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Speculative Trading and Stock Market Volatility

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Abstract

This paper examines whether speculative activity has an effect on stock market volatility. With data from 1919 to 1987, we analyze the relation between stock return volatility, estimated from the daily Dow Jones price index, and indicators of speculative activity, including expected share turnover and the growth rate in margin credit. The analysis finds no destabilizing effect of speculation in the post-World War II period or in the period prior to the 1929 Crash. However, we do find evidence of a relation between speculation and volatility during 1934-46, a period in which prior research has found significant mean reversion in stock returns.

SPECULATIVE TRADING AND STOCK MARKET VOLATILITY

"Hasty attempts to control speculation by simple enactments
have invariably proved either futile or mischievous."
Alfred Marshall Principles of Economics (1910, p.719).

The contribution of speculation to volatility in financial markets has been a concern of policymakers in the U.S. at least since the turn of the century. The committee appointed by Governor Hughes of New York to study securities markets after the Panic of 1907 made recommendations "directed to the removal of various evils now existing and to the reduction of the volume of speculation of the gambling type." The Great Crash of 1929 reinforced anti-speculation sentiments and led to substantial federal regulation, including the initial margin requirements set by the Federal Reserve Board. The October 1987 crash renewed interest in proposals to dampen volatility by limiting speculative trading. Many of the proposals put forth by the post-crash studies, such as the 1988 Brady Report, concern trading in stock index futures which, because of their low transaction costs, are viewed as facilitating speculative activity.

There is no doubt that stock market volume has grown significantly since the introduction of stock index futures in 1982. Figure 1 shows that daily share turnover (shares traded divided by shares outstanding) on the New York Stock Exchange (NYSE) has more than doubled from .11 percent in the 1976-81 period to .23 percent in the 1983-88 period. Much of the increase has occurred in the stocks of the major market indexes. Figure 2 shows that the ratio of the volume of stocks in the Dow Jones 65 Composite to overall NYSE volume has risen from 12 percent in 1976 to 19 percent in 1988.

At issue in current policy discussions is the effect that this increase in turnover has had on stock market volatility. The Market Crashes of October 1987 and October 1989 have convinced many that the growth in turnover is evidence of irrational speculation, or what has been referred to as noise trading, in securities markets (Summers and Summers (1989)). Noise traders, who do not base their investment decisions on market fundamentals, are said to have a greater relative presence when trading costs are low (De Long, Shleifer, Summers, and Waldmann (1988), Stiglitz (1989)) and are also said to be influenced by fads and to trade in a herd-like manner (Shiller (1981)). The above-cited papers suggest that since noise traders invest on incorrect, stale or irrelevant information, they induce excess volatility in securities markets.

Recent findings by Shiller (1981) on excess volatility, and related research by Fama and French (1988) and Poterba and Summers (1988) on mean reversion, lend support to the argument that the volatility of stock prices often exceeds that justified by changes in market fundamentals. However, these results are also consistent with an efficient stock market in which expected returns display intertemporal variation due to changes in risk premia or in the degree of risk aversion. (See, e.g., Ferson and Harvey (1990).) More importantly, from the perspective of this study, the prior research does not establish whether the observed "excess volatility" is at all related to speculative activity.

Due to the ambiguity of existing evidence, the appropriate policy response to the recent growth in trading activity is unclear. If the surge in turnover represents destabilizing speculation, then increasing the costs of trading could lower volatility. According to this view, raising margin requirements in some markets (Brady Commission (1988)), reinstituting the federal securities transactions tax (Summers and Summers (1989) and Stiglitz (1989)), and imposing larger capital gains taxes on short-term investments (Tobin (1988)) should reduce stock market volatility. In contrast, if higher trading costs interfere with the provision of liquidity, then such policy initiatives could increase volatility (Grossman and Miller (1988)).

To address these policy issues, a series of recent papers has examined whether the initial margin requirements set by the Federal Reserve Board dampen stock market volatility. (See Hardouvelis (1988, 1989, 1990), Hsieh and Miller (1990), Kupiec (1989), Salinger (1989), and Schwert (1988).) As with the studies on mean reversion and excess volatility, this recent research has produced ambiguous results. Although Hardouvelis (1988, 1990) concludes that initial margins can be used to dampen excess volatility, the other authors argue otherwise. The debate on the effectiveness of initial margins has involved the discussion of econometric technique, the use of particular measures of stock volatility, and the sensitivity of regression estimates to the choice of subperiods. A main point in the debate is that the focus on initial margins does not directly address whether speculation affects stock volatility.

