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Stock returns and volatility
A firm-level analysis

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Abstract

It has been previously documented that individual firms' stock return volatility rises after stock prices fall. This paper finds that this statistical relation is largely due to a positive contemporaneous relation between firm stock returns and firm stock return volatility. This positive relation is strongest for both small firms and firms with little financial leverage. At the aggregate level, the sign of this contemporaneous relation is reversed. The reasons for the difference between the aggregate- and firm-level relations are explored.

Key words: Volatility; Leverage effect; Selection bias
JEL classification: G12

1. Introduction

Previous research has shown that individual firms' stock return volatility rises after stock prices fall (Black, 1976; Christie, 1982; Cheung and Ng, 1992). Two of the most popular explanations for this well-known relation are the leverage effect and time-varying risk premia. The leverage effect posits that a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity (Black, Christie). The popularity of this explanation is such that the term 'leverage effect' is often applied to the statistical relation itself, rather than the hypothesized explanation. In this paper the term applies only to the hypothesized explanation.

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The time-varying risk premia explanation argues that a forecasted increase in return volatility results in an increase in required expected future stock returns and therefore an immediate stock price decline (Pindyck, 1984; French, Schwert, and Stambaugh, 1987). Another possibility is asymmetry in the volatility of macroeconomic variables. Some empirical evidence suggests that real variables are more volatile in recessions (Schwert, 1989a; French and Sichel, 1991). If so, a forecast of lowered gross domestic product (GDP) growth results in an immediate fall in stock prices, followed by higher stock return volatility in the period of low GDP growth.

In this paper, I propose a new interpretation for the negative relation between current stock returns and changes in future stock return volatility at the firm level. In large part, this relation is the result of a *positive* contemporaneous relation between returns and return volatility. Consider the following specification adopted by Christie. Define a firm's stock return from the end of period $t-1$ to the end of period t as r_t. Define an estimate of the standard deviation of this return as σ_t. The negative relation corresponds to $\lambda_0 < 0$ in the following regression:

$$\log\left(\frac{\sigma_{t+1}}{\sigma_t}\right) = \alpha_0 + \lambda_0 r_t + \varepsilon_{t+1,0}\,. \tag{1}$$

The standard interpretation of this negative coefficient is that a positive r_t corresponds to a decrease in σ_{t+1}. I argue here that the primary reason for $\lambda_0 < 0$ is that a positive r_t corresponds to an *increase* in σ_t. There is no clear relation between r_t and σ_{t+1}.

The basic approach I take is simple. The coefficient λ_0 in Eq. (1) equals the difference between the coefficients λ_2 and λ_1 in the following regressions:

$$\log(\sigma_t) = \alpha_1 + \lambda_1 r_t + \varepsilon_{t,1}\,, \tag{2a}$$

$$\log(\sigma_{t+1}) = \alpha_2 + \lambda_2 r_t + \varepsilon_{t+1,2}\,. \tag{2b}$$

I find that for the typical firm traded on the American or New York Stock Exchanges, λ_1 is strongly positive (a result that is qualitatively similar to positively skewed stock returns), while the sign of λ_2 depends on the frequency over which these relations are estimated. It is positive at the daily frequency and negative at the monthly frequency. In both cases, λ_1 exceeds λ_2, so λ_0 is negative in Eq. (1).

These results are based on stock returns of almost 2,500 firms that were traded on either the Amex or NYSE at the beginning of 1977. For each firm, I estimated (1), (2a), (2b), and related regressions at both daily and monthly frequencies using daily stock returns from 1977 through 1991 (or until the firm disappeared from the Amex/NYSE Center for Research in Security Prices tape).

Previous research has linked a firm's λ_0 in (1) with other characteristics of the firm. Christie finds that across firms λ_0 and financial leverage are strongly negatively correlated, while Cheung and Ng (1992) find that λ_0 and firm size are strongly positively correlated. I reexamine both of these conclusions. I find that Christie's result, which is based on a sample of very large firms, disappears when a broader set of firms is examined. I confirm Cheung and Ng's result, but find that this positive correlation is driven by a *negative* correlation between firm size and λ_1 in (2a). Roughly speaking, stock returns of small firms are more positively skewed than stock returns of large firms. I also find that λ_1 is substantially larger for firms that are eventually delisted than for firms that survive throughout my sample period.

The positive contemporaneous correlation between stock returns and stock return volatility at the firm level stands in contrast to the well-known negative contemporaneous correlation between aggregate stock returns and aggregate stock return volatility (French, Schwert, and Stambaugh, 1987; Campbell and Hentschel, 1992). I examine this issue in the context of a multifactor model for stock returns. My results (which should be regarded as exploratory) show that idiosyncratic firm returns are positively skewed, a market factor is negatively skewed, and a separate factor associated with small firms appears to be positively skewed.

The paper is organized as follows. Section 2 discusses the existing literature on the relation between stock returns and volatility. It also discusses my data set. Section 3 presents the empirical evidence documenting the positive relation between stock returns and volatility. Section 4 discusses the differences between aggregate and firm-level relations. Section 5 concludes.

2. Preliminaries: Previous research and data description

2.1. Previous research

Black (1976) conducted the first empirical work on the relation between stock returns and volatility. Using a sample of 30 stocks (basically the Dow Jones Industrials), he constructed monthly estimates of stock return volatility over the period 1962–1975 by summing squared daily returns and taking the square root of the result. For each stock i, he then estimated

$$\frac{\sigma_{i,t+1} - \sigma_{i,t}}{\sigma_{i,t}} = \alpha_0 + \lambda_0 r_{i,t} + \varepsilon_{i,t+1} \,. \tag{3}$$

Although he did not report detailed results of his regressions, he found that λ_0 was always negative and usually less than -1. A similar approach was taken by Christie (1982). He constructed quarterly estimates of return volatility for 379 firms (all of which existed throughout the period 1962–1978). He then estimated (1) over 1962–1978 for each firm and found a mean λ_0 of -0.23.

