THE JOURNAL OF FINANCE • VOL. XLVII, NO. 5 • DECEMBER 1992

Stock Price Dynamics and Firm Size: An Empirical Investigation

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ABSTRACT

We show that after controlling for the effects of bid-ask spreads and trading volume the conditional future volatility of equity returns is negatively related to the level of stock price. This "leverage effect" is stronger for small, as compared to large, firms. We also document that while the essential characteristics of the relations between stock price dynamics and firm size are stable, the strengths of the relationships appear to change over time.

A NUMBER OF EMPIRICAL studies have documented that stock volatility tends to fall subsequent to an increase in stock prices and rise following a decline in stock prices, an observation commonly attributed to the "leverage effect." As explained by Black (1976), leverage can induce future stock volatility to vary inversely with the stock price: a fall in a firm's stock value relative to the market value of its debt causes a rise in its debt-equity ratio and increases its stock volatility. For example, Black (1976) and Christie (1982) use individual securities and French, Schwert, and Stambaugh (1987), Gallant, Rossi, and Tauchen (1990), Schwert (1990), and Nelson (1991) use market indices to provide evidence consistent with the leverage effect. However, these papers demonstrate a leverage effect either intertemporally or cross-sectionally for some assets. Relatively little work has examined the intertemporal behavior of individual assets by taking into account conditional heteroskedasticity and changing expected returns.

In this paper we examine and characterize the cross-sectional and temporal relations between stock price dynamics and firm size. In particular, we investigate the possibility of an inverse relation between future stock volatility and stock price and whether this effect varies across time and/or across firms with different market capitalization. Our study uses the exponential GARCH (EGARCH) formulation of Nelson (1991) as a model for the time-series behavior of individual security returns. Nonparametric methods are

* Economics Board, University of California at Santa Cruz and Department of Finance, University of Texas at Austin, respectively. The first author acknowledges support from the GICES. We appreciate the comments and suggestions of Simon Benninga, Louis Chan, Ray Chou, Daniel Friedman, David Hsieh, Paul Laux, Jack Michaelsen, Danny Quah, Ehud Ronn, A. J. Senchack, the editor René Stulz, Seha Tinic, Sheridan Titman, an anonymous referee, and participants at the 1991 Western Finance Association meeting and the 1991 North American Summer Meeting of the Econometric Society. We also thank Serra Tinic for her expositional suggestions.

then applied to test for systematic cross-sectional and temporal patterns in the relations between stock return dynamics and the firms' market values.

We use two different sets of daily return data: (1) American and New York Stock Exchanges (AMEX-NYSE) stock returns calculated using closing transaction prices, and (2) NASDAQ-National Market System (NMS) security returns computed with closing bid prices. Our empirical results indicate a reliable negative relation between future stock volatility and stock price in both sets of market data. This can be interpreted as a manifestation of leverage effect. Furthermore, the leverage effect is greater for small than for large firms, thereby implying that for a given percentage change in stock price small firms would experience a greater variation in their stock volatilities. Our results remain unaltered even after accounting for the bid-ask spread and trading volume.

The plan of this paper is as follows. In Section I, we describe the data and methodology. Section II contains the evidence for AMEX and NYSE stocks. In Section III, we examine the stability of the model parameters over the same period. In Section IV, the results are corroborated by testing the leverage hypothesis and controlling for bid-ask errors and trading volume. The final section summarizes the paper.

I. Data and Methodology

A. Data

Daily return data used in this study were obtained from the CRSP files. Our sample contains 251 AMEX-NYSE stocks with no missing returns between July 1962 and December 1989. The stock returns were adjusted for any stock splits, stock repurchases, or dividends paid during the entire sample period. To investigate the stability of stock price dynamics, we also examine three nonoverlapping subperiods: (1) July 1962 to December 1969, (2) January 1970 to December 1979, and (3) January 1980 to December 1989.[1]

Trading on the NMS started in April 1982, and during the first year it was limited to the most actively traded stocks (approximately 40 stocks). In order to consolidate an adequately large sample, our analysis uses daily returns for 250 NMS stocks with continuous closing bid prices from January 1984 to December 1990.

B. Empirical Methodology

Consistent with Pagan and Schwert (1990),[2] and the observed stock return seasonal patterns, our preliminary data analysis indicates that daily security

[1] We also considered larger samples that include stocks continuously traded during each subperiod. This method derived 770 stocks in the first subperiod, 873 stocks in the second, and 895 stocks in the last subperiod. The results of both approaches were qualitatively the same and therefore, for brevity, we report only those pertaining to the original sample of 251 securities.