In this paper, we attempt to decrease the ambiguity in the prior research. One of our contributions is that we use daily, rather than monthly, data to estimate stock return volatility so as to avoid some of the econometric problems pointed out in the recent debate on initial margins and volatility. We also use a longer time series, starting in 1919, in order to examine the relation between volatility and speculation in the 1920s and early 1930s. This is a period prior to the federal regulation of securities markets and spans a period of time which, according to market folklore, experienced rampant speculation. Finally, since our analysis finds no consistent relation between initial margins and volatility, we focus our empirical analysis on the relation between stock market volatility and measures of speculative activity such as daily share turnover and the margin credit extended to securities investors.

In our analysis, turnover is divided into expected and unexpected components to distinguish between the effects of "noise trading" and "information trading" on stock market volatility. The decomposition of turnover into noise and information components is based on recent theories of noise trading. For example, De Long, Summers, Shleifer and Waldmann (1988) model noise traders as being more responsive to trading costs than information traders. Following this line of argument, we model turnover as a function of trading costs to estimate expected turnover (noise trading) and unexpected turnover (information trading). Similarly, we use Shiller's observation that noise traders behave in a herd-like or faddish manner to model noise trading as the predicted value in a regression of turnover on a distributed lag of turnover.

In the empirical analysis of the 1919-1987 period, we find no consistent evidence of irrational speculation. In particular, the results indicate that unexpected, information-driven turnover has much greater explanatory power for volatility than do our constructed proxies for noise trading. Moreover, we find no significant relation between volatility and our proxies for speculative activity in the post-World War II period or in the period prior to the 1929 Crash. Evidence of a significant association between the measures of speculative activity and stock return volatility is restricted to the 1934-46 time period.

I. Initial Margin Requirements and Volatility

The Federal Reserve was empowered by Congress with setting initial margins requirements in October 1934 on the assumption that limiting the credit available to securities investors would dampen the irrational speculation that purportedly led to the Great Crash in 1929.[1] Recently, there has been a rebirth of proposals for trading impediments to stem the irrational trading practices felt to have caused the October 1987 market crash. The policy proposals received little attention among academics until Hardouvelis (1988, 1990) presented evidence that higher initial margins significantly reduce stock market volatility. His findings are consistent with the view that initial margin requirements impede irrational speculation and can be used to decrease the deviation of stock prices from fundamental values.

Not surprisingly, the studies by Hardouvelis produced a controversy in the academic community. Hsieh and Miller (1990), Kupiec (1989), Salinger (1989), and Schwert (1988) present evidence that refutes the results reported by Hardouvelis (1988, 1990). The criticism of Hardouvelis includes problems with econometric technique, sensitivity of the estimates to choice of subperiods, and the lack of a direct analysis of the relation between volatility and speculation.

Some of the criticism of Hardouvelis concerns the measures of volatility used in his analysis. The measure that has received the most attention is the rolling standard deviation:

$$\sigma_{rt} = \left[\sum_{j=11}^{0} (r_{t-j} - \bar{R})^2 / 11 \right]^{1/2} \tag{1}$$

[1] For a review of margin regulation, see the 1984 study by the Board of Governors of the Federal Reserve.

where r_t is the rate of return on a market index in month t and $\bar{R}$ is the average return for months t-11 to t.[2] Hsieh and Miller (1990) point out that this measure of volatility suffers from high autocorrelation and nonstationarity.

As an alternative measure of stock volatility, we compute volatility as the average daily volatility in a given month. Following French, Schwert, and Stambaugh (1987), we estimate stock return volatility as:

$$\sigma_{dt} = \left[\left(\sum_{i=1}^{N_t} r_{it}^2 / N_t + 2 \sum_{i=1}^{N_t-1} r_{it}\, r_{i+1t} / (N_t-1)\right]^{1/2}, \tag{2}$$

where r_{it} is the return on a market index on day i in month t and there are N_t trading days in month t. French, Schwert, and Stambaugh (1987, p.5) note three advantages of this measure of volatility compared to measures using monthly data such as the rolling standard deviation:

> First, by sampling the returns process more frequently, we increase the accuracy of the standard deviation estimate for any particular interval. Second, the volatility of stock returns is not constant. We obtain a more precise estimate of the standard deviation for any month by using only returns within that month. Finally, our monthly standard deviation estimates use non-overlapping samples of returns, whereas adjacent rolling twelve-month estimators share eleven returns.