Christie also considered whether this negative coefficient could be explained by the leverage effect. The leverage hypothesis assumes that the volatility of log changes in a firm's net asset value (debt plus equity) is constant over time and concludes that the volatility of log changes in the firm's equity varies over time with the firm's debt/equity ratio. A decline in the value of the firm's assets will fall (almost) entirely on the value of equity, thereby raising the firm's debt/equity ratio and raising the future volatility of stock returns. According to this hypothesis, λ_0's for firms with large debt/equity ratios should be lower than λ_0's for firms with small debt/equity ratios. Christie confirmed this hypothesis, concluding (p. 425) that his evidence suggested '... leverage is a dominant, although probably not the only, determinant ...' of λ_0.

Nelson's (1991) exponential GARCH (EGARCH) model has been used to estimate the asymmetric response to stock returns of conditional stock return volatility. Define h_t as the log of the one-day-ahead conditional standard deviation of the shock to day t's stock return, ε_t. In an EGARCH model, this conditional volatility depends on lagged volatility, lagged absolute returns, and lagged returns, as in:

$$\varepsilon_t = \exp(h_t)z_t, \qquad \mathrm{E}(z_t) = 0, \quad \mathrm{E}(z_t^2) = 1\,, \tag{4a}$$

$$h_t = b_0 + b_1 z_{t-1} + b_2|z_{t-1}| + b_3 h_{t-1}\,. \tag{4b}$$

Cheung and Ng (1992) fit EGARCH models to 251 firms with no missing returns on the Center for Research in Security Prices (CRSP) Amex/NYSE daily tape between July 1962 and December 1989. They find $b_1 < 0$ for over 95% of the firms. In addition, they find a strong positive correlation across firms between b_1 and firm size (as measured by total equity outstanding).

2.2. Data description

I follow much of the previous work in this area by using daily stock returns from the CRSP tape. One feature common to Black, Christie, and Cheung and Ng is that they examine only firms that exist throughout their sample periods, with two effects that are relevant here. First, their samples are, on average, larger firms. Second, their samples cannot capture the behavior of firm stock returns near the time that firms exit the CRSP tape.

Firms disappear from the CRSP tape for reasons that may have implications for the relation between stock returns and volatility. Two examples are takeovers and bankruptcy. A company that is subject to a takeover could experience both a few large positive stock returns and high stock return volatility at the time news about the takeover is revealed. Stock returns of companies that go bankrupt could be characterized by large negative stock returns and high stock return volatility surrounding the events that drive the firm to bankruptcy. If so, a survivorship bias will remove firms with highly positively skewed returns and/or firms with highly negatively skewed returns.

For this paper I considered a broader set of firms. There are 2,617 firms with stock returns for January 3, 1977 on the CRSP Amex/NYSE daily tape. Of these firms, 2,494 have at least 12 months of observations after this date with which to estimate (1). This set of 2,494 firms is the universe of firms examined here.

For each firm, I construct monthly stock returns and estimates of the standard deviation of monthly stock returns from January 1977 through the last month in which the firm appeared on the 1991 version of the CRSP tape (no later than December 1991). Monthly returns are defined as the sum of log daily returns in the month less the one-month Treasury bill return from Ibbotson (1992). (No equivalent adjustment was made to the daily returns owing to the lack of a daily riskless interest rate series.) Standard deviations were estimated by the square root of the sum of squared log daily returns in the month. (Results using demeaned daily returns were not materially different.) If there are N_t days in month t, the estimated standard deviation is

$$\sigma_t \equiv \left[\sum_{i=1}^{N_t} r_{t,i}^2\right]^{1/2}. \tag{5a}$$

For the 3,600 cases (1.1% of all observations) in which a firm has fewer than 15 nonmissing daily returns in a given month, the firm's return and standard deviation for that month are set to missing values. For the 23 cases in which a firm's daily returns in a month are all zero, the firm's standard deviation for that month is set to missing instead of zero because I work with log standard deviations.

French, Schwert, and Stambaugh (1987) propose an alternative volatility estimate that adjusts for first-order autocorrelation in returns:

$$\sigma_t \equiv \left[\sum_{i=1}^{N_t} r_{t,i}^2 + 2\sum_{i=1}^{N_t-1} r_{t,i} r_{t,i+1}\right]^{1/2}. \tag{5b}$$

I use (5a) for firm stock return volatility because (5b) results in a negative variance estimate if the first-order autocorrelation of daily returns in a given month is less than −0.5. Most of the firms examined here (1,691 of 2,494) have at least one month for which this is true. Later in the paper I examine returns on stock portfolios, which exhibit greater return autocorrelation. For these portfolios I estimate return volatility with (5b).

Of the 2,494 firms, 680 (27%) are denoted 'continuously traded firms' because they have no missing daily or monthly observations in the period 1977–1991. Table 1 presents summary statistics concerning both the set of 2,494 firms and the subset of continuously traded firms.

For each firm with a debt/equity ratio on Compustat for 1977, I calculate the mean year-end debt/equity ratio (using the book value of debt and the market value of equity) over all nonmissing debt/equity ratios for the years 1977–1991. For each firm with reported debt/equity ratios, I thus have a single measure of debt/equity. There is sufficient data to compute a debt/equity ratio for 2,102 of

Table 1

Descriptive statistics for all firms on the CRSP Amex/NYSE daily tape on January 3, 1977 with at least 13 months of post-1976 data

A firm's statistics are computed over 1977–1991, or until the firm disappears from the CRSP tape. Monthly stock return standard deviations (denoted σ_t) are estimated with squared daily returns. Firms with no missing daily or monthly observations in the period 1977–1991 are denoted 'continuously traded firms'.