[2] Pagan and Schwert (1990) compare various models for conditional stock volatility and find that the EGARCH model provides a better description of squared returns than any other parametric procedure.

returns of individual firm i, $r_{i,t}$, can be modeled as:

$$r_{i,t} = \sum_{j=1}^{5} a_{i,j} D_{j,t} + b_i h_{i,t} + c_i r_{i,t-1} + u_{i,t}, \tag{1}$$

$$\ln h_{i,t} = \sum_{j=1}^{5} \alpha_{i,j} D_{j,t} + \beta_i \ln h_{i,t-1} + \sum_{j=1}^{2} \lambda_{i,j} z_{i,t-j} + \theta_i \ln P_{i,t-1}, \tag{2}$$

where

$$u_{i,t} \sim N(0, h_{i,t}),$$
$$z_{i,t-k} = \left[|\psi_{i,t-k}| - (2/\pi)^{0.5} + \gamma_i \psi_{i,t-k} \right],$$
$$u_{i,t-k} = \psi_{i,t-k} \sqrt{h}_{i,t-k},$$
$$\psi_{i,t} \sim \text{i.i.d. } N(0,1).$$

$D_{j,t}$ is a dummy variable representing the day of the week, and $h_{i,t}$ is the variance of the error term $u_{i,t}$, conditioned on information available at time $t-1$.

The relations in (1) and (2) describe an AR(1)-EGARCH(1, 2)-in-mean model with the logarithm of lagged stock price $P_{i,t-1}$ (henceforth "the log price"), incorporated in the conditional variance equation. The attractiveness of an EGARCH formulation is that it captures the asymmetric effect of lagged shocks on conditional volatility (see Black (1976), Christie (1982), Glosten, Jagannathan and Runkle (1989), Schwert (1990), and Nelson (1991)). The log price in equation (2) allows us to investigate the leverage effect. Black (1976) and Christie (1982) demonstrate that the coefficient θ_i should be negative if leverage induces an inverse relationship between stock price and volatility.[3] Relation (2) therefore provides a direct test of the leverage effect and controls for heteroskedasticity and possible serial correlation in stock returns.

Nonparametric procedures are employed to test the hypothesis of no association between each parameter in the model and a firm's market capitalization.[4] These procedures are particularly useful when the form of distributions is a priori unknown or when there is a problem in the unit of measurement. For subsequent empirical analyses the Spearman rank correlation test is used (see Kendall and Stuart (1973)). Consider a set of paired data $\{(x_i, y_i); i = 1, 2, \ldots, n\}$, the Spearman rank correlation coefficient r_s is given by

$$r_s = \text{Cov}(r_{x_i}, r_{y_i}) / \sigma_{x_i} \sigma_{y_i} \tag{3}$$

where r_{z_i} is the rank assigned to z_i with standard deviation σ_{z_i}; $z = x, y$.

[3] The inverse relationship is also implied by the constant elasticity of variance diffusion models examined by Cox (1975) and Cox and Ross (1976). Beckers (1980) tests the model by rewriting it in the log-linear form,

$$\ln \sigma_t^2 = \kappa_0 + \kappa_1 \ln S_t + \xi_t$$

where S_t is the stock price and ξ_t is a random error term.

[4] Throughout this empirical analysis, a firm's market capitalization represents the average year-end market value of its equity, which is determined by multiplying the number of shares outstanding by the market price.

Under the null hypothesis of no correlation, r_s has zero mean and variance $1/(n-1)$. When n is large the distribution of r_s is approximately normal.

We use the Noether method to test for time trends in the model parameter estimates. Suppose three observations z_1, z_2, and z_3 are recorded. If the z's are random realizations of a continuous random variable, each possible permutation of these three numbers has a $^1/_6$ probability of occurrence. Consider n independent triplets of these observations and let w be the frequency with which $z_1 < z_2 < z_3$. Under the randomness hypothesis, w has a binomial distribution of $(w; n, ^1/_6)$. For large n, w can be approximated by a normal distribution with mean $n/6$ and variance $5n/36$. The randomness hypothesis can be tested against an alternative hypothesis of a monotonic increasing, decreasing, or cyclical trend.