We compare graphically the measure of volatility generated from daily data with the rolling standard deviation used by Hardouvelis.[3] The data are presented from October 1934, when the Federal Reserve began regulating initial margins, through December 1987, the final year in the Hardouvelis study. Figure 3a plots the daily measure, σ_{dt}, and the rolling standard

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[2] In Hardouvelis (1990), a slightly different version of the moving average definition is used to calculate an annual measure of volatility. In the most recent version, the estimated residuals from a twelfth-order autoregression of real rates of return are substituted for the rate of return in equation (1). Hardouvelis notes that the change does not produce any substantial difference in the behavior of the series. Pagan and Ullah (1988) note problems that arise in using the moving average definition of volatility such as its being a misleading measure of the true variance of a time series when the series is nonstationary. Hardouvelis (1990) also uses a measure of volatility based on monthly data to examine the robustness of his results.

[3] In the graphical comparison, the daily measure is not weighted by the number of days in the month to preserve scale with the other measure.

deviation of monthly returns, σ_{rt}. The daily measure shows considerable variation over time, while the rolling standard deviation is quite smooth since adjacent observations share data from 11 months.[4]

To examine the sensitivity of the Hardouvelis results to the choice of volatility measure, we reestimate the Hardouvelis specification, substituting our daily measure of volatility, σ_{dt}, as the dependent variable. The following equation is estimated with ordinary least squares (OLS):

$$\sigma_{d,t} = \beta_0 + \beta_\sigma \sigma_{d,t-1} + \beta_r r_{t-1} + \beta_{\sigma I} \sigma_{IPI,t} + \beta_{\pi C} \pi_{CPI,t} + \beta_{\pi I} \pi_{IPI,t} + \beta_M \text{Margin}_t + \beta_{CR} \, \% \blacktriangle \text{ Credit Ratio}_{t-1} + u_t \tag{3}$$

Following Hardouvelis (1988, 1990), we examine the relation between stock market volatility, σ_{dt}, and initial margin requirements, Margin_t, controlling for two variables said to capture the Federal Reserve's reaction function which include past stock returns, r_{t-1}, and lagged growth in the margin credit ratio, $\% \blacktriangle$ Credit Ratio_{t-1}. We also control for general economic activity with lagged volatility, $\sigma_{d,t-1}$, the standard deviation of the industrial production index, σ_{IPI}, and growth rates of the consumer price index, π_{CPI}, and the industrial production index, π_{IPI}.[5] Twelve monthly seasonal dummy variables are also included in the regression. Given the conditional heteroscedasticity and serial correlation of the residuals, asymptotic t-statistics are calculated from covariance consistent standard errors for the parameter estimates.[6]

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[4] Hardouvelis argues that it is important to use an annual measure of stock volatility in order to test for long swings in stock prices associated with the pyramiding-depyramiding process reviewed in Garbade (1982). However, our daily volatility measure is more appropriate in addressing the current policy concerns about daily and even intraday stock price movements.

[5] Data sources are discussed in the Appendix. We use the specification from a version of the Hardouvelis study preceding the one in the American Economic Review. In the earlier version, lagged volatility is used as a regressor, but is dropped in the published version. Hardouvelis' results are not affected by the change in specification.

[6] The covariance consistent standard errors are calculated using the correction method proposed by Hansen (1982) with the weighting scheme for the sample autocovariance function suggested by Doan and Litterman (1982). Special attention is paid to setting the lag length, q, in the autocovariance function because of the sensitivity of hypothesis testing to this choice. Since the data are monthly, a lag length of 12 is initially set for the

Table 1a reports the results of an OLS estimation of equation (3) in levels for the full 1934-87 sample and two subperiods: October 1934-December 1946 and January 1947-December 1987. The use of subperiods is motivated by the findings of Kupiec (1989), Salinger (1989), and others that Hardouvelis's (1988, 1990) regression results are sensitive to the fact that the 1930s had both high volatility and low margin levels. (See Figure 3b.) Furthermore, Kim, Nelson and Startz (1989) find evidence of a structural change in the behavior of stock returns following World War II.[7]

The results for the full sample, presented in the first row of Table 1a, indicate a coefficient on the initial margins variable that is negative but not significant at the 0.05 level (although the coefficient is significant at the 0.10 level). The subperiod regressions are presented in the second and third rows of Table 1a. For the 1934 to 1946 period, the estimates indicate a positive, insignificant relation between initial margins and volatility. For the 1947 to 1987 period, there is a negative, insignificant relation between margins and volatility. The reversal in the sign on the coefficient of the initial margins variable emphasizes the non-robustness of the relation between initial margins and volatility.