	Across all firms ($N = 2,494$)		Across continuously traded firms ($N = 680$)	
Firm characteristic	Mean	Median	Mean	Median
Mean year-end debt/equity ratio[a]	5.78	0.69	1.14	0.61
Mean year-end capitalization ($mm)	809.3	94.9	1839.7	575.8
Mean daily return (%)	0.052	0.056	0.044	0.049
Daily return 1st-order autocorrelation	−0.014	0.011	0.011	0.027
Skewness of daily returns	0.486	0.315	−0.184	0.031
Mean σ_t (%)	11.217	9.776	8.916	8.062
ρ_1 of $\log(\sigma_t)$[b]	0.377	0.380	0.408	0.399
ρ_2 of $\log(\sigma_t)$[b]	0.172	0.188	0.219	0.219
ρ_3 of $\log(\sigma_t)$[b]	0.109	0.121	0.132	0.135
ρ_4 of $\log(\sigma_t)$[b]	0.036	0.042	0.040	0.039
ρ_5 of $\log(\sigma_t)$[b]	0.065	0.065	0.073	0.073
ρ_6 of $\log(\sigma_t)$[b]	0.032	0.037	0.056	0.051
ADF(6) statistic[c]	−2.49	−2.61	−3.06	−3.09
% of ADF(6) < 5% critical value[c]	39.0		62.9	

[a] Firm debt/equity ratios are from Compustat. Only 2,102 of the 2,494 firms have Compustat data, of which 644 are continuously traded firms.

[b] ρ_i is the partial autocorrelation coefficient at lag i for $\log(\sigma_t)$. These autocorrelations are computed only for those firms with at least 36 months of data and no missing observations over the time for which the firm is on the CRSP tapes.

[c] ADF(6) is the test statistic for the augmented Dickey–Fuller test (six lags) for $\log(\sigma_t)$. The 10%, 5%, and 1% critical values for this test are −2.58, −2.89, and −3.51, respectively.

the 2,494 firms (84%) and for 644 of the 680 continuously traded firms (95%). For each firm, I use CRSP data to calculate the mean year-end size (market value of equity) over 1977–1991. I therefore have a single measure of size for each firm.

As Table 1 documents, continuously traded firms are, on average, much larger and have lower debt/equity ratios than the average firm. The median size of continuously traded firms is over six times larger than the median size of all firms, while the median debt/equity ratio of continuously traded firms is approximately 10% lower than the corresponding median ratio for all firms.

For each firm I calculate the mean daily return, the first-order autocorrelation of this daily return, the skewness of daily returns, and the mean estimated monthly standard deviation from (5a). For each of the 2,141 firms with over 36 months of data and no missing monthly observations during the time the firm was on the CRSP tape, I calculate the first six partial autocorrelations of the log of the standard deviation of monthly returns, as well as an augmented Dickey–Fuller (ADF) test statistic (six lags) for nonstationarity of this log. Table 1 reports that the median autocorrelation is minimal. Continuously traded firms' returns exhibit greater autocorrelation, but the magnitude is sufficiently small that estimating volatility with (5a) instead of (5b) is appropriate.

Table 1 also reports that, for the median firm, much of a given volatility shock dies out quickly, but nonstationarity cannot be rejected. The median first-order autocorrelation of $\log(\sigma_t)$ is less than 0.40. The median partial autocorrelation coefficients beyond three months are all less than 0.10. However, only 835 firms, or 39% of the 2,141 firms for which ADF statistics were calculated, have ADF statistics less than the 5% critical value (one-tailed), while 63 firms, or 3% of these firms, have ADF statistics greater than the 95% critical value. (The 95% and 5% critical values for this ADF test are −0.05 and −2.58, respectively; see Fuller, 1976.) This inability to reject nonstationarity probably owes more to a lack of power than true nonstationarity. The mean number of observations of σ_t for these firms is 138. There is stronger evidence for stationarity among the continuously traded firms, all of which have 180 observations of σ_t. Of these firms, 428, or 63%, have ADF statistics less than the 5% critical value, while only two firms have ADF statistics greater than the 95% critical value.

There are two difficulties in interpreting these ADF results. First, σ_t is a noisy estimate of true volatility, so the AR coefficients will be biased downward, resulting in overrejection of nonstationarity (Pagan and Ullah, 1988; Schwert, 1989b). Second, it is not clear how to evaluate the joint significance of the individual ADF statistics, or even if the concept of joint significance is meaningful here. On balance, continuously traded firms appear to have stationary log standard deviations, while the evidence for other firms is mixed.

3. Empirical evidence

I examine the relation between firm stock returns and firm volatility at the monthly and daily frequencies. At the monthly frequency, I use ordinary least-squares to estimate (1), (2a), and (2b) on each firm's data. Estimation of (2a) or (2b) implicitly assumes that we are interested in the variation in volatility around the sample mean of volatility. There are two problems with this assumption. First, the regressions are not meaningful if volatility is nonstationary. Second, even if volatility is stationary, we are often more interested in the *change* in volatility, i.e., the variation in volatility relative to a prior level. Both problems can be solved by subtracting $\log(\sigma_{t-1})$ from the left-hand sides of both equations.

The results from this alternative approach are not qualitatively different from those reported for (2a)–(2b), so I do not report them here.