II. Results

A. Diagnostic Tests

To verify the adequacy of the specification in equations (1) and (2), we perform diagnostic checks for serial correlation in the first and second moments of the 251 resulting residual series. The Ljung-Box (1978) portmanteau test is performed on the first twelve lags of standardized residuals, $\psi_{i,t}$, and squared standardized residuals, $\psi_{i,t}^2$. Under the null hypothesis, these test statistics are distributed asymptotically as $\chi^2(11)$.

The average cross-sectional test statistic for the level is 7.91 with standard error of 5.23; for the squares it is 13.88 with a corresponding standard error of 9.2. None of these test statistics are significant at conventional levels. In testing for serial correlation, 4 of the 251 standardized residuals and 7 of the squared standardized residuals lie within the 5% critical region. These tests further reinforce Pagan and Schwert's (1990) finding that the EGARCH formulation adequately fits stock return data.

B. AMEX-NYSE Evidence

Maximum likelihood estimates of the model (1) and (2) for 251 stocks are obtained for each period.[5] Consistent with existing literature, we find day-of-the week effects in the returns. For this reason only cross-sectional averages of the other model parameters, together with the Spearman rank correlation coefficients, are presented in Table I.[6] Note that a pair of ranked variables represents ranked firm market capitalization and the ranked parameter in question.[7]

Several interesting observations emerge from Table I. First, the cross-sectional averages of $\hat{c}_i$'s are statistically positive, with magnitudes ranging

[5] The Davidon-Fletcher-Powell numerical algorithm is used to obtain maximum likelihood estimates of the model.

[6] Details of these results are contained in an earlier version of this paper, and are available from the authors upon request.

[7] We also calculated the Spearman rank correlation using firms' median year-end market values of equity, and the results were qualitatively unchanged.

from 0.008 (Panel B) to 0.045 (Panel D). These results suggest evidence of a partial adjustment in daily stock prices and are also consistent with Amihud and Mendelson (1987), who report that 24 out of 30 Dow Jones stocks have positive first-order autocorrelation coefficients. In contrast, we further show that the absolute value of $\hat{c}_i$ is negatively correlated with firm size; the smaller the firm, the longer its price takes to adjust to new information arriving in the market.

Second, unexpected shocks exhibit asymmetric effects on conditional volatility and diverse impacts on firms of various market capitalizations. While the average cross-sectional $\hat{\lambda}_{i,1}$ is significantly positive, the average cross-sectional $\hat{\gamma}_i$ is statistically negative (except for subperiod 1). The signs of $\hat{\lambda}_{i,1}$ and $\hat{\gamma}_i$ are consistent with those obtained by Nelson (1991), who uses daily excess returns of the CRSP value-weighted stock index. Given that $\hat{\lambda}_{i,1}$ is positive, a negative $\hat{\gamma}_i$ implies that unexpected negative stock returns tend to have a larger impact on future conditional stock volatility than unexpected positive stock returns. This corresponds with evidence of asymmetric informational effects on stock volatility. The significant rank correlation coefficients between firm size and $\lambda_{i,1}$ and γ_i parameters further indicate that the impact of shocks on volatility varies inversely with firm size. For example, the same shock will have a greater effect on the conditional stock volatility of smaller firms.

Finally, the average cross-sectional stock price elasticity of variance $\hat{\theta}_i$ is -0.06 using the full sample period (Panel A), and the subperiod $\hat{\theta}_i$'s are between -0.112 (Panel B) and -0.325 (Panel D).[8] The negative sign is consistent with the leverage effect hypothesized by Black (1976) and Christie (1982). Using 66 quarterly data on 379 firms for the period 1962 to 1978, Christie (1982) estimates the elasticity of variance to be -0.40. Based on daily returns of 47 stocks, Beckers (1980) obtains an average value of -0.552. Similar to these studies, our estimated $\hat{\theta}_i$'s fall well within the range of estimates obtained and within the limits of -2 and 0 as implied by the constant elasticity of variance (CEV) model (see Cox (1975) and Cox and Ross (1976)). In contrast, French, Schwert, and Stambaugh (1987) regress the estimated log σ of monthly S & P 500 index against the logarithm return on the index, and obtain a θ estimate of -3.38. They, therefore, conclude that leverage cannot fully explain the negative relation between stock returns and volatility. Kupiec (1990) assumes that future stock volatility is linearly related to stock price and finds no significant relationship between the two variables. His result, however, does not invalidate a nonlinear relationship between future stock volatility and stock price. In fact, if stock prices can be described by a CEV model then the implied theoretical relationship between stock price and its variance should be linear.

