tag{10}$$

$$\partial g(z_{t-s})/\partial z_{t-s} = 1 + \delta_{t-s} \quad \text{for } z_{t-s} > 0 \tag{11}$$

$$\text{and } |-1 + \delta_{t-s}| > |1 + \delta_{t-s}|. \tag{12}$$

As mentioned in section 1.2, a negative $\delta_{t-s}$ is in line with the recent findings of Pagan and Schwert (1990), Nelson (1991), Campbell and Hentschel (1992), and Gallant, Rossi, and Tauchen (1992), among others. A negative $\delta_{t-s}$ implies that volatility rises following “bad news” and falls following “good news.”

The term $\delta_{t-s} = \delta_0 + \delta_M M_{t-s}$ in the modified equation $g(z_{t-s}), s = 1, \ldots, p$, allows for an asymmetric nonlinear short-term relation between margins and conditional short-term volatility. Provided that $\delta_{t-s} < 0$, a negative and statistically significant value for $\delta_M$ implies that increases in margin requirements are associated with larger absolute values of the asymmetry coefficient $\delta_{t-s}$. Therefore, following large declines in stock prices, the higher the level of initial margin requirements, the higher the market volatility; and, following large increases in prices, the higher the level of initial margin requirements, the lower the market volatility.

Finally, observe that from Equations (8) and (9), the expected value of the long-run elasticity of volatility with respect to a permanent change in margin

[10] Another way to illustrate that negative past innovations have a greater impact on current conditional volatility than positive past innovations of the same magnitude is as follows. Let $|z_1| = |z_2|$, where $z_1 < 0$ and $z_2 > 0$. Because $\mathrm{E}|z_1| = \mathrm{E}|z_2|, g(z_1) - g(z_2) = \delta_{t-s} z_1 - \delta_{t-s} z_2 = \delta_{t-s}(z_1 - z_2) > 0$, for $\delta_{t-s} < 0$, indicating that volatility shocks due to negative innovations are larger to volatility due to positive innovations of the same magnitude.

requirements during normal periods is as follows:

$$E_t\left\{\lim_{k\to\infty}(\partial \ln \sigma_{t+k}/\partial \ln M_{t-1})\right\} = 1/2(\alpha_M M_{t-1})/(1-\gamma) \tag{13}$$

where $\partial$ denotes partial derivative.

### 2.3 The distribution of the error term of conditional returns

Contrary to conventional practice, the conditional distribution of returns is not simply assumed to be normal. Instead, it is modeled using the generalized error distribution (GED),

$$\begin{aligned} f(R_t \mid \mu_t, \sigma_t, v) \\ &= (0.5v/\sigma_t)\Gamma(3/v)^{1/2}\exp\{-(\Gamma(3/v)/\Gamma(1/v))^{v/2}|\varepsilon_t/\sigma_t|^v\}, \end{aligned} \tag{14}$$

where $\Gamma(.)$ is the gamma function and $v$ is a scale parameter that controls the shape of GED. The GED distribution accounts for excess kurtosis present in U.S. stock market returns data, e.g., Theodossiou (1998). Note that for $v = 2$, the GED gives the normal distribution and for $v = 1$ it gives the Laplace (double exponential) distribution. The "theoretical" kurtosis for the GED is given by $K^* = \Gamma(5/v)\Gamma(1/v)\Gamma(3/v)^{-2}$. For $v = 1, K^* = 6$ and for $v = 2, K^* = 3$. Values of $1 < v < 2$ imply that $3 < K^* < 6$, in which case the GED density has fatter tails and is more peaked in the middle (leptokurtic) than the normal density.[11]

Estimates for the parameter vector $\Theta \equiv (\beta_0, \ldots, v)$ are obtained by maximizing the sample log-likelihood function

$$L(\Theta|k, p, q) = \sum_{t=1}^{T} \ln f(\mu_t, \sigma_t, v|R_t), \tag{15}$$

which is highly nonlinear in the parameters. The maximization of L(.) is based on the Bernt et al. (1974) algorithm. The specification of the lag order of the conditional mean and the conditional variance (i.e., $k, p$, and $q$) is accomplished by means of the log-likelihood ratio test. Also, residual-based diagnostic tests are performed to assess the robustness of the models.

## 3. The EGARCH-M Model Results

We now turn to the complete EGARCH-M model estimation. The maximum likelihood estimates of the various EGARCH-M models for daily, weekly, and monthly returns are reported in Tables 4, 5, and 6, respectively. In each table, different versions of the model are presented, with and without the

[11] Discussion on the properties and moments of the GED can be found in Nelson (1991), p. 366. Also, note that if $z$ is a standardized GED random variable, then $E|z| = \Gamma(2/v)/[\Gamma(3/v)\Gamma(1/v)]^{1/2}$. For $v = 2$, $E|z| = \sqrt{2}/\pi$.

presence of margins. Each table has three panels. Panel A presents the estimates of the conditional mean equation, panel B the estimates of the conditional volatility equation, and panel C the model diagnostics. The tables present the estimation results over the full sample period from October 1934 through September 1994.