A problem with estimating equation (3) in levels is that regressing a highly nonstationary variable such as volatility on initial margins, which is effectively a step function and therefore also nonstationary, can produce the "spurious regression phenomenon" of Granger and Newbold (1974).[8] Hsieh and Miller (1990) reestimate the margin-volatility regression using the rolling

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autocovariances used in calculating the asymptotic t-values. As a check on this lag length, sample autocorrelations for the residuals up to 24 lags are examined and compared to their asymptotic standard errors of $1/T^{1/2}$, where T is the effective number of observations. The last sample autocorrelation found to be significant at approximately the 0.10 level over the range of autocorrelations from lag 13 to 24 is used to set the value for q. RATS is used to calculate the asymptotic t-values, and a factor of .90 is used to dampen the Bartlett weights to assure the positive definiteness of the covariance matrix.

[7] See also Officer (1973), Schwert (1989b), and Christie and Huang (1991).

[8] In the spurious regression phenomenon, two random walk-like series will appear to be significantly related, even if changes in the series are independent of each other.

standard deviation measure of volatility in first differences and find that there is no consistent relation between initial margins and volatility.[9] Our Augmented Dickey-Fuller tests confirm that both daily volatility and initial margins are nonstationary and the tests indicate that first differencing is the appropriate specification.[10]

Table 1b presents OLS estimates of equation (3) in first differences for the October 1934 to December 1987 time period. Like Hsieh and Miller (1990), we find a positive insignificant association between initial margins and stock volatility in the first-differenced specification. These results suggest that initial margins have not been an effective tool in controlling fluctuations in stock market volatility. Subperiod regressions in first differences are presented in the second and third rows of Table 1b. For the 1934 to 1946 period, the estimates indicate a negative, insignificant relation between initial margins and volatility. For the 1947 to 1987 period, there is a positive, insignificant relation between margins and volatility. Again, the reversal in the sign on the coefficient of the initial margins variable emphasizes the non-robustness of the relation between initial margins and volatility.

II. Direct Analysis of Speculation and Volatility

A. Introduction

The lack of a significant relation between initial margins and volatility suggests that a

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[9] Similarly, Kupiec (1989) reestimates the margin-volatility regression with a Garch-in-Mean model and finds no statistically significant relation between initial margins and stock market volatility.

[10] Schwert (1987, 1989a) shows that the high-order autoregressive extension of the ADF test proposed by Said and Dickey (1984) performs well compared to the tests proposed by Phillips (1987), Phillips and Perron (1988), and others, when the data are generated by unknown pure AR or mixed ARMA processes. The ADF regressions include a constant, lagged values of the dependent variable, and are estimated both with and without a trend. The lag length was set initially at $12(T/100)^{1/4}$ as recommended by Schwert, but was increased if necessary to produce serially uncorrelated residuals. For the period October 1934 to December 1987, both volatility and initial margins have a unit root based on the ADF tests. For volatility, the computed t-values are -3.14 and -3.18, with and without a trend. For initial margins, the computed t-values are -2.88 and -2.89, respectively. Critical values for the equations with trend are -3.41 and -3.96 at the 5 and 1 percent significance levels. For the equations without trend, the critical values are -2.86 and -3.43, respectively. These values are taken from Fuller (1976, p.373).

more fruitful line of research is to directly examine the relation between speculation and volatility. As such, this section provides an analysis of the relation between our daily estimate of volatility and two measures of speculative activity -- margin credit and share turnover. These two variables have long been suggested as proxies for speculative activity. For example, Galbraith (1961, p. 25) states in his analysis of the 1929 Crash that "...even the most circumspect friend of the market would concede that the volume of brokers' loans -- of loans collateralled by the securities purchased on margin -- is a good index of the volume of speculation." Similarly, Keynes (1964) and Granger and Morgenstern (1970), among others, consider share turnover to be a proxy of speculative activity. Moreover, proponents of a securities transaction excise tax justify their proposal on the basis of the high level of turnover in recent years (Summers and Summers (1989)).

Our regression analysis spans the period from January 1919 through December 1987. Extending the sample back to 1919, the first year for which we have a complete set of data, affords the opportunity to obtain richer insights into the relation between speculation and volatility.[11] This longer time period provides us with 15 years of data prior to the federal regulation of securities markets in 1934, and permits us to study the late 1920s and early 1930s, periods held to have experienced rampant speculation.