Except in the first subperiod, the Spearman rank correlation coefficients

[8] Among the 251 stocks examined, less than 5 percent of the $\hat{\theta}_i$'s have positive values. Black (1976) and Cox (1975) argue that because dividends can have an impact on stock volatility, it is plausible that the price elasticity of variance may have a positive value for some range of firm values.

Table I

Cross-Sectional Averages of Maximum Likelihood Estimates of the Model Given by Equations (1) and (2) Using Daily Return Data on 251 AMEX-NYSE Firms. The Sample Period is July 1962 to December 1989.

$$r_{i,t} = \sum_{j=1}^{5} a_{i,j} D_{j,t} + b_i h_{i,t} + c_i r_{i,t-1} + u_{i,t}, \qquad (1)$$

$$\ln h_{i,t} = \sum_{j=1}^{5} \alpha_{i,j} D_{j,t} + \beta_i \ln h_{i,t-1} + \sum_{j=1}^{2} \lambda_{i,j} z_{i,t-j} + \theta_i \ln P_{i,t-1}, \qquad (2)$$

where

$$u_{i,t} \sim N(0, h_{i,t}),$$
$$z_{i,t-k} = [|\psi_{i,t-k}| - (2/\pi)^{0.5} + \gamma_i \psi_{i,t-k}],$$
$$u_{i,t} = \psi_{i,t-k} \sqrt{h}_{i,t},$$
$$\psi_{i,t} \sim \text{i.i.d. } N(0,1),$$

r_{it} is the daily security return of individual firm i, $D_{j,t}$ is a dummy variable representing the day of the week, $h_{i,t}$ is the variance of the error term $u_{i,t}$, and $\ln P_{i,t-1}$ is the logarithm of lagged stock price.

Estimate	Mean[a]	Median	Maximum	Minimum	r_s^b
Panel A. Full Sample Period: July 1962 to December 1989					
$\hat{b}_i$	0.250 (0.0364)	0.067	4.100	−1.360	−0.361 (−5.689)
$\hat{c}_i$	0.034 (0.0051)	0.056	0.175	−0.223	−0.489 (−7.711)
$\hat{\beta}_i$	0.918 (0.0038)	0.928	0.977	0.492	0.266 (4.195)
$\hat{\lambda}_{i,1}$	0.292 (0.0037)	0.288	0.579	0.140	−0.279 (−4.395)
$\hat{\gamma}_i$	−0.127 (0.0059)	−0.127	0.201	−0.497	−0.329 (−5.193)
$\hat{\lambda}_{i,2}$	−0.083 (0.0040)	−0.086	0.212	−0.365	0.138 (2.181)
$\hat{\theta}_i$	−0.056 (0.0039)	−0.046	0.037	−0.565	0.251 (3.967)
Panel B. Subperiod: July 1962 to December 1969					
$\hat{b}_i$	4.938 (0.4151)	2.226	34.246	−3.681	−0.046 (−0.730)
$\hat{c}_i$	0.008 (0.0065)	0.032	0.208	−0.318	−0.359 (−5.670)
$\hat{\beta}_i$	0.632 (0.0172)	0.702	0.977	−0.411	0.007 (0.110)
$\hat{\lambda}_{i,1}$	0.272 (0.0062)	0.277	0.961	−0.116	−0.027 (−0.433)
$\hat{\gamma}_i$	0.038 (0.0505)	0.225	0.992	−0.516	−0.206 (−3.259)
$\hat{\lambda}_{i,2}$	0.023 (0.0069)	−0.172	0.945	−0.519	0.110 (1.736)
$\hat{\theta}_i$	−0.325 (0.0325)	−0.185	0.448	−3.873	−0.129 (−1.824)
Panel C. Subperiod: January 1970 to December 1979					
$\hat{b}_i$	1.342 (0.1536)	0.082	11.095	−0.860	−0.419 (−6.617)
$\hat{c}_i$	0.039 (0.0083)	0.068	0.228	−0.197	−0.525 (−8.308)
$\hat{\beta}_i$	0.812 (0.0128)	0.892	0.980	−0.295	0.376 (5.944)
$\hat{\lambda}_{i,1}$	0.282 (0.0196)	0.267	5.036	0.504	−0.191 (−3.017)
$\hat{\gamma}_i$	−0.089 (0.0092)	−0.086	0.571	−0.791	−0.254 (−4.020)