### 3.1 Estimates of the conditional mean equation of stock returns

In panel A of Table 4, daily stock market returns are modeled as a second-order autoregressive process, AR(2). The presence of serial correlation in daily stock returns may be the result of stale prices in the aggregate index. Such serial correlation is less evident at the weekly and monthly horizon of Tables 5 and 6. In the monthly sample, including the return at the fifth lag absorbs some serial correlation. Re-estimating all these models without any

**Table 4**
**EGARCH-M models of daily stock market returns with margin requirements**

| Coefficients | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Panel A. Conditional mean of returns | | | | |
| $\beta_0$ | 0.0309 | 0.0416 | 0.0402 | 0.0408 |
| | (4.15)* | (1.77) | (8.23)* | (8.37)* |
| $\beta_M$ | | −0.0138 | | |
| | | (−0.40) | | |
| $\beta_1$ | 0.1099 | 0.1093 | 0.1082 | 0.1083 |
| | (14.1)* | (14.1)* | (14.1)* | (14.1)* |
| $\beta_2$ | −0.0493 | −0.0500 | −0.0501 | −0.0501 |
| | (−6.61)* | (−6.70)* | (−6.75)* | (−6.75)* |
| $\lambda$ | 0.0168 | 0.0133 | | |
| | (1.48) | (1.14) | | |
| Panel B. Conditional variance of returns | | | | |
| $\alpha_0$ | −0.0066 | 0.0032 | 0.0040 | 0.0040 |
| | (−2.89)* | (0.92) | (1.22) | (1.20) |
| $\alpha_N$ | 0.0018 | 0.0090 | 0.0094 | 0.0105 |
| | (0.31) | (1.46) | (1.54) | (1.68) |
| $\alpha_M$ | | −0.0232 | −0.0245 | −0.0272 |
| | | (−4.08)* | (−4.70)* | (−4.91)* |
| $\alpha_{MBEAR}$ | | | | 0.0131 |
| | | | | (2.67)* |
| $\theta_1$ | 0.2477 | 0.2406 | 0.2394 | 0.2420 |
| | (17.6)* | (17.5)* | (17.5)* | (17.6)* |
| $\theta_2$ | −0.0733 | −0.0674 | −0.0675 | −0.0695 |
| | (−4.50)* | (−4.20)* | (−4.23)* | (−4.36)* |
| $\theta_3$ | −0.0682 | −0.0661 | −0.0647 | −0.0653 |
| | (−5.69)* | (−5.56)* | (−5.45)* | (−5.49)* |
| $\gamma$ | 0.9908 | 0.9895 | 0.9899 | 0.9891 |
| | (784.4)* | (724.5)* | (767.2)* | (713.2)* |
| $t(\gamma = 1)$ | −7.27* | −7.70* | −7.79* | −7.85* |
| $\delta_0$ | −0.4502 | −0.0576 | | |
| | (−12.92)* | (−0.49) | | |
| $\delta_M$ | | −0.7000 | −0.7951 | −0.7995 |
| | | (−3.66)* | (−13.7)* | (−12.8)* |
| Elasticity | | −0.5522 | −0.6080 | −0.6257 |
| Null hypothesis | | $(H_0: \beta_M = \alpha_M = \delta_M = 0)$ | $(H_0: \alpha_M = \delta_M = 0)$ | $(H_0: \alpha_M = \alpha_{MBEAR} = \delta_M = 0)$ |
| L-ratio | | 25.6* | 200.8* | 207.6* |

**Table 4**
**(continued)**

| Coefficients | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Panel C. Model diagnostics | | | | |
| $v$ | 1.2542 | 1.2529 | 1.2523 | 1.2533 |
| | (95.7)* | (96.4)* | (97.6)* | (97.6)* |
| Log-L | −18,107.0 | −18,094.2 | −18,094.9 | −18,091.4 |
| Mean of $z_t$ | −0.0265 | −0.0267 | −0.0244 | −0.0243 |
| Min of $z_t$ | −13.3187 | −14.2333 | −14.3217 | −14.2828 |
| Max of $z_t$ | 6.3341 | 6.6336 | 6.6934 | 6.6321 |
| Variance of $z_t$ | 1.0212 | 1.0226 | 1.0229 | 1.0227 |
| Kurtosis of $z_t$ | 8.7670* | 9.4342* | 9.5207* | 9.5038* |
| Kurtosis $K^*$ based on $v$ | 4.5103 | 4.5153 | 4.5181 | 4.5140 |
| Skewness of $z_t$ | −0.5947* | −0.6370* | −0.6412* | −0.6337* |
| LB(24) | 49.5* | 51.1* | 49.8* | 49.4* |
| LB(48) | 72.3* | 74.3* | 73.3* | 73.5* |
| $LB^2(24)$ | 32.8 | 32.3 | 32.6 | 33.4$^\flat$ |
| $LB^2(48)$ | 46.0 | 43.8 | 43.8 | 45.0 |

The estimated model is

$$R_t = \mu_t + \varepsilon_t = \beta_0 + \beta_M M_{t-1} + \sum_{s=1}^{2} \beta_s R_{t-s} + \lambda\sigma_t^2 + \varepsilon_t,$$

$$\ln(\sigma_t^2) = \alpha_t + \alpha_M M_{t-1} + \alpha_{MBEAR}\mathrm{BEAR}_t M_{t-1} + \sum_{s=1}^{3} \theta_s[|z_{t-s}| - E|z_{t-s}| + (\delta_0 + \delta_M M_{t-s})z_{t-s}] + \gamma \ln(\sigma_{t-1}^2).$$

The sample covers the period October 15, 1934, to September 9, 1994, and includes 15,803 usable observations. Daily continuously–compounded returns are constructed from the S&P 500 stock market index using the formula $R_t = 100 * \ln(SP_t/SP_{t-1})$, where $SP_t$ is the value of the index at time $t$. $R_t$ has a sample mean of 0.025%, a minimum of –22.8997% and a maximum of 9.1914%. In the returns equations, $R_t$, $\mu_t$ is the conditional mean of $R_t$ based on the information available up to time $t$ and $\varepsilon_t$ is the models error used as a proxy for market innovations. Margin requirements, $M_t$, are expressed in decimals; thus, they vary from zero to one. $\mathrm{BEAR}_t$ takes the value of one during bear periods and zero otherwise. A bear period is defined as in Table 3, column 2, over a minimum four-month horizon of consecutive negative total monthly returns. In the conditional variance of returns equation, $z_{t-s} \equiv \varepsilon_{t-s}/\sigma_{t-s}$ are past standardized errors, $\alpha_t = \alpha_0 + \ln(1 + \alpha_N N_t)$ is the intercept expressed as a function of the number of non-trading days between two successive trading days. The elasticity measure is calculated using Equation (13).