Note that logs of volatility, instead of levels, are used in these regressions. The choice of logs versus levels will not affect the signs of the estimated coefficients, but will affect interfirm comparisons of estimated coefficients because of cross-sectional differences in average return volatility levels across firms. A given log change in volatility corresponds to a greater level change for firms with high volatility than firms with low volatility. Because firm size and debt/equity ratios are correlated with firms' average volatility levels (the Spearman rank correlation between firm mean estimated monthly volatility and firm size is -0.58, and the rank correlation of volatility with firm debt/equity ratios is 0.28), the choice of logs versus levels will affect the results of correlations (across firms) of the estimated regression coefficients with both of these firm-specific variables.

My use of logs is consistent with previous literature. It is also consistent with Christie's model of leverage, which has implications for the log of volatility instead of the level of volatility. For example, the model implies that two firms with different average levels of volatility but equal debt/equity ratios should have identical regression coefficients in (1).

I estimate regressions similar to (1), (2a), and (2b) to measure the relation between stock returns and volatility at the daily frequency. Day t's return volatility is estimated by the absolute value of day t's return, $|r_t|$. (Results using absolute demeaned returns were not substantially different.) An alternative approach is to use squared returns. However, daily stock returns are characterized by fat tails. For such distributions, it is usually more efficient to estimate volatility relationships with absolute residuals than with squared residuals (Davidian and Carroll, 1987; Schwert and Seguin, 1990).

To facilitate comparisons between results using monthly volatility and results using daily volatility, it would be convenient to use logs of these daily volatility estimates. However, daily absolute returns are often zero. I therefore use a firm's mean daily absolute return (estimated over the entire sample) to roughly scale the firm's estimated coefficients from daily volatility regressions, as illustrated in the following equations:

$$(|r_{t+1}| - |r_t|)/\overline{|r|} = \alpha_0 + \lambda_0 r_t + \varepsilon_{t+1,0}\,, \tag{6}$$

$$|r_t|/\overline{|r|} = \alpha_1 + \lambda_1 r_t + \varepsilon_{t,1}\,, \tag{7a}$$

$$|r_{t+1}|/\overline{|r|} = \alpha_2 + \lambda_2 r_t + \varepsilon_{t+1,2}\,. \tag{7b}$$

This scaling is designed to adjust for differing average levels of volatility across firms. The difference between this normalization and using logs can be illustrated by comparing (1) and (6). In (1), changes in volatility are essentially measured as a fraction of the immediately prior level of volatility. In (6), changes are measured as a fraction of the average level of volatility.

Table 2

Summary of ordinary least-squares regressions of firm stock return volatility on firm stock returns, January 1977 through December 1991

$\text{Volatility}_{t+1} - \text{Volatility}_t = \alpha_0 + \lambda_0 r_t + e_{t+1,0}$,

$\text{Volatility}_t = \alpha_1 + \lambda_1 r_t + e_{t,1}$,

$\text{Volatility}_{t+1} = \alpha_2 + \lambda_2 r_t + e_{t+1,2}$.

Regression coefficient	All firms			Continuously traded firms[a]		
	Mean λ	r_d	r_s	Mean λ	r_d	r_s
Monthly ($\text{Volatility}_t \equiv \log(\sigma_t)$)						
λ_0	−0.741	0.021	0.252	−0.360	−0.137	0.216
	(0.143)	[0.347]	[0.000]	(0.069)	[0.000]	[0.000]
λ_1	0.461	−0.127	−0.352	−0.007	−0.070	−0.274
	(0.151)	[0.000]	[0.000]	(0.076)	[0.075]	[0.000]
λ_2	−0.281	−0.103	−0.146	−0.367	−0.231	−0.057
	(0.102)	[0.001]	[0.000]	(0.069)	[0.000]	[0.139]
Daily ($\text{Volatility}_t \equiv \lvert r_t\rvert/\overline{\lvert r\rvert}$)						
λ_0	−6.361	0.230	0.037	−3.551	0.057	0.118
	(0.822)	[0.000]	[0.067]	(0.377)	[0.147]	[0.002]
λ_1	7.210	−0.216	−0.135	3.118	−0.030	−0.287
	(1.160)	[0.000]	[0.000]	(0.494)	[0.453]	[0.000]
λ_2	0.856	−0.156	−0.296	−0.433	0.042	−0.315
	(0.356)	[0.000]	[0.000]	(0.255)	[0.291]	[0.000]

Regressions are estimated over both monthly and daily frequencies for the 2,494 firms on the CRSP Amex/NYSE daily tape on January 3, 1977 that have at least 13 months of post-1976 data. The estimation period is January 1977 through December 1991 or until the firm disappears from the CRSP tape. Monthly returns are the sum of log daily returns less the one-month T-bill return. Monthly stock return standard deviations (denoted σ_t) are estimated with squared daily returns. Standard errors for mean coefficients are in parentheses. Spearman rank correlations with mean year-end debt/equity ratios are denoted r_d and are computed only for those 2,102 firms (644 continuously traded firms) with Compustat data. Spearman rank correlations with mean year-end market capitalization are denoted r_s. P-values of two-tailed tests of these correlations are in brackets. These p-values assume that firm statistics are independent across firms.

[a]These firms are the 680 firms with no missing daily or monthly observations over January 1977 to December 1991.

Table 2 summarizes the results. The mean regression coefficients are reported for both the set of all firms and the subset of continuously traded firms. The first rows of the 'Monthly' and 'Daily' sections confirm the sign of the relation examined by Black, Christie, and Cheung and Ng, although the strength of this relation depends on the selection criteria of the sample. Firm stock returns and future changes in stock return volatility are negatively related. This relation is twice as large for the entire sample of firms as it is for the continuously traded firms. The mean λ_0 from the monthly regressions implies that an increase in month t's stock return of one percentage point corresponds to a 0.73% decline in stock return volatility from month t to month $t+1$. An estimate of the standard error for this mean regression coefficient is given in parentheses. The construction of this estimate (and all other standard errors reported in Table 2) is discussed in the Appendix. The mean λ_0 from the daily regressions implies that an increase in the day t stock return of one percentage point corresponds to a 6.43% decline in stock return volatility from day t to day $t+1$. Although the estimated daily coefficient is much larger than the estimated monthly coefficient, the standard deviation of monthly returns, and therefore the standard deviation of the right-hand side variable in (2a) and (7a), is approximately five times as large as the standard deviation of daily returns [the right-hand side variable in (2b) and (7b)].