B. Time Series Properties of the Two Speculative Measures

Figure 4a plots the margin credit ratio and daily volatility for the entire sample period from January 1919 to December 1987. Figure 4b plots daily share turnover for the same period. There are several features of the time plots that deserve comment. First, both the margin credit ratio and turnover rate display much more variation over the sample period than initial margins and therefore should provide more powerful tests for both the full sample and subperiods. There were only 22 margin changes between October 1934 and December 1987, with the last change

[11] For the same reason, Officer (1973) also uses 1919 as the initial year in much of his empirical analysis.

made in January 1974. Second, much of the historical movement in turnover can be attributed to changes in trading costs. For example, the rapid increase in turnover in recent years is associated with the deregulation of brokerage commissions in 1975. Third, there is a sharp drop in the margin credit ratio that occurs over the 1929-34 period. This is a period before initial margin requirements went into effect. Schwert (1989b) observes that 1929-34 was a period of transition during which both investors and lenders apparently concluded that the relatively large amount of personal leverage before 1929 was not optimal. Finally, although both the margin credit ratio and share turnover were very high in the 1920s, volatility was historically very low. This casts doubt on the popular argument that the rampant speculation of the 1920s was associated with abnormally high stock market volatility. In fact, for the better part of the 1919-34 period, volatility was at average levels while both turnover and margin credit were substantially above average.

C. Margin Credit and Stock Volatility

The effect of margin credit on stock volatility reported in previous studies is divided. For example, Hardouvelis (1990) and Hsieh and Miller (1990) report a significant, negative coefficient on the margin credit variable. Salinger (1989) estimates a regression that includes the contemporaneous margin credit ratio and the lagged growth rate in the margin credit ratio.[12] He finds a significant positive coefficient on the current margin credit ratio, but a significant negative coefficient on the lagged growth rate in the margin credit ratio. As noted by Hardouvelis, the finding of a negative effect of margin credit on stock volatility is counterintuitive in a theoretical framework in which destabilizing speculative activity increases volatility. Previous studies (e.g., Hardouvelis (1988)) attribute the negative effect of margin credit to econometric problems. For example, the feedback from volatility to margin credit might create a simultaneous equations bias. Alternatively, the use of monthly volatility measures

[12] Actually, Salinger uses the change in margin credit divided by the value of the NYSE. For our purposes, this variable is close enough to the growth rate in the margin credit ratio to be interpreted as such.

such as the rolling standard deviation might induce an errors-in-variables problem.

To address the relation between margin credit and volatility, we first estimate simple bivariate equations with volatility regressed on the growth rate in the margin credit ratio. To be consistent with the Hardouvelis specification, the lagged growth rate of the margin credit ratio is used as the regressor. Our use of lagged margin credit also avoids the simultaneous equations bias since lagged margin credit is a predetermined variable. The regression is estimated in first differences to adjust for stochastic nonstationarity of daily volatility and includes twelve monthly seasonal dummies.[13]

Table 2 reports estimates of the bivariate regression for the full sample and three subperiods.[14] For the full sample, the margin credit variable is positive and significant. For the first and third subperiods, margin credit has a positive but insignificant effect on volatility. For the October 1934 to December 1946 subperiod, the coefficient is positive and highly significant. In addition, the coefficient for the second subperiod is much larger than for the other two subperiods. An F-test indicates, however, that the coefficients on margin credit are not statistically different from each other across the subperiods.[15]

In order to check the robustness of the results on margin credit, a multiple regression is estimated to adjust for possible omitted variable problems. Table 3 reports estimates of the multiple regression in first differences for the full sample and three subperiods. The control variables used in the specification are the same as in equation (3). The results differ somewhat from those reported in Table 2. For the full sample, the coefficient on margin credit is positive, but it is now much smaller in size and is insignificant. However, the subperiod results for the

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[13] For the period 1919-87, the computed t-values in the ADF regressions for daily volatility with and without trend are -3.51 and -3.49, respectively.

[14] The full sample starts in April 1920, since 1919 was used to create some of the variables used in the multiple regression. In addition, several observations are lost in 1920 in the process of first differencing and lagging.

[15] The computed F-value is 1.67, which is not significant at traditional levels.

multiple regression are basically the same as for the bivariate regression. The coefficient on margin credit is positive in each of the three subperiods, but is statistically significant only in the 1934-46 period. Similar to the bivariate regression results, an F-test does not find significant differences in the margin credit coefficients across the subperiods.[16]

C. Turnover and Stock Volatility

As noted by Salinger (1989), and indicated in Figure 4a, margin credit as a fraction of the value of NYSE stocks is now historically small. At the end of 1987, margin credit comprises only 1.7 percent of NYSE value.[17] More importantly, current policy concerns do not focus on margin credit, but instead are related to the effect of the speculative component of turnover on stock volatility. As noted above, turnover has long been considered a measure of the level of speculation. In fact, those proposing the implementation of a transaction tax on securities trading base their policy prescription on the high levels of turnover in recent years (Summers and Summers (1989)).