Table I—*Continued*

$\hat{\lambda}_{i,2}$	0.041 (0.0207)	−0.016	5.010	−0.258	−0.033 (−0.518)
$\hat{\theta}_i$	−0.248 (0.0297)	−0.089	0.111	−3.746	0.445 (6.752)
Panel D. Subperiod: January 1980 to December 1989					
$\hat{b}_i$	1.010 (0.1247)	0.356	7.219	−5.381	−0.111 (−1.747)
$\hat{c}_i$	0.045 (0.0042)	0.056	0.169	−0.236	−0.235 (−3.715)
$\hat{\beta}_i$	0.814 (0.0088)	0.844	0.974	−0.168	0.198 (3.134)
$\hat{\lambda}_{i,1}$	0.313 (0.0064)	0.303	0.847	0.034	−0.299 (−4.729)
$\hat{\gamma}_i$	−0.155 (0.0103)	−0.150	0.824	−1.105	−0.290 (−4.578)
$\hat{\lambda}_{i,2}$	−0.257 (0.0063)	−0.037	0.495	−0.750	0.091 (1.439)
$\hat{\theta}_i$	−0.112 (0.0109)	−0.060	0.116	−1.325	0.327 (4.643)

[a] Standard errors of the means are in parentheses.
[b] r_s denotes the Spearman rank correlation coefficient of firm size and the model parameter with its asymptotic t-statistic in parentheses.

indicate a strong positive correlation between $\hat{\theta}_i$ and firm size. The variance of smaller firms' stock returns tends to be more price elastic than that of larger firms. In terms of Black's (1976) and Christie's (1982) arguments, smaller firms are more inclined to experience a greater increase in their stock volatility following a percentage fall in their stock price than are larger firms, ceteris paribus. This is consistent with our finding that the impact of shocks on prices of small firms is more uncertain and, consequently, results in wider price movements and hence larger volatility.

Further, we calculate the Spearman rank correlations between $\hat{\theta}_i$ and the firms' average debt-equity (D/E) ratios, and between D/E ratios and firm size.[9] D/E ratios are calculated using the book value of long-term debt plus current liabilities divided by the market equity value as of the same date. The accounting information is obtained from the COMPUSTAT annual industrial tape which contains the most recent 20 years of individual firms' accounting data. The data are from 1969 through 1988. The files have debt figures for only 244 firms in our sample. The Spearman rank correlation coefficients are as follows:

	Second Subperiod (Jan. '71–Dec. '80)	Third Subperiod (Jan. '81–Dec. '89)
1. $\hat{\theta}_i$ and D/E ratio	−0.2311	−0.3327
t-statistics	(−3.6028)	(−5.1863)
2. D/E ratio and firm size	−0.3269	−0.1737
t-statistics	(−5.0960)	(−2.7072)

In general, the smaller the firm, the higher the D/E ratio and the larger

[9] We would like to thank Seha Tinic for suggesting this approach.

the absolute value of $\hat{\theta}_i$. Although the evidence is ascribed to the last 20 years of our sample period, and to a slightly smaller sample size, it nevertheless strengthens our previous finding that the smaller the firm the more price elastic its volatility.

Subperiod results show that $\hat{\theta}$'s have increased monotonically from -0.325 in the 60's (Panel B) to -0.112 in the 80's (Panel D). The trend in $\hat{\theta}_i$ implies that the variance of stock returns, in general, has become less responsive to changes in stock prices across the sample period. This also has implications for the firms' D/V ratios, where D is the market value of debt and V is the market value of the firm. For instance, using the Modigliani and Miller model with risk-free debt, it can be shown that the elasticity of variance with respect to the stock price is given by $-2D/V$. Our subperiod $\hat{\theta}$'s suggest that the D/V ratios are decreasing over time. A plausible explanation for the decreasing D/V ratios is that firms on average have experienced enhanced liquidity over the sample period. This rationale appears parallel to evidence provided by Bernanke, Campbell, and Whited (1990): based on a sample of more than 1000 firms they report that the average market value debt-asset ratios decreased from about 0.312 in 1970–1981 to 0.309 in 1982–1988.[10]

III. The Stability of the Model Parameters

Likelihood ratio tests are performed to determine the stability of the parameters across the three subperiods. The test statistic is asymptotically distributed as $\chi^2(34)$. The average test statistic is 346.4, which is statistically significant at any reasonable level. The results also show that 228 of the 251 test statistics reject the null hypothesis that the model parameters in equations (1) and (2) are equal across the three subperiods.