The second and third rows of the 'Monthly' and 'Daily' sections report the results that are at the heart of this paper. Firm stock returns and volatility are contemporaneously positively correlated. The mean estimated coefficients from the monthly regressions imply that an increase in month t's stock return of one percentage point corresponds to a 0.46% increase in month t stock return volatility. Month $t+1$ volatility falls 0.28%. At the daily frequency, the positive relation between returns and volatility is even stronger. A positive day t return corresponds to higher volatility on both days t and $t+1$. [It should be noted that $\lambda_2 - \lambda_1$ does not precisely equal λ_0 because the sample periods for (1) and (2b) are smaller than the sample period for (2a) due to missing returns for some firms.]

For the continuously traded firms, the relation between stock returns and volatility is substantially less positive. At the monthly frequency, the mean λ_1 is close to zero, while at the daily frequency the mean λ_1 is less than half as large as the mean λ_1 for the entire sample of firms. In addition, there is a stronger negative relation between period t returns and period $t+1$ volatility for these firms than there is for the entire sample of firms.

3.1. Variations with firms' debt/equity ratios and sizes

The theory underlying the leverage effect shows that highly leveraged firms should exhibit a stronger negative relation between stock returns and volatility than should less highly leveraged firms. This theory was tested by Christie and Cheung and Ng, who (as previously mentioned) find an inverse relation between period t firm stock returns and changes in firm stock return volatility from period t to $t+1$. They also find that this inverse relation is stronger for firms with large debt/equity ratios. Cheung and Ng note that this inverse relation is also stronger for smaller firms. I reexamine these conclusions by looking at the Spearman rank correlations between the individual firm regression coefficients (λ_0, λ_1, and λ_2) and firms' debt/equity ratios and sizes.

The columns in Table 2 labeled r_d report rank correlations between each of the regression coefficients and firms' debt/equity ratios (D/E). P-values of two-tailed tests that these correlations are zero are in parentheses. Unlike the standard errors for the mean coefficients, these p-values are not corrected for nonzero cross-correlations among the estimated regression coefficients. There are three main conclusions to draw from these correlations. The first is that the negative relation between λ_0 and D/E found by Christie and Cheung and Ng does not hold for the large sample of firms examined in this paper. Over the entire set of 2,494 firms, there is a *positive* correlation between λ_0 and D/E (although this correlation is insignificant in the monthly data). The result of Christie and Cheung and Ng is confirmed only with monthly data for the subset of continuously traded firms. The lack of a positive correlation between λ_0 and D/E in daily data appears inconsistent with the negative correlation found by Cheung and Ng (also using daily data). However, their EGARCH model produces far smoother estimates of stock return volatility than absolute daily returns. In this respect, their volatility estimates are more like the monthly volatility estimates examined here.

The second conclusion is that, notwithstanding the above result, highly leveraged firms exhibit stronger negative relations between stock returns and volatility than do less highly leveraged firms, which is not reflected in a negative correlation between λ_0 and D/E because this negative relation holds not only for λ_2 (the relation between the period t stock return and the period $t+1$ stock return volatility), but also for λ_1 (the contemporaneous relation between stock returns and volatility).

The third conclusion is that there is some reason, other than the leverage effect, that underlies at least part of the correlation between firm debt/equity ratios and these regression coefficients. Recall that the theory underlying the leverage effect has no implications for the strength of the contemporaneous relationship between stock returns and volatility. Therefore, there is some other factor that is inducing the negative correlations between firm debt/equity ratios and λ_1.

The columns of Table 2 labeled r_s report rank correlations of λ_0, λ_1, and λ_2 with size. The positive correlations of size with λ_0 at both the monthly and daily frequency are in accord with the results of Cheung and Ng. For both the set of all firms and the set of continuously traded firms, smaller firms exhibit stronger negative relations between period t returns and the change in volatility between t and $t+1$ than do larger firms.

However, the table also reports that λ_1 and λ_2 are *negatively* correlated with size at both the monthly and daily frequencies. Smaller firms exhibit stronger *positive* relations between stock returns and volatility than do larger firms. In other words, the stock returns of small firms are more positively skewed than the stock returns of large firms. Therefore, the positive correlation of λ_0 with size is a consequence of the fact that the size effect in λ_1 is stronger than the size effect in λ_2. In daily data, the rank correlation between λ_1 and firm size is actually less than the the rank correlation between λ_2 and firm size. However, there is much more variation in λ_1 across firms than in λ_2.

3.2. Is there a survivorship bias?

One of the clearest points documented in Table 2 is that there are large differences between the mean estimated coefficients for all firms and the mean estimated coefficients for continuously traded firms. Are continuously traded firms different because they are large firms, because they are surviving firms, or both? I examine this issue by comparing mean regression coefficients across survivors and nonsurvivors of similar sizes.[1] For space considerations, I restrict my attention to Eq. (2a).

I first define subsets of firms by survivorship status. Survivors are the 1,078 firms that have stock return data on the CRSP tape at the end of 1991 as well as at the beginning of 1977, have not been temporarily delisted during these 15 years, and have no more than 12 missing monthly observations. Nonsurvivors are the 1,385 firms that disappear from the CRSP tape prior to the end of 1991. Merger/Exchange firms are the 1,086 nonsurvivors delisted because of merger or exchange of stock. Bankrupt firms are the 91 nonsurvivors delisted because of bankruptcy, liquidation, or failure to meet the listing exchange's financial guidelines for continued listing.