Numbers in parentheses below the coefficient estimates are $t$-statistics. * denotes statistical significance at the 5% level and the symbol $\flat$ statistical significance at the 10% level in a two-tailed test.

The parameter $v$ is the scaling parameter for the conditional distribution of returns. Log-L is the sample log-likelihood function evaluated at the MLE estimators. Parentheses include the $t$-values for the estimators. LB($N$) and $LB^2(N)$ are the Ljung-Box $\chi^2$ statistics for $N$ lags on $z_t$ and $z_t^2$, which test the null hypothesis of no serial correlation in each series. The kurtosis based on the estimated parameter $v$ is calculated using the formula $K = \Gamma(5/v)\Gamma(1/v)/\Gamma(3/v)^2$, where $\Gamma(.)$ is the gamma function. The skewness and kurtosis for $z_t$ are calculated using the formulas $m_3/s^3$ and $m_4/s^4$, where $s^2, m_3, m_4$ are respectively the sample variance, third and fourth centered sample moments of the estimated $z_t$. The statistic $t(\gamma = 1)$ tests the null hypothesis that the parameter $\gamma = 1$.

autoregressive terms in the conditional mean does not affect the remaining parameter estimates in any discernible way.

Consistent with the findings of the previous literature, panel A of Table 4 shows that the coefficient $\lambda$ for the conditional variance is statistically insignificant (models 1 and 2), indicating that there is very weak positive linkage between conditional stock market volatility and conditional mean returns. At the weekly and monthly frequencies this linkage is even weaker, so no results are presented including $\sigma_t^2$ in the conditional mean equation.

The association of margin requirements with the conditional mean of returns is quite interesting. The coefficient $\beta_M$ is negative and, in the weekly and monthly samples, statistically significant at the 5 and 10% levels respectively. It follows from model 4, that an increase in margin requirements by

**Table 5**
**EGARCH-M models of weekly stock market returns with margin requirements**

| Coefficients | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Panel A. Conditional mean of returns | | | | |
| $\beta_0$ | 0.2028 | 0.4318 | 0.4323 | 0.4621 |
| | (6.68)* | (3.42)* | (3.48)* | (3.62)* |
| $\beta_M$ | | −0.3906 | −0.3924 | −0.4174 |
| | | (−1.95)$^{\flat}$ | (−1.98)* | (−2.10)* |
| Panel B. Conditional variance of returns | | | | |
| $\alpha_0$ | 0.0381 | 0.0800 | 0.0797 | 0.0869 |
| | (4.57)* | (4.07)* | (4.08)* | (4.13)* |
| $\alpha_M$ | | −0.0653 | −0.0644 | −0.0795 |
| | | (−2.48)* | (−2.48)* | (−2.82)* |
| $\alpha_{MBEAR}$ | | | | 0.0981 |
| | | | | (3.62)* |
| $\theta_1$ | 0.1770 | 0.1753 | 0.1754 | 0.1656 |
| | (8.22)* | (7.74)* | (7.75)* | (7.33)* |
| $\gamma$ | 0.9699 | 0.9633 | 0.9632 | 0.9599 |
| | (172.0)* | (148.6)* | (148.6)* | (141.9)* |
| $t(\gamma = 1)$ | −5.34* | −5.66* | −5.68* | −5.93* |
| $\delta_0$ | −0.4021 | 0.0642 | | |
| | (−5.12)* | (0.25) | | |
| $\delta_M$ | | −0.9213 | −0.8165 | −0.6528 |
| | | (−2.03)* | (−5.20)* | (−3.98)* |
| Elasticity | | −0.4452 | −0.4379 | −0.4953 |
| Null hypothesis | | ($H_0$: $\beta_M = \alpha_M = \delta_M = 0$) | ($H_0$: $\beta_M = \alpha_M = \delta_M = 0$) | ($H_0$: $\beta_M = \alpha_M = \alpha_{MBEAR} = \delta_M = 0$) |
| L-ratio | | 16.12* | 51.1* | 59.1* |
| Panel C. Model diagnostics | | | | |
| $v$ | 1.5062 | 1.5213 | 1.5226 | 1.5215 |
| | (49.9)* | (41.3)* | (44.0)* | (44.1)* |
| Log-L | −6,393.4 | −6,385.4 | −6,385.4 | −6,377.4 |
| Mean of $z_t$ | −0.0428 | −0.0433 | −0.0430 | −0.0447 |
| Min of $z_t$ | −9.7249 | −9.3873 | −9.3323 | −9.6456 |
| Max of $z_t$ | 4.1384 | 4.1851 | 4.1760 | 4.3764 |
| Variance of $z_t$ | 1.0096 | 1.0080 | 1.0079 | 1.0080 |
| Kurtosis of $z_t$ | 6.6676* | 6.2068* | 6.1571* | 6.4856* |
| Kurtosis $K^*$ based on $v$ | 3.7477 | 3.7135 | 3.7111 | 3.7135 |
| Skewness of $z_t$ | −0.6865* | −0.6474* | −0.6446* | −0.6315* |
| LB(12) | 13.0 | 13.2 | 13.1 | 13.6 |
| LB(24) | 35.3$^{\flat}$ | 35.0$^{\flat}$ | 35.0$^{\flat}$ | 35.1$^{\flat}$ |
| $LB^2(12)$ | 4.0 | 3.8 | 3.9 | 4.3 |
| $LB^2(24)$ | 11.6 | 11.3 | 11.3 | 12.9 |

The estimated model is

$$R_t = \mu_t + \varepsilon_t = \beta_0 + \beta_M M_{t-1} + \varepsilon_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_M M_{t-1} + \alpha_{MBEAR}\mathrm{BEAR}_t M_{t-1} + \theta_1[|z_{t-1}| - E|z_{t-1}| + (\delta_0 + \delta_M M_{t-1})z_{t-1}] + \gamma \ln(\sigma_{t-1}^2).$$