Next, we investigate for any time trend in the model parameters; the results of which are reported in Table II. These tests not only reinforce several of our findings in the preceding section, but also provide a formal statistic to examine any structural shift in the model parameters. As indicated in Table II, all model parameter estimates, except for b_i, γ_i, and $\lambda_{i,2}$, tend to exhibit a monotonic increasing trend. Of particular interest is the time trend displayed by $\hat{\theta}_i$: 61 out of 251 $\hat{\theta}$-triplets show a monotonic ascending trend. Applying the Noether type test, the observed number of increasing triplets has an asymptotic p-value of 0.001. Therefore, there is strong evidence of an upward trend in the cross-sectional average elasticity estimate.

IV. Effects of the Bid-Ask Spread and Trading Volume

A. NASDAQ-NMS Evidence

Studies have shown that one major source of measurement errors in stock prices is the existence of bid-ask spreads. One may therefore infer that the

[10] Warshawky (1990, p. 281) also shows that the nonfinancial corporate business debt-to-asset ratio at market value has declined since 1982.

Table II

Results on Tests for Monotone Time Trends in the Estimates of the Model Given in Equations (1) and (2) Across Three Subperiods: (1) July 1962–December 1969, (2) January 1970–December 1979, and (3) January 1980–December 1989.

$$r_{i,t} = \sum_{j=1}^{5} a_{i,j} D_{j,t} + b_i h_{i,t} + c_i r_{i,t-1} + u_{i,t}, \tag{1}$$

$$\ln h_{i,t} = \sum_{j=1}^{5} \alpha_{i,j} D_{j,t} + \beta_i \ln h_{i,t-1} + \sum_{j=1}^{2} \lambda_{i,j} z_{i,t-j} + \theta_i \ln P_{i,t-1}, \tag{2}$$

where

$$u_{i,t} \sim N(0, h_{i,t}),$$
$$z_{i,t-k} = [|\psi_{i,t-k}| - (2/\pi)^{0.5} + \gamma_i \psi_{i,t-k}],$$
$$u_{i,t} = \psi_{i,t-k}\sqrt{h}_{i,t},$$
$$\psi_{i,t} \sim \text{i.i.d. } N(0,1),$$

r_{it} is the daily security return of individual firm i, $D_{j,t}$ is a dummy variable representing the day of the week, $h_{i,t}$ is the variance of the error term $u_{i,t}$, and $\ln P_{i,t-1}$ is the logarithm of lagged stock price.

Estimate	H_1	H_2
$\hat{b}_i$	21 (1.000)	60 (0.001)
$\hat{c}_i$	63 (0.000)	26 (0.996)
$\hat{\beta}_i$	62 (0.000)	16 (1.000)
$\hat{\lambda}_{i,1}$	73 (0.000)	27 (0.994)
$\hat{\gamma}_i$	18 (1.000)	89 (0.000)
$\hat{\lambda}_{i,2}$	27 (0.994)	66 (0.000)
$\hat{\theta}_i$	61 (0.001)	27 (0.994)

H_1 tests the randomness hypothesis against the alternative hypothesis that the subperiod estimates of each model parameter display a monotonic increasing trend, while H_2 tests against that of a monotonic decreasing trend. p-Values are in parentheses.

observed negative correlation between the log price and conditional volatility is induced by spurious variance generated by bid-ask spreads (see Amihud and Mendelson (1987) and Kaul and Nimalendran (1990)). The recently available NASDAQ-NMS data set, with daily closing bid prices, provides us the opportunity to test the leverage effect hypothesis, after accounting for the presence of bid-ask errors.[11]

Estimates of model (1) and (2) using 250 NMS stocks are reported in Table III. Even with bid returns, the average cross-sectional $\hat{\theta}_i$ is -0.122 and statistically different from zero. This is in accord with the AMEX-NYSE

[11] We thank the referee for suggesting the tests conducted in this section.