The size of the Merger/Exchange group is much larger than that of the Bankrupt group. Because mergers and acquisitions dominated business news in the 1980s, one might be tempted to view this period as an anomaly. However, the observed pattern is typical. Over 1926–1976, 983 firms are delisted because of merger or exchange, while 100 firms are delisted because of bankruptcy, liquidation, or failure to meet listing guidelines.

Table 3 documents that survivors are, on average, much larger than nonsurvivors. The median survivor has a mean year-end market capitalization of $311 million, while the corresponding figure for the median nonsurvivor is $45 million. Table 3 also reports the mean regression coefficient λ_1 for each of these four groups. The mean coefficient for survivors is 0.11, which is substantially smaller than the mean coefficient of 0.74 for nonsurvivors. To determine how much of this difference owes to variations in survivorship status and how much to variations in firm size, I split each group into four size-sorted subgroups. The size breakpoints correspond to the quartile breakpoints for survivors, so there are many more nonsurvivors in the small-firm subgroups than in the large-firm subgroups.

The results (reported in Table 3) show that most of the difference between survivors and nonsurvivors is attributable to a survivorship bias instead of

[1] I thank the referee for suggesting this investigation.

Table 3

Ordinary least-squares regressions of monthly stock return volatility on contemporaneous stock returns, January 1977 through December 1991: Summary of results by survivorship status

$$\log(\sigma_t) = \alpha_1 + \lambda_1 r_t + e_{t,1}\,.$$

			Mean λ_1 by firm size ($mm)[b,c]			
Firm type[a,b]	Median size ($mm)[c]	Mean λ_1	$0 < s < 72$	$72 \leqslant s < 311$	$311 \leqslant s < 1130$	$1130 \leqslant s$
Survivors (1,078)	311.0	0.107	0.403	0.168	−0.076	−0.065
			(269)	(270)	(270)	(269)
Nonsurvivors (1,385)	44.7	0.744	0.795	0.748	0.529	0.569
			(811)	(366)	(164)	(44)
Merger/Exchange (1,084)	64.3	0.871	1.013	0.813	0.563	0.569
			(566)	(318)	(156)	(44)
Bankrupt (91)	26.6	0.566	0.500	0.992	−0.183	–
			(62)	(22)	(7)	

Regressions are estimated for each firm on the CRSP Amex/NYSE daily tape on January 3, 1977 that has at least 13 months of post-1976 data. The estimation period is January 1977 through December 1991 or until the firm disappears from the CRSP tape. Monthly stock returns are the sum of log daily returns less the one-month T-bill return. Monthly stock return standard deviations (denoted σ_t) are estimated with squared daily returns.

[a]A firm is a survivor if (1) it is on the CRSP tape at the end of 1991 and was not temporarily delisted prior to that time and (2) it has no more than 12 months of missing observations. A firm is a nonsurvivor if it was delisted prior to the end of 1991. Those firms that were delisted because of merger or exchange of stock are included in the merger/exchange group. The bankrupt group includes those firms that were delisted because of bankruptcy, liquidation, or failure to meet its exchange's financial guidelines for continued listing.

[b]The number of firms in each group is given in parentheses.

[c]Firm size is measured by the mean year-end value of equity over all year-ends for which the firm existed in 1977–1991.

variations in firm sizes. Holding firm size (approximately) constant, survivors have much smaller regression coefficients than do nonsurvivors. The subgroup means imply that a (hypothetical) group of survivors that had the same size distribution as that of the 1,385 nonsurvivors would have a mean regression coefficient of 0.27, versus 0.74 for the actual group of nonsurvivors. Put another way, the mean contemporaneous relation between monthly returns and monthly return volatility is almost three times as large for nonsurvivors as it is for a group of equal-sized survivors.

A feasible explanation for the effect of the survivorship bias on the estimated coefficients is the behavior of a firm's stock returns when news about the firm's acquisition or merger is revealed. Such news should lead to a higher stock price as well as increased volatility, leading to higher observed estimates of both λ_1 and λ_2. If so, much of the difference between equal-sized survivors and non-survivors should be traceable to the behavior of the nonsurvivor's stock price during the time that it is 'in play'. To test this intuition, I reestimate (2a) for the nonsurvivors, omitting the last six months of data for each firm. The mean λ_1 for this group falls from 0.74 to 0.55.

This decline of 0.19 in λ_1 confirms that the relation between stock returns and volatility near the time that a firm exits the CRSP tape differs from the relation at other times. However, the mean λ_1 of 0.55 is still substantially larger than the mean λ_1 for an equal-sized group of survivors (0.27). Either much of the news about a firm's acquisition is revealed earlier than six months before the firm is delisted, or there is some other difference between survivors and nonsurvivors.

There are too few firms in the bankrupt category to draw any strong conclusions. However, it is interesting to note that bankrupt firms in the smallest size category have a mean λ_1 that is close to that of survivors in this size category, suggesting that firms nearing bankruptcy do not exhibit both large negative returns and large return volatility.