The sample covers the period October 20, 1934, to September 2, 1994, and includes 3,118 usable weekly observations. See the notes of Table 4 for variable definitions and other explanations. The sample mean of $R_t$ is 0.1265%, its minimum −19.0832%, and its maximum 16.3707%. Asterisk, *, denotes statistical significance at the 5% level and the symbol $\flat$ statistical significance at the 10% level in a two-tailed test.

five percentage points, say from 0.5 to 0.55 or by 10%, is associated with a drop in the required rate of return on the aggregate stock market by 2.1 basis points at the weekly horizon (1.04% annualized), which accounts for 16.5% of the weekly required rate of return, and by nine basis points at the monthly horizon (1.08% annualized), which accounts for 16.3% of the

**Table 6**
**EGARCH-M models of monthly stock market returns with margin requirements**

| Coefficients | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Panel A. Conditional mean of returns | | | | |
| $\beta_0$ | 0.6399 | 1.7216 | 1.8480 | 1.8828 |
| | (4.39)* | (2.82)* | (3.00)* | (3.15)* |
| $\beta_5$ | 0.1103 | 0.1098 | 0.0931 | 0.0924 |
| | (3.07)* | (3.05)* | (2.60)* | (2.60)* |
| $\beta_M$ | | −1.8875 | −1.8759 | −1.8098 |
| | | $(-1.92)^\flat$ | $(-1.89)^\flat$ | $(-1.89)^\flat$ |
| Panel B. Conditional variance of returns | | | | |
| $\alpha_0$ | 0.1817 | 0.2698 | 0.2089 | 0.3039 |
| | (2.59)* | $(1.90)^\flat$ | $(1.91)^\flat$ | (2.20)* |
| $\alpha_M$ | | −0.0829 | −0.0929 | −0.1032 |
| | | (−0.79) | (−1.03) | (−0.98) |
| $\alpha_{MBEAR}$ | | | 0.2687 | 0.2519 |
| | | | (2.94)* | (2.42)* |
| $\alpha_{MBULL}$ | | | | −0.1914 |
| | | | | (−2.24)* |
| $\theta_1$ | 0.1710 | 0.1574 | 0.1511 | 0.1521 |
| | (3.46)* | (2.96)* | (2.87)* | (2.70)* |
| $\gamma$ | 0.9363 | 0.9224 | 0.9405 | 0.9192 |
| | (39.9)* | (28.3)* | (39.5)* | (30.5)* |
| $t(\gamma = 1)$ | −2.71* | −2.38* | −2.50* | −2.68* |
| $\delta_0$ | −0.4740 | | | |
| | $(-1.92)^\flat$ | | | |
| $\delta_M$ | | −1.0477 | | |
| | | $(-1.81)^\flat$ | | |
| Elasticity | | −0.2671 | −0.3900 | −0.3194 |
| Null hypothesis | | ($H_0$: $\beta_M = \alpha_M = \delta_M = 0$) | ($H_0$: $\beta_M = \alpha_M = \alpha_{MBEAR} = 0$) | ($H_0$: $\beta_M = \alpha_M = \alpha_{MBEAR} = \alpha_{MBULL} = 0$) |
| L-ratio | | 10.9* | 14.6* | 20.9* |
| Panel C. Model diagnostics | | | | |
| $v$ | 1.3632 | 1.3882 | 1.4064 | 1.4092 |
| | (17.4)* | (17.3)* | (17.3)* | (17.7)* |
| Log-L | −2,038.3 | −2,036.2 | −2,034.4 | −2,031.3 |
| Mean of $z_t$ | −0.0411 | −0.0371 | −0.0484 | −0.0503 |
| Min. of $z_t$ | −6.4101 | −6.2912 | −6.2034 | −6.4072 |
| Max. of $z_t$ | 2.3580 | 2.4279 | 2.5269 | 2.6068 |
| Variance of $z_t$ | 1.0231 | 1.0193 | 1.0159 | 1.0163 |
| Kurtosis of $z_t$ | 6.5640* | 6.3025* | 6.2315* | 6.2181* |
| Kurtosis $K^*$ based on $v$ | 4.1269 | 4.0519 | 3.9998 | 3.9919 |
| Skewness of $z_t$ | −0.8594* | −0.8549* | −0.7923* | −0.7388* |
| LB(12) | 9.7 | 9.5 | 11.1 | 12.8 |
| LB(24) | 21.6 | 20.3 | 22.1 | 24.1 |
| $LB^2(12)$ | 6.5 | 6.8 | 6.2 | 6.6 |
| $LB^2(24)$ | 15.1 | 15.6 | 14.4 | 15.3 |

The estimated model is

$$R_t = \mu_t + \varepsilon_t = \beta_0 + \beta_5 R_{t-5} + \beta_M M_{t-1} + \varepsilon_t$$

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \alpha_M M_{t-1} + \alpha_{MBEAR}\,\mathrm{BEAR}_t M_{t-1} + \alpha_{MBULL}\,\mathrm{BULL}_t M_{t-1}$$
$$+\theta_1[|z_{t-1}| - E|z_{t-1}| + (\delta_0 + \delta_M M_{t-1})z_{t-1}] + \gamma \ln\left(\sigma_{t-1}^2\right).$$

The sample covers the period October 1934 to August 1994 and includes 716 usable observations. See the notes of Table 4 for variable definitions and other explanations. The sample mean of $R_t$ is 0.5547%, its minimum 28.8270%, and its maximum 23.1614%. $\mathrm{BEAR}_t$ ($\mathrm{BULL}_t$) takes the value of unity during bear (bull) periods and zero otherwise. A bear (bull) period is defined as in Table 3, column 2, over a minimum four-month horizon of consecutive negative (positive) total monthly returns.

monthly required rate of return. As discussed earlier, one interpretation of this finding is that during periods of higher margin requirements, the risk premium declines due to the perceived beneficial effects of the more stringent regulatory restriction.