In recent work, Hardouvelis (1990) and Schwert (1989b) study the effect of trading volume on stock market volatility. Hardouvelis includes the growth in trading volume in his unrestricted vector autoregression (VAR) analysis and concludes that initial margins serve to decrease trading volume. However, his treatment of volume is only incidental to the major focus of his study. Schwert regresses volatility on a distributed lag of NYSE volume growth and finds a significant positive relation between the two. This suggests that stock market volatility is higher when trading activity is greater, a result that could stem from trading volume proxying either for the presence of noise traders or for information. Schwert points out that unexpected changes in both volatility and volume are highly correlated. Also, in a four-variable unrestricted

[16] The computed F-value is 1.64, which is not significant at traditional levels.

[17] Hardouvelis (1989) points out that the proportion of volume accounted for by margin traders can be nontrivial even if margin credit is small. Unfortunately, it is not possible to test this hypothesis since a time series on NYSE margin volume is not readily available.

VAR model for the period 1885-1987, he finds that volume growth significantly affects volatility.

Our analysis of the relation between volatility and volume is most closely related to the analysis by Schwert. However, in contrast to Schwert's estimates of the relation between volatility and first differences in volume, we first difference both variables (and use share turnover rather than volume as our independent variable). Our specification allows us to ask whether an increase in trading, brought about by a policy change that lowers the cost of speculative trading, results in an increase in volatility. The Schwert specification implicitly assumes that a permanent increase in volume brought about by a policy shift results in only a temporary increase in volatility.

Tables 4 and 5 present bivariate and multivariate regressions of the first difference of daily volatility on the first difference of daily turnover. The regressions are estimated in first differences to adjust for the nonstationarities in both volatility and turnover and they include twelve monthly seasonal dummies.[18] The coefficients on the turnover variable in the bivariate regressions, reported in Table 4, are positive and statistically significant for the full period as well as in each of the three subperiods. Similarly, the multiple regressions reported in Table 5, which include the same control variables from equation (3), also show significant positive coefficients for turnover.

Our results indicate a positive relation between turnover and volatility.[19] There are two

[18] For the period 1919-87, the computed t-values in the ADF regressions for daily share turnover with and without trend are -.83 and -1.44, respectively.

[19] One of the referees suggested that we estimate a VAR with volatility and turnover since the feedback between the two could influence the results in our regressions given that current turnover is used as a regressor. We estimate an unrestricted VAR that includes 12 lags of volatility, returns, and turnover as well as twelve monthly seasonal dummies. We do not include margin credit since this would produce collinearity problems given that both turnover and margin credit are measures of speculative activity. Unlike Hardouvelis (1990), all variables are first differenced to account for the unit root behavior of volatility and turnover. We find significant bidirectional causality between volatility and turnover. In addition, coefficient sum tests indicate a significant negative effect of volatility on turnover. The finding that increased stock volatility leads to a decrease in turnover suggests that increased market

explanations for this positive association. According to the first, the stock market is dominated by rational traders, and when new information about fundamentals arrives in the market, prices change and investors trade to rebalance their portfolios. The second assumes that the market is dominated by destabilizing speculators, such as noise traders, whose unwarranted trading of stocks produces unnecessary stock price variability.

To distinguish between the informed and speculative components of turnover, we employ a regression strategy that has been used by authors such as French, Schwert and Stambaugh (1987) and Schwert (1977b) to decompose a time series into expected and unexpected parts. In our application, a given set of variables based on recently proposed models of noise trading behavior are used in a first-stage auxiliary regression to generate predicted, or expected turnover, which serves as our measure of speculative activity. The residual from the first-stage regression is used to represent unexpected turnover, which may be related to the flow of information to the stock market. In the second-stage regression, volatility is regressed on the estimates of expected and unexpected turnover and the previously used proxies for market fundamentals in the fashion specified below:[20]

$$\sigma_{dt} = \text{f(Market Fundamentals)} + \beta_1 \text{ Turnover}_t^* + \beta_2 \text{ (Turnover}_t - \text{Turnover}_t^*)_t + e_t \tag{4}$$

$$\text{Turnover}_t = \text{Turnover}_t^* + u_t = A_t\alpha + u_t \tag{5}$$

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uncertainty associated with greater volatility deters risk-averse traders from entering the stock market. This evidence is consistent with Schwert's (1988) finding that volatility is higher in recessions and the results from the trading volume literature (see, e.g., Karpoff, 1987) showing that volume is lower in bear markets than in bull markets.