Another potential bias in Christie (but not in Black or Cheung and Ng) is the requirement that firms have debt/equity ratios available on Compustat. Given the recent interest in the effects of a Compustat bias,[2] I briefly discuss the implications of this bias on the relation between stock returns and volatility (these results are not reported in any table). The mean λ_1 for the 2,102 firms with Compustat data is 0.43, while the mean λ_1 for the 392 firms without Compustat data is 0.64. The difference between these two means is entirely a consequence of the fact that firms with Compustat data are much more likely to be survivors than are firms without Compustat data. Of the firms with Compustat data, 48% are survivors, while only 17% of the firms without Compustat data are survivors. The mean λ_1 for surviving firms with Compustat data is 0.11, which is essentially identical to the mean of 0.10 for survivors without Compustat data. Similarly, the mean λ_1

[2] A Compustat bias can distort the relation between book/market value and subsequent firm performance. See Kothari, Shanken, and Sloan (1993) and Breen and Korajczyk (1994).

for nonsurvivors with Compustat data is 0.73, while the mean for nonsurvivors without Compustat data is 0.75.

3.3. Results for an earlier period

This paper focuses on the 1977–1991 period because I have Compustat data for only those years. However, since much of the previous work in this area focuses on earlier time periods, it is important to know whether the results in this paper are robust over time. Therefore, I consider the 1962–1978 period examined by Christie.

There are 1,960 firms on the CRSP daily tape as of July 3, 1962 with sufficient data to estimate (1) on at least 12 monthly observations. A subset of 449 firms have no missing observations through December 1978. Christie's sample of firms is a subset of these 449 firms. His sample was chosen in part based on Compustat data, so I am unable to precisely match my firms with his. As a check that my sample of continuously traded firms is similar to his sample of firms, I replicate his regression of log-differenced quarterly volatility on lagged quarterly returns on my subset of 449 firms. The resulting mean regression coefficient is −0.26, which is very close to Christie's mean coefficient of −0.23.

Table 4 summarizes the results of ordinary least-squares estimation of (1), (2a)–(2b), (6), and (7a)–(7b) on all 1,960 firms over July 1962 to December 1978. A comparison of the results in Tables 2 and 4 reveals that the periods 1977–1991 and 1962–1978 exhibit similar relations between stock returns and volatility. These similarities are most pronounced in the regression results for the full samples of firms. None of the mean coefficients switches signs; three of the six mean coefficients vary less than 10% across the two periods. The results for the continuously traded firms exhibit greater differences across the two periods, with the earlier period exhibiting a stronger positive contemporaneous relationship between returns and volatility than the later period. On balance, the results presented in this section appear to be robust over time.

4. Reconciling the difference between firm and aggregate returns

The previous section documented a strong positive contemporaneous relation between firm stock returns and volatility at both daily and monthly frequencies. Earlier work has documented the opposite relation at the aggregate level. For example, Campbell and Hentschel (1992) note the negative skewness in daily returns on the CRSP value-weighted index, while French, Schwert, and Stambaugh (1987) conclude that monthly value-weighted index returns and contemporaneous innovations in this index's return volatility (from an ARIMA model) are strongly negatively related. Additional evidence confirming a negative contemporaneous relation between aggregate returns and volatility is presented below.

Table 4

Summary of ordinary least-squares regressions of firm stock return volatility on firm stock returns, July 1962 through December 1978

$$\text{Volatility}_{t+1} - \text{Volatility}_t = \alpha_0 + \lambda_0 r_t + e_{t+1,0}\,,$$

$$\text{Volatility}_t = \alpha_1 + \lambda_1 r_t + e_{t,1}\,,$$

$$\text{Volatility}_{t+1} = \alpha_2 + \lambda_2 r_t + e_{t+1,2}\,.$$

Regression coefficient	Mean coefficients for:	
	All firms	Continuously traded firms[a]
Monthly (Volatility$_t \equiv \log(\sigma_t)$)		
λ_0	−0.937	−0.827
	(0.138)	(0.061)
λ_1	0.663	0.253
	(0.159)	(0.079)
λ_2	−0.268	−0.574
	(0.149)	(0.079)
Daily (Volatility$_t \equiv \lvert r_t\rvert/\overline{\lvert r\rvert}$)		
λ_0	−5.865	−3.891
	(0.470)	(0.213)
λ_1	7.323	4.747
	(0.730)	(0.303)
λ_2	1.439	0.856
	(0.340)	(0.170)

Regressions are estimated over both monthly and daily frequencies for the 1,960 firms on the CRSP Amex/NYSE daily tape on July 2, 1962 that have at least 13 months of data. The estimation period is July 1962 through December 1978 or until the firm disappears from the CRSP tape. Monthly returns are the sum of log daily returns less the one-month T-bill return. Monthly stock return standard deviations (denoted σ_t) are estimated with squared daily returns. Standard errors for mean coefficients are in parentheses.

[a]These firms are the 449 firms with no missing daily observations over July 1962 to December 1978.

What explains this difference between firm returns and aggregate returns? One possibility is that some common factor is negatively skewed, while idiosyncratic returns are positively skewed. There may also be multiple common factors, some of which are negatively skewed and predominantly influence the returns to large firms (and therefore influence the returns to value-weighted indexes), while others are positively skewed and predominantly influence the returns to small firms.

In this section I evaluate these explanations, focusing on the relation between monthly returns and volatility summarized by the coefficient λ_1 in (2a). To preview my results, I find strong evidence that idiosyncratic firm returns are positively skewed. I also find evidence of a positively skewed common factor in small firm returns, but this evidence is not strong.

I first examine the relation between firm size and λ_1. As discussed earlier, firm size and λ_1 are negatively correlated. Therefore the mean equal-weighted λ_1 for the 2,494 firms in my sample (0.46) is larger than the mean size-weighted λ_1 for these firms (0.12), as reported in the first row of Table 5. This first row also reports a more detailed breakdown of λ_1 by firm size. The 2,494 firms were divided into five size-sorted quintiles, and mean (equal-weighted) λ_1's for each quintile were computed. All of these means are positive, but there is substantial cross-sectional variation. The largest firms have a mean λ_1 equal to 0.07, while the smallest firms have a mean λ_1 equal to 0.70.