It is difficult to find plausible alternative explanations to this negative association. The first such explanation that comes to mind is that of reverse causation: margin requirements increase in anticipation of lower subsequent market returns. However, the historical behavior of the Federal Reserve has been the opposite: the Federal Reserve raised margins because it anticipated further unusual increases, not declines, in stock prices [Hardouvelis (1990)]. A second explanation could be that since the Federal Reserve raised margins at times of rising stock prices, and since—in violation of the market efficiency hypothesis or perhaps due to a systemic risk increase—typically such an unusual increase in stock prices is followed by a decline in prices, a negative relationship can emerge without the presence of either a causal or a predictive link.

### 3.2 Estimates of the conditional variance equation of stock returns without the presence of the margin variable

Panel B of Tables 4, 5, and 6 presents the results for the conditional variance of returns. Model 1, in the first column of panel B, is similar to the models estimated by Pagan and Schwert (1990) and Nelson (1991) because the margin variable is excluded from the equations. In the daily horizon of Table 4, an EGARCH (1,3) model fits the data best, i.e., the conditional volatility equation includes one own-lag and three lags for past volatility shocks. In the weekly and monthly horizons of Tables 5 and 6, the best model is an EGARCH (1,1).

Observe that the coefficients for past volatility shocks and the logarithm of past conditional variance are similar across the five models of each table, regardless of model specification. All coefficients for the logarithm of past conditional variances are very close to unity, indicating high persistence of volatility over time. For example, the coefficient $\gamma = 0.9908$ in the daily horizon implies that it would take approximately $249 = \ln(0.1)/\ln(0.9908)$ business days for the influence of current volatility on future volatility, measured by the logarithm of conditional variance, to diminish to one-tenth the size of its influence on next period's volatility. In the weekly and monthly horizons, the persistence is stronger. For example, the coefficient $\gamma = 0.9363$ in the monthly horizon implies that it would take 35 months for the influence of current volatility to diminish to one-tenth its current influence on next period's volatility.

Despite the high persistence in volatility, the $t$-statistics for testing the null hypothesis that the autoregressive parameter $\gamma$ of the conditional variance is unity reject the null strongly. In the daily data, the $t$-values range between $-7.27$ and $-7.85$. These $t$-statistics all reject the hypothesis of a unit root in the conditional variance of daily returns. The equivalent $t$-statistics for weekly data range from $-5.34$ to $-5.93$ and for monthly data they range between $-2.38$ and $-2.71$, thus, they also reject the hypothesis of a unit root.

In the daily and weekly horizons, the asymmetry coefficient $\delta_0$ of model 1, the model without margins, is negative and statistically significant, confirming the established stylized fact for the postwar period that past negative shocks on the conditional mean have a stronger association with current conditional volatility than past positive shocks [Nelson (1991)]. Also, consistent with the evidence of Glosten, Jagannathan, and Runkle (1993), who use only the postwar subsample, in the monthly horizon of Table 6, $\delta_0$ is much weaker and is statistically significant only at the 10% level.

### 3.3 Estimates of the conditional variance equation of stock returns with the margin variable

In Tables 4 and 5 for the daily and weekly returns, model 2 adds the margin variable as an explanatory variable in both the conditional mean and the conditional variance equation. Thus, estimates are presented for the parameters $\beta_M$, $\alpha_M$, and $\delta_M$. Model 3 is similar to model 2 but more parsimonious, excluding some of the variables that are insignificant in models 1 and 2. Model 4 adds $\mathrm{BEAR}_t M_{t-1}$ as an explanatory variable and thus distinguishes the bear periods from the remaining sample in examining the direct relation between margins and volatility. In Table 6 for the monthly returns, bull periods are separated as well because they show statistically significant differences.

The last row of panel B in Tables 4, 5, and 6 presents a likelihood ratio test statistic for the joint null hypothesis that the included margin variables have zero coefficients in each model. These statistics overwhelmingly reject the null hypothesis, indicating that the inclusion of margin variables in the overall specification of the conditional variance and the conditional mean is important.

In Tables 4 and 5, coefficient $\alpha_M$, which captures the association between the level of margin requirements and volatility, is statistically significant in all versions of the basic model. However, at the monthly horizon of Table 6, the coefficient $\alpha_M$ is insignificant, a piece of evidence consistent with the results of Kupiec (1990), who utilized monthly data and a simpler GARCH-M(1,1) model of the level of the S&P 500 index instead of its return. Perhaps, monthly returns lack statistical power to detect the relationship of margins with volatility, e.g., Andersen and Bollerslev (1997). Recall that in the regressions of Table 1, which showed a stronger association between margins and volatility, the sample was monthly but the volatility measure reflected daily volatility. These regression estimates are more comparable to the daily EGARCH-M estimates rather than the monthly ones. The daily estimates in Table 4 do show a significant coefficient $\alpha_M$.

The expected value of the long-run elasticity of volatility with respect to margins during normal and bull periods, calculated using Equation (13) in model 4, is −0.63 in the daily sample of Table 4 and −0.50 in the weekly sample of Table 5. These elasticities are based on the assumption that the current level of initial margins is 50%, $M_{t-1} = 0.5$, and that margins change permanently. The elasticities imply that a 10% increase in margins—an increase from 0.50 to 0.55—would reduce daily volatility by about 6.3% and weekly volatility by about 5.0%.