[20] Our approach also resembles the method discussed in Hasbrouck (1988), who examines the impact of trading volume on bid-ask spreads in equity markets. Microstructure models of financial markets with asymmetrically informed agents incorporate the notion that trading conveys information that leads to price changes. Any private information that informed traders possess will be inferred from the part of the trade that is unanticipated, in other words, the trade innovation. In the model specification, predicted or expected turnover conveys no new information, while unexpected turnover represents the trade innovations of informed traders.

where Turnover_t denotes the turnover rate, Turnover_t^* is expected turnover, u_t represents unexpected turnover, i.e., the difference between turnover and expected turnover, and the orthogonality condition, $E(e_t u_t) = 0$, is assumed to hold to assure consistency of the estimates. A_t represents a row vector of first-stage auxiliary regressors used to decompose turnover into its expected and unexpected parts.[21]

Two different sets of variables are specified for the row vector A in the first-stage regressions. These include: (1) 12 lags of turnover, and (2) trading costs as proxied by the current brokerage commission, seat price, and initial margin requirement. The first set of variables incorporates Shiller's (1981) idea that autocorrelated misperceptions guide the behavior of investors and produce herd-like behavior or fads. Cutler, Poterba and Summers (1989) also model destabilizing speculators as trading on past returns, instead of the rational expectation of future returns. The second set of first-stage variables captures the notion put forth by De Long, Shleifer, Summers and Waldmann (1988) that destabilizing speculators are relatively more sensitive to trading costs than are informed traders. Previous work by Schwert (1977a, 1977b) and our own preliminary tests (available on request) indicate that turnover is significantly related to our proxies for trading costs. These regressions examine whether the component of turnover predicted by trading costs has an effect on stock volatility.

The regressions with expected and unexpected turnover are estimated in first differences to adjust for the nonstationarity of volatility and turnover. The control variables in equation (3) are included as well as twelve monthly seasonal dummies. An instrumental-variable correction

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[21] Both expected and unexpected turnover are known as generated regressors. Concerning the so-called "generated regresssor problem," Pagan (1984) shows that two-stage least-squares or instrumental variable estimation provides correct standard errors for β_1, while OLS estimation provides correct standard errors for β_2. With regard to efficiency, none of the first-stage schemes provides fully efficient estimates since all the predetermined variables in the second-stage regression are not included in the information sets of the first-stage auxiliary regressions that are used to generate expected and unexpected turnover. The generated regressor problem, similar in nature to an errors in variables problem, refers to the fact that conventional OLS formulas provide inconsistent estimators for the true standard error. The OLS are downward biased, resulting in inflated test statistics. See Pagan (1984) for further discussion.

for the generated regressor problem is used when the initial OLS estimates indicate the coefficient on expected turnover is significant at the 0.05 level.[22] No correction is made when the asymptotic t-statistic is not significant at the 0.05 level.[23]

Table 6 presents estimates of the two-stage regression model for the full sample and several different subperiods. Included as subperiods are 1920:4-28:12 (a period of high levels of speculation but average volatility), the period 1920:4-34:9 (a period prior to federal regulation of securities markets), the period 1934:10-1946:12 (a period of high volatility), and 1947:1-1987:12 (the post-World War II period). Only estimates for the expected and unexpected components of turnover are reported for the multiple regressions. To allow for possible structural changes in the relationship between turnover and the two sets of auxiliary regressors, the first-stage regressions are estimated over the particular subperiod only.

Panel A of Table 6 presents results for the decomposition based on 12 lags of turnover. This decomposition models the herd-like or faddish behavior of noise traders (e.g., Shiller (1981)). For the full sample, our proxy for noise trading (expected turnover) is positive but insignificant, while our proxy for information trading (unexpected turnover) is positive and significant at the 0.05 level.

Panel A also presents subperiod results for the twelfth-order autoregression scheme. The

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[22] Expected turnover lagged a period is used as an instrumental variable in the correction scheme. Lagged values of the variable being instrumented are frequently used as instrumental variables in time series applications. This is valid only if the lagged instrument is uncorrelated with the regression error. By definition, "good" instrumental variables are highly correlated with the variable that is instrumented, and uncorrelated in the limit with the error term. If Z denotes the set of instrumental variables and X is the original design matrix, then good instrumental variables should not be highly correlated with the other explanatory variables in order for $Z'X$ to be well-conditioned for inversion. Also, the elements of Z should not interact unfavorably with the error covariance matrix, i.e., the elements of $Z'\Sigma Z$ should not be large, where Σ is the error covariance matrix. See Bowden and Turkington (1984, pp.79-81).