Table III

Cross-Sectional Averages of Maximum Likelihood Estimates of the Model Given by Equations (1) and (2) Using Daily Return Data Calculated From Closing Bid to Bid Prices of 250 NASDAQ-NMS Firms For the Sample Period January 1984 to December 1990.

$$r_{i,t} = \sum_{j=1}^{5} a_{i,j} D_{j,t} + b_i h_{i,t} + c_i r_{i,t-1} + u_{i,t}, \tag{1}$$

$$\ln h_{i,t} = \sum_{j=1}^{5} \alpha_{i,j} D_{j,t} + \beta_i \ln h_{i,t-1} + \sum_{j=1}^{2} \lambda_{i,j} z_{i,t-j} + \theta_i \ln P_{i,t-1}, \tag{2}$$

where

$$u_{i,t} \sim N(0, h_{i,t}),$$
$$z_{i,t-k} = [|\psi_{i,t-k}| - (2/\pi)^{0.5} + \gamma_i \psi_{i,t-k}],$$
$$u_{i,t} = \psi_{i,t-k} \sqrt{h_{i,t}},$$
$$\psi_{i,t} \sim \text{i.i.d. } N(0,1),$$

r_{it} is the daily security return of individual firm i, $D_{j,t}$ is a dummy variable representing the day of the week, $h_{i,t}$ is the variance of the error term $u_{i,t}$, and $\ln P_{i,t-1}$ is the logarithm of lagged stock price.

Estimate	Mean[a]	Median	Maximum	Minimum	r_s^b
$\hat{b}_i$	0.509 (0.0780)	0.211	5.363	−4.869	−0.265 (−4.182)
$\hat{c}_i$	0.133 (0.0081)	0.137	0.850	−0.779	0.420 (6.633)
$\hat{\beta}_i$	0.762 (0.0121)	0.801	1.549	−0.801	0.221 (3.489)
$\hat{\lambda}_{i,1}$	0.519 (0.0283)	0.437	5.697	0.119	−0.064 (−1.001)
$\hat{\gamma}_i$	−0.085 (0.0245)	−0.099	2.576	−2.098	−0.162 (−2.554)
$\hat{\lambda}_{i,2}$	−0.035 (0.0322)	−0.015	5.385	−2.524	0.052 (0.817)
$\hat{\theta}_i$	−0.122 (0.0181)	−0.092	0.059	−2.499	0.211 (3.327)

[a] Standard errors of the means are in parentheses.
[b] r_s denotes the Spearman rank correlation coefficient of firm size and the model parameter with its asymptotic t-statistic in parentheses.

results and therefore indicates that the spurious variance generated by bid-ask errors cannot be the cause of the observed leverage effect.

Consistent with Table I, the rank correlation coefficient of $\hat{\theta}_i$ and firm size is statistically positive, suggesting that conditional volatilities of small firms are more price elastic than those of large firms. Based on the available accounting information of 224 firms, the rank correlation coefficient between $\hat{\theta}_i$ and the D/E ratio is -0.06, and that between the D/E ratio and firm market capitalization is -0.0002. Although these correlations are weak, the signs of the coefficients are the same as those for the AMEX-NYSE stocks.

B. Trading Volume

A recent study by Gallant, Rossi, and Tauchen (1990), who use daily returns on the S & P composite index and total NYSE trading volume, illustrates that the leverage effect becomes insignificant after conditioning volatility on lagged trading volume. To investigate this finding, we use individual securities and re-estimate the EGARCH model by incorporating trading volume in the conditional variance equation. The results are presented in Table IV.[12] The trading volume coefficient $\hat{\nu}_i$'s are consistent with the positive relationship between volume and conditional volatility reported in Gallant, Tauchen, and Rossi (1990). Other parameter estimates, however, are similar to those reported in Tables I and III. Specifically, the significance of θ's is unaltered by the inclusion of trading volume.

V. Summary

Using the EGARCH model, we find consistent patterns in the time-series properties of security returns across firms of different market values. Although the nature of the relations between stock price dynamics and firm size is maintained, our nonparametric tests show that the strengths of the relations change over time. We also find evidence of shifts in the model parameters across time, suggesting that the parameter estimates depend on the selection of the sample period.

We document that the sampled AMEX-NYSE stocks exhibit a negative relation between stock price and future stock volatility, a phenomenon commonly attributable to the leverage effect. Results show that small firms' stock volatilities tend to be more responsive to changes in their stock prices. Further, conditional variances of stock returns on average have become less sensitive to changes in stock prices. This is perhaps a consequence of the firms' enhanced liquidity across the sample period.