Consistent with the regression results of Table 3, the association of margins with volatility is also estimated to be substantially weaker during bear periods. In all three frequencies, the coefficient $\alpha_{MBEAR}$ is positive and statistically significant, while the sum $\alpha_M + \alpha_{MBEAR}$, which captures to total association of margins with volatility during bear periods is close to zero. When it comes to monthly volatility, in Table 6, in addition to the positive and significant coefficient $\alpha_{MBEAR}$, the coefficient $\alpha_{MBULL}$ is negative and statistically significant as well, indicating a stronger (more negative) relation between margins and volatility during bull periods relative to normal periods. Observe that unlike Table 6, Tables 4 and 5 do not report separate estimates for $\alpha_{MBULL}$. As was the case with the daily volatility of the earlier regression models in Table 3, the association of both daily and weekly volatility with margins, while stronger during bull periods, is not statistically different from the association during normal periods.

Margins also play an important role in the asymmetric association of past news with current conditional volatility. The negative asymmetry parameter $\delta_0$ of model 1, which is statistically significant in the daily and weekly horizons of Tables 4 and 5, is explained almost entirely by the variation in margin requirements in model 2. The estimated parameters $\delta_{t-s}$ are associated negatively and significantly with the level of margin requirements, $M_{t-s}$, and have an intercept close to zero, i.e., $\delta_0 \simeq 0$ and $\delta_M < 0$. The asymmetry coefficient becomes more negative (more pronounced) when margins are high, and less negative (less pronounced) when margins are low. Thus, ceteris paribus, at times when stock prices decline, subsequent volatility is higher the higher the margin requirement. Similarly, at times when stock prices increase, subsequent volatility is lower, the higher the margin requirement.[12]

The absorption of the asymmetry parameter $\delta_0$ in the daily and weekly horizons by the level of margin requirements is striking because it is hard to imagine that a variable like margin requirements that has changed only 22 times over the sample period can "explain away" the asymmetry. This finding is perhaps less puzzling if one recalls that (a) the negative relation between conditional volatility and past returns is a tail phenomenon [Gallant,

[12] In the monthly volatility of Table 6, when coefficients $\delta_0$ and $\delta_M$ are estimated simultaneously, they both become statistically insignificant, a result—not reported—equivalent to the regression results in Table 1, model 5, in which both coefficients $\delta_R$ and $\delta_{RM}$ are statistically insignificant.

Rossi, and Tauchen (1992)], i.e., it occurs for large changes in prices, and (b) margins are supposed to play a critical role exactly at times of very large increases or decreases in prices: at times when prices increase drastically, the disruption-preventive role of margins is enhanced, whereas, at times when prices fall rapidly, it is the liquidity constraining role of margins which is enhanced.[13]

### 3.4 EGARCH-M model diagnostics

The first row of panel C in Tables 4, 5, and 6 shows that the estimated scaling parameter $v$ for the conditional distributions of returns ranges around 1.25 in the daily, 1.52 in the weekly, and 1.4 in the monthly horizon. In the daily horizon, therefore, the distribution is much closer to the Laplace distribution ($v = 1$) than to the normal distribution ($v = 2$). Observe also that the theoretical kurtosis based on the estimated scaling parameter $v$ is smaller than the empirical kurtosis estimated using the standardized residuals. This difference is particularly pronounced in the daily and weekly horizons and may be due to the negative skewness present in the distribution of returns as well as the presence of data outliers.

The remaining rows of panel C contain additional useful information. The LB statistics are used to test the null hypothesis of no serial correlation in the standardized residual and squared standardized residual series, $z_t$ and $z_t^2$. Serial correlation in the $z_t$ series may imply that the conditional mean of returns is misspecified. Similarly, serial correlation in the $z_t^2$ series may imply that the conditional variance equation of returns is misspecified. For daily data, the LB statistics are calculated using 24 and 48 lags and, for weekly and monthly data, using 12 and 24 lags. In the daily horizon of Table 4, some serial correlation remains despite the presence of two autoregressive terms in the conditional mean equation. Nevertheless, additional autoregressive terms in the existing conditional mean equation are not warranted because their inclusion provides statistically insignificant autoregressive coefficients. On the other hand, the LB tests on the squared residuals, denoted by $\mathrm{LB}^2(N)$, are statistically insignificant in all three tables, providing no evidence of misspecification in the conditional variance equation.

## 4. Interpretation: Which Hypothesis Explains the Negative Association Between Initial Margin Requirements and Volatility?

It is time now to explore possible explanations of the preceding evidence, beginning with hypotheses which assign a neutral noncausal role to margin requirements. The first such hypothesis states that the observed negative

[13] While striking, the absorption of the asymmetry parameter by the level of margin requirements is, nevertheless, consistent with earlier findings by Gallant, Rossi, and Tauchen (1992) that the negative relationship between conditional volatility and past returns disappears once the analysis includes additional conditioning variables. Specifically, the above authors showed that the asymmetry disappears in the daily horizon when one conditions with respect to past trading volume.

association of margin requirements with future volatility reflects a reverse causation from anticipated future volatility to current margins. In this interpretation, margin requirements are innocuous; namely, they do not increase the cost of trading by imposing a binding constraint on the behavior of investors. While a reverse causation is possible, it does not appear plausible for two reasons: first, it implies that the Federal Reserve used to raise margins in anticipation of lower volatility, a behavior that is counterintuitive and contradicts, for example, the current behavior of the futures exchanges when they decide to change futures margins [e.g., Hardouvelis and Kim (1995) and Booth et al. (1997)]. Moreover, there is no evidence for such behavior in the published documents of the Federal Reserve in which Federal Reserve officials explain their actions. Second, in practice, the neutrality assumption that underlies this interpretation may be too strong. While it is true that, in the long run, financial market participants find ways around regulatory restrictions, it is not clear that these methods carry zero added cost. Moreover, over time, the participants in financial markets are not the same. New entrants may face a higher cost of trading due to the margin regulation than older seasoned participants.