[23] An instrumental-variable correction is not required for the unexpected turnover estimates since only a contemporaneous term is included as a regressor in the second-stage regressions. Pagan (1984) shows that OLS estimates of the standard errors on the current unexpected component are valid. This would not be the case, however, if lagged unexpected terms were also included as explanatory variables.

noise trading measure is highly significant and positive in the 1934:10-46:12 subperiod, but it is insignificant in all the other subperiods. It appears that the 1930s, a period characterized by historically high volatility, account for the finding of speculative trading having a significant effect on stock volatility. Unexpected turnover is positive and significant at the 0.05 level for the 1934:10-46:12 subperiod and at the 0.10 level for the 1920:4-34:9 subperiod. With the instrumental-variable correction, unexpected turnover is insignificant in the 1947:1-87:12 subperiod. However, when OLS is used (complete results available on request), unexpected turnover is positive and significant at the 0.01 level in this subperiod.[24] It is interesting to note the absence of a significant relation between either component of turnover and volatility for the 1920:4-28:12 subperiod. This was a period of high turnover, but relatively stable volatility.[25] Our measure of noise trading is not associated with volatility during this period, a result which constrasts sharply with market folklore.

Panels B and C of Table 6 present the full period and subperiod results for two trading cost decompositions of turnover. In Panel B, proxies for trading costs include initial margins, brokerage commission rates, and seat prices. Because of the absence of federal regulation of initial margins prior to October 1934, Panel B does not incorporate the earlier subperiod analysis. In Panel C, trading costs include only commission rates and seat prices in order to include the 1919-34 period in the estimation. For both trading cost specifications of expected turnover, the coefficient of unexpected turnover is positive and highly significant for the full sample as well as for the 1934:10-46:12 and the 1947:1-87:12 subperiods. In contrast, expected turnover (noise trading proxy) is not significant at the 0.05 level in any of the subperiods.

In summary, the strongest statistical evidence of a relation between our measures of

[24] The instrumental-variable correction lowers the marginal significance of unexpected turnover, probably because lagged expected turnover is correlated with current unexpected turnover.

[25] Officer (1973) emphasizes the "normal" volatility prior to 1929. See Friedman and Schwartz (1963, Chap. 6) for an interesting discussion of the 1920s.

speculation and stock volatility is in the period from October 1934 to December 1946. This holds for both margin credit and our constructed measures of noise trading activity.[26] The strongest evidence of an effect of noise trading on volatility occurs with the herd-like or faddish behavior decomposition specification for expected turnover. Ironically, during the 1920-28 period, a time when the turnover rate is at an historical high, there is no apparent relation between this measure of speculation and volatility.

III. Summary and Conclusion

In the aftermath of the October 1987 stock market crash, many proposals have been put forth by policymakers and academics to increase trading costs for the purpose of reducing speculative activity and dampening stock volatility. To address the appropriateness of these proposals, we examine the relation between stock volatility and measures of speculative activity such as daily share turnover and the margin credit extended to securities investors.

A novel aspect of our empirical approach is the decomposition of turnover into expected and unexpected components to distinguish between the effects of noise trading and information trading on stock market volatility. The decomposition of turnover into noise and information components is based on current theories of noise trading that model noise traders as being more responsive to trading costs than information traders (De Long, Shleifer, Summers, and Waldmann (1988)) and as behaving in a herd-like or faddish manner (Shiller (1981)). Of course, since these models represent only a small subset of irrational trading strategies, our results cannot be taken as conclusive. Nonetheless, our study represents a first attempt at testing the effect of noise trading behavior, as currently modelled, on stock volatility.

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[26] In bivariate and multiple regressions not reported, but available on request, the results regarding the effect of the margin credit ratio on volatility in the 1920-28 subperiod are mixed. In the bivariate regression, the margin credit ratio is positive but insignificant with a t-value of 1.56. In the multiple regression, margin credit is positive and significant at the 0.05 level. However, the coefficient on margin credit is much smaller for this subperiod (.005) than for the 1934-46 subperiod (.016), and the t-value is 2.0 compared to a value of 2.7 in the 1934-46 period.

We find no consistent relation between our measures of speculative activity and stock volatility in the post-World War II period nor in the period before the 1929 Crash. Our results do provide, however, evidence of a statistical relation between speculative activity and volatility in the 1934-46 period. This period experienced much higher volatility than more recent periods and corresponds roughly to the period in which Fama and French (1988) and Poterba and Summers (1988) find their strongest evidence of mean reversion in stock prices. Although the results from this time period do suggest a possible relation between speculation and volatility in periods of high volatility, the lack of a more consistent relation between volatility and measures of speculation, especially in the recent past, does not support the idea that policies aimed at increasing the costs of trading will reduce volatility.