Results based on daily bid returns for NMS stocks suggest that spurious variance generated due to the existence of bid-ask spreads cannot account for the observed leverage effect. The leverage effect also remains unaltered even after volatility is conditioned on trading volume.

While the causes of systematic patterns observed in stock price dynamics across firms of different market value remain uncertain, our empirical results yield new information on the nature of individual stock dynamics and their cross-sectional relation with firm size. Hopefully, these results provide a better understanding of stock price dynamics and act as a guide to building models that explain the intertemporal and cross-sectional behavior of stock prices.

[12] Results for AMEX-NYSE stocks are based on the January 1986 through December 1989 period because trading volume data are only available from January 1986.

Table IV

Cross-Sectional Averages of Maximum Likelihood Estimates of the Model Given by Equations (1) and (2) With Lagged Trading Volume Incorporated in the Conditional Variance Equation (2′).

Daily return data on the 251 AMEX-NYSE stocks are calculated from closing prices over the period January 1986 to December 1989, and those of the 250 NASDAQ-NMS stocks are calculated from closing bid prices over the sample period January 1984 to December 1990.

$$r_{i,t} = \sum_{j=1}^{5} a_{i,j} D_{j,t} + b_i h_{i,t} + c_i r_{i,t-1} + u_{i,t}, \tag{1}$$

$$\ln h_{i,t} = \sum_{j=1}^{5} \alpha_{i,j} D_{j,t} + \beta_i \ln h_{i,t-1} + \sum_{j=1}^{2} \lambda_{i,j} z_{i,t-j} + \theta_i \ln P_{i,t-1} + \nu_i \ln \mathrm{Vol}_{i,t-1}, \tag{2′}$$

where

$$u_{i,t} \sim N(0, h_{i,t}),$$
$$z_{i,t-k} = [\,|\psi_{i,t-k}| - (2/\pi)^{0.5} + \gamma_i \psi_{i,t-k}],$$
$$u_{i,t} = \psi_{i,t-k}\sqrt{h}_{i,t},$$
$$\psi_{i,t} \sim \text{i.i.d. } N(0,1),$$

r_{it} is the daily security return of individual firm i, $D_{j,t}$ is a dummy variable representing the day of the week, $h_{i,t}$ is the variance of the error term $u_{i,t}$, $\ln P_{i,t-1}$ is the logarithm of lagged stock price, and $\ln \mathrm{Vol}_{i,t-1}$ is the logarithm of lagged trading volume.

	AMEX-NYSE		NASDAQ-NMS	
Estimate	Mean[a]	r_s^b	Mean	r_s
$\hat{b}_i$	−0.091 (0.175)	−0.044 (−0.670)	0.257 (0.101)	−0.063 (−0.987)
$\hat{c}_i$	0.029 (0.017)	−0.122 (−1.845)	0.120 (0.011)	0.419 (6.615)
$\hat{\beta}_I$	0.762 (0.015)	0.188 (2.856)	0.679 (0.036)	0.006 (0.098)
$\hat{\lambda}_{i,1}$	0.484 (0.031)	−0.164 (−2.488)	0.536 (0.046)	−0.110 (−1.690)
$\hat{\gamma}_i$	−0.364 (0.055)	−0.274 (−4.161)	−0.180 (0.112)	−0.235 (−3.471)
$\hat{\lambda}_{i,2}$	0.074 (0.037)	0.077 (1.166)	0.080 (0.044)	−0.011 (−0.168)
$\hat{\theta}_i$	−0.209 (0.050)	0.271 (4.109)	−0.299 (0.055)	0.032 (0.485)
$\hat{\nu}$	0.096 (0.011)	0.061 (0.927)	0.066 (0.010)	0.171 (2.700)

[a] Standard errors of the means are in parentheses.

[b] r_s denotes the Spearman rank correlation coefficient of firm size and the model parameter with its asymptotic t-statistic in parentheses.

Results based on daily bid returns for NMS stocks suggest that spurious variance generated due to the existence of bid-ask spreads cannot for the observed leverage effect. The leverage effect also remains unaltered even after volatility is conditioned on trading volume.

While the causes of systematic patterns observed in stock price dynamics across firms of different market value remain uncertain, our empirical results yield new information on the nature of individual stock dynamics and their cross-sectional relation with firm size. Hopefully, these results provide a better understanding of stock price dynamics and act as a guide to building models that explain the intertemporal and cross-sectional behavior of stock prices.

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