A second related interpretation in which, again, margins play no causal role is as follows: the Federal Reserve raises margins reacting to third variables such as the recent rapid increase of margin credit and stock prices [see Hardouvelis (1990)]; subsequently, these variables themselves cause volatility to decline. A priori, this could be a plausible interpretation if it were substantiated. Yet, the earlier exhaustive analysis of Hardouvelis (1990) shows that the negative association between margins and volatility is even stronger once one controls for such third factors. In the present article, we did not pursue this type of analysis in great detail. Among the possible third factors that could generate a spurious negative relation, the only one for which we have daily information, is stock prices and we already controlled for it in our model. We showed that the inclusion of the lagged stock return in the regression model strengthens the margin coefficient (compare models 2 and 3 of Table 1).

A third possible interpretation is that, in a market of rational investors, higher margins raise the cost of trading and cause volatility to decline. However, models based on rational investors alone typically predict that when the cost of trading increases from the imposition of higher margins and rational investors leave the market, volatility increases, rather than decreases, as liquidity dries up. To build a theoretical model without the presence of irrational investors that explains this association is a major challenge.[14]

[14] Chowdhry and Nanda (1995) take a step in this direction: in their model, a fall in price is equivalent to an increase in the borrowing constraint of risk-averse investors as their wealth declines, while an increase in price is equivalent to a relaxation of the constraint. The rigidity of the margin requirement creates instability. Their model suggests the same margin rule similar to the one derived from the empirical evidence of this paper: during times of large price increases, it is prudent to raise margin requirements, while, during times of large price declines, it is prudent to lower them.

The final interpretation is in line with the pyramiding–depyramiding story, which takes for granted the presence of irrational investors alongside rational ones. According to this interpretation, during bullish markets, initial margin requirements impose a constraint on excessive speculation and result in lower subsequent market disruptions and volatility because they force irrational investors to reduce their participation in the market. The pyramiding–depyramiding story can also explain the observed asymmetry during bear markets: In a bear market, when prices drop by large amounts and investors capital approaches the minimum maintenance margin of 25%, more brokers would require that investors deposit additional funds to recapitalize their position to the level of the initial margin requirement. The requirement to come up with the cash puts further downward pressure on prices either because other stocks are sold to generate cash or because brokers liquidate their customers positions by selling the original stocks that they keep as collateral. In these circumstances, a lower initial margin requirement would reduce the liquidity need of customers who receive margin calls and, hence, would soften the downward pressure on prices and the turmoil in the market. Lower initial margin requirements would also reduce the cost of arbitrage, encouraging other rational investors, who view the drop in prices as unwarranted, to enter the market and purchase stocks, thus smoothing the decline in prices and the depyramiding process and reducing volatility.[15]

The negative relationship between current margin requirements and the subsequent conditional mean of stock returns is also hard to explain with models that assume margins are neutral, even if one were to resort to obscure interactions with third factors [Hardouvelis (1990)]. This negative relationship, however, can easily be interpreted as a reduction in the risk premium once margins are increased. The reduction in systemic risk is in line with the pyramiding–depyramiding hypothesis and was the purpose of the margin regulation in the first place.

## 5. Summary and Policy Conclusion

Following the original Hardouvelis (1990) study, which provides evidence of a negative relation between initial margin requirements and volatility, a number of authors concluded that margins are unrelated to volatility and that the negative association reported in Hardouvelis (1990) is most likely the result of bias arising from the spurious regression phenomenon of Granger-Newbold (1974). The Granger-Newbold bias can arise when two highly autocorrelated time series, like margin requirements and volatility, are regressed on each other in level form.

[15] In the Japanese stock market, following a price decline, the authorities reduce margin requirements and subsequently prices rebound immediately. See Figure II of Hardouvelis and Peristiani (1992). Another piece of evidence consistent with the liquidity story is provided by Seguin and Farrell (1993). They find that during the crash of 1987, U.S. stocks eligible for margin trading fell less than U.S. stocks ineligible for margin trading.

Our analysis shows that both the volatility and the margin series are highly autocorrelated, but stationary, and that the Granger-Newbold bias in the level regressions is neither economically nor statistically significant. These results imply that the specification of the regression equations in level form provides unbiased estimates of the true relationships. The specification in first-differences could provide unbiased estimates as well, provided that the lagged levels of margin requirements and volatility are included in the regressions in a manner similar to the inclusion of error-correction terms in cointegrated systems. When this is done, the regressions in first-difference form also point to a negative association.

Our regressions in levels are consistent with the manner in which a vast set of models in the finance literature, the GARCH models, treat volatility. Although highly autocorrelated, stock market volatility is treated as a stationary process, and correctly so. In this paper, we also examine the relation between margin requirements and volatility within an EGARCH-M model, applied at three different frequencies, daily, weekly, and monthly. Not surprisingly, these models also reveal a negative association between margins and volatility. For example, according to the weekly EGARCH-M estimates, a permanent increase in margin requirements by 10% during "normal" periods (e.g., from 0.5 to 0.55) would be associated with an average reduction in volatility by 4.95%, revealing an elasticity of approximately one-half.

One interpretation of the negative association is that higher margins cause the undesirable excess component of volatility to decline. This interpretation is reinforced by the simultaneous finding that higher margins are associated with lower-risk premia: The same increase of margin requirements by 10% is associated with a decline in the risk premium of weekly returns by two basis points, or 1.04 percentage points annualized.

A major new finding in the paper is that the relation between margin requirements and volatility is a nonlinear one, varying both according to the size of the previous price change and according to the overall direction of the market, that is, whether it is a bull, a sideways, or a bear market. Recall that a stylized fact in the finance literature is that, ceteris paribus, volatility rises following a decline in stock prices and falls following a rise in stock prices. Both the regression models and the EGARCH-M models show that the asymmetry between returns and volatility becomes stronger when margins are high and weaker when margins are low. Put differently, at times when stock prices decline, if margin requirements are low, the subsequent volatility is not as high as it would be if margin requirements were high. Conversely, at times when stock prices rise, if margin requirements are low, subsequent volatility is not as low as it would be if margin requirements were high.

There is also a major asymmetry in the relation between margin requirements and volatility across bull, normal, and bear periods. The negative relation is slightly stronger in bull periods but disappears during bear periods.

The asymmetry across bull and bear markets is detected both in the regression models and in the EGARCH-M models at all three frequencies.

The asymmetries in the relation between margins and volatility are consistent with the pyramiding–depyramiding process of stock prices that was discussed in the introduction and provide a clear policy conclusion: according to our results, when stock prices tumble and margin calls are issued by brokers, it would be stabilizing to avoid further margin calls and to reduce the cost of arbitrage by temporarily lowering the level of initial margin requirements. Conversely, when stock prices keep rising as in the case of a bubble, it would be stabilizing to have higher margin requirements.

The above policy conclusion is quite intuitive and transcends the specific case of margin requirements: regulators should impose restrictions to avoid problems before these problems actually occur, not in the middle of a crisis. For example, in the middle of a bear market, they should avoid imposing a transactions tax on stock trading or even on the frequent churning of stocks. Similarly, in banking, regulators should not and would not enforce stricter capital standards on a banking system that is on the verge of collapse. They would enforce stricter capital standards during normal periods and ahead of time to prevent such future bankruptcies.

Should a policy of active management of margin requirements restart in the United States? Assuming that the regulatory authority can measure the market sentiment, i.e., can assess whether there is a bull, normal, or bear period, the empirical estimates in the paper give a positive answer. Nevertheless, some may argue that today's financial environment is fundamentally different from what it used to be 60 or even 30 years ago. Today, there are many innovations in the market that help circumvent the regulatory restrictions on broker lending. Such examples are the futures and options contracts that were mentioned earlier, or the relatively newer equity swaps. While this argument is true, one should not lose sight of the fact that financial market innovations are primarily utilized by institutional investors. These innovations are usually too costly for individual investors. Small investors, those who will soon proliferate in the developing Internet trading market, are constrained by margin requirements because, for the purposes of buying stocks, a broker loan is a far easier and cheaper transaction than, say, a home equity or any other type of loan.

Should policy makers in emerging markets follow an active margin policy? In these markets, the answer is a clearer yes. Unlike the U.S. market, emerging markets usually suffer from lack of liquidity, high volatility, insider trading, an inadequate regulatory framework, etc. In such markets, the need for stricter rules on borrowing is much more pronounced. Moreover, margin restrictions are more effective in constraining borrowing behavior than they are in the United States since financial innovations, which usually originate in the United States, arrive at these countries with a considerable delay.

# Appendix: Assessing the Importance of the Granger-Newbold Spurious Regression

To estimate the size of the potential bias due to the Granger-Newbold spurious regression phenomenon and to find the lowest 2.5% area of the $t$-distribution of the OLS regression coefficients under the null, we run bootstrap simulations, following the steps described below:

(i) Estimate the regression $\sigma_{d,t} = \gamma_0 + \gamma_1\sigma_{d,t-1} + \gamma_2\sigma_{d,t-2} + \theta_R|R_{d,t-1}| + u_t$, for $t = 1, 2, \ldots, T$, using OLS. Let $\gamma_{0,OLS}$, $\gamma_{1,OLS}$, $\gamma_{2,OLS}$, and $\theta_{R,OLS}$ denote the estimated OLS parameters and $u_{OLS} = (u_{OLS,1}, u_{OLS,2}, \ldots u_{OLS,T})$' denote the vector of OLS residuals.

(ii) Draw with replacement from $u_{OLS}$ to generate a new vector of residuals $u_{SIM}$ of the same size. Then, calculate recursively a "bootstrap" volatility series $\sigma_{SIM,t}$ using the residuals $u_{SIM,t}$, and the OLS coefficients $\gamma_{0,OLS}$, $\gamma_{1,OLS}$, $\gamma_{2,OLS}$, and $\gamma_{R,OLS}$, along with the variables $|R_{d,t-1}|$, $\sigma_{SIM,t-1}$, and $\sigma_{SIM,t-2}$. As starting values for the volatilities $\sigma_{SIM,0}$ and $\sigma_{SIM,-1}$, use the average sample volatility. Note that by construction, $\sigma_{SIM,t}$ retains the statistical properties of the observed series $\sigma_{d,t}$, but it is unrelated to $M_{t-1}$, $R_{d,t-1}$, and the cross product $R_{d,t-1}M_{t-1}$.

(iii) Run the regressions in Models 1–5 using the artificial series $\sigma_{SIM,t}$, its past artificial values $\sigma_{SIM,t-1}$ and $\sigma_{SIM,t-2}$, and the actual series $|R_{d,t-1}|$, $M_{t-1}$, and $R_{d,t-1}$ and save the coefficient estimates with their $t$-statistics. Notice that by regressing on the actual level of the $M_{t-1}$ series, we preserve not only its autocorrelation properties but all its empirical characteristics.

(iv) Repeat steps (ii) and (iii) 10,000 times and generate an empirical distribution for each regression coefficient as well as an empirical distribution of its $t$-statistic.

(v) Use the distribution of coefficient estimates to construct the average coefficient and its standard deviation. The average coefficient for each of the variables $M_{t-1}$, $R_{d,t-1}$ and $R_{d,t-1}M_{t-1}$ is an estimate of the bias in the original OLS regression coefficient. The ratio of the average coefficient to the standard deviation is the reported $t$-statistic on the bias. The empirical distribution of the $t$-statistic, on the other hand, can be used to perform hypothesis testing on the original OLS regression coefficient under the null. For this reason, the value of the $t$-statistic at the lowest 2.5% cutoff point of the distribution is reported in curved brackets, {}. OLS $t$-statistics lower (algebraically) than this cutoff statistic indicate statistical significance at the 5% level in a two-tailed test.

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