To what extent is this cross-sectional variation consistent with a simple one-factor model of skewed returns? In a one-factor model, the common factor must be negatively skewed to match the sign of the skewness of aggregate returns. Therefore, idiosyncratic returns must be sufficiently positively skewed to ensure that firm returns are positively skewed. In the simplest one-factor model, each firm's idiosyncratic return is equally positively skewed. This model is consistent with an inverse relation between firm size and λ_1 if small firms have larger idiosyncratic return variances than large firms. If so, small firms will have a greater share of their excess returns driven by a positively skewed component, hence their λ_1's will be greater than the λ_1's for large firms.

For each firm, I construct daily 'idiosyncratic' returns as the residuals from a regression of raw returns on lags 0 through 2 of CRSP value-weighted index returns. The term 'idiosyncratic' is a bit of a misnomer. This procedure removes only a value-weighted factor from firm returns; there may be other common factors that are not removed. I then construct monthly idiosyncratic returns and return volatilities in the same manner in which I earlier constructed excess monthly returns and return volatilities. The second row of Table 5 reports the mean λ_1's by group for regressions of monthly idiosyncratic return volatility on idiosyncratic returns. To avoid confusion, I henceforth refer to λ_1's calculated using monthly returns less the T-bill return as excess return λ_1's. Those calculated using idiosyncratic returns are idiosyncratic return λ_1's.

The mean idiosyncratic return λ_1's range from 0.36 for the quintile of largest firms to 0.79 for the quintile of smallest firms. This range is roughly two-thirds the range, across quintiles, of mean excess return λ_1's. Therefore, approximately one-third of the cross-sectional variation (by size) in excess return λ_1's can be explained by the greater volatility of small firm idiosyncratic returns. (The mean standard deviation of idiosyncratic returns ranges from 3.99% per day for the smallest size-sorted portfolio to 1.63% per day for the largest size-sorted portfolio.) The remainder of this cross-sectional variation must be explained by some combination of greater positive skewness of small firms' (truly) idiosyncratic returns or a positively skewed common factor that disproportionately affects small firms.

I look for evidence of such a common factor by examining the returns to portfolios of stocks. I consider seven portfolios: the CRSP value-weighted and

Table 5

A comparison of firm-level and aggregate-level regressions of monthly stock returns on contemporaneous return volatility, January 1977 through December 1991

$\log(\sigma_t) = \alpha_1 + \lambda_1 r_t + e_{t,1}$.

	Value-weighted	Equal-weighted	Size-sorted quintiles[a] 1	2	3	4	5
Mean λ_1 for individual firms[b]							
Excess returns	0.117	0.461	0.699	0.726	0.538	0.274	0.067
Idiosyncratic returns	0.368	0.678	0.786	0.909	0.790	0.547	0.360
λ_1 for portfolio of firms[c]							
Excess returns	−1.187	−1.354	0.073	−1.357	−1.675	−1.535	−0.928
	(0.539)	(0.556)	(0.563)	(0.563)	(0.542)	(0.547)	(0.533)
Idiosyncratic returns	–	−0.106	0.969	−0.629	−1.460	−1.460	1.067
		(1.375)	(1.328)	(0.900)	(1.282)	(1.722)	(4.250)

Regressions are estimated for both excess returns and idiosyncratic returns. Monthly excess returns are summed log daily returns less the one-month T-bill return. Monthly idiosyncratic returns are summed daily residuals from a regression of log daily returns on lags zero through two of the CRSP value-weighted return. Monthly return volatility is estimated with squared daily returns (raw or idiosyncratic, respectively).

[a] 1 = smallest, 5 = largest.

[b] Individual firm regression coefficients are estimated for the 2,494 firms on the CRSP Amex/NYSE daily tape on January 3, 1977 that have at least 13 months of post-1976 data. They are estimated from January 1977 through December 1991 or until the firm disappears from the CRSP tape. The value- and equal-weighted columns report the size-weighted and unweighted means of these coefficients (a firm's size is measured by its mean year-end value of equity over all year-ends for which it existed in 1977–1991). The quintile columns report unweighted means for all firms in a given size-sorted quintile.

[c] A given group's portfolio λ_1 is based on the returns to the portfolio. For the value- and equal-weighted groups, these portfolio returns are the corresponding CRSP indexes. For the size-sorted quintiles, these portfolios are formed using all firms on the CRSP Amex/NYSE tape (not just the 2,494 firms for which individual coefficients were estimated). Here firm size is measured by the prior year's ending equity value. Portfolio regressions are estimated from January 1977 through December 1991 and use an AR(1) correction. Standard errors are in parentheses. Because idiosyncratic returns are residuals from a regression on the CRSP value-weighted index, there is no idiosyncratic value-weighted return.

equal-weighted indexes and five size-sorted portfolios. These portfolios were created using every firm on the CRSP Amex/NYSE tape (not just the 2,494 firms previously considered in this paper). Firms were placed in size-sorted quintiles according to their previous year-end market value. Equal-weighted daily and monthly return indexes were then constructed for each portfolio.

The first-order autocorrelations of the portfolios' daily returns are large, ranging from 0.12 for the value-weighted index to 0.32 for the smallest quintile. I therefore use (5b) to construct estimates of volatility. I then estimate (2a) for each portfolio's return over the period January 1977 to December 1991. The error terms were corrected for first-order serial correlation.

Estimated λ_1's are displayed in the third row of Table 5. The coefficient for the value-weighted index is -1.19 and reliably negative, confirming the negative contemporaneous relation between market returns and return volatility. A similar relation is reported for the equal-weighted return index, as well as the four largest quintiles. These estimates of λ_1 range from -0.93 to -1.36. All are significant at the 10% level and all but the estimate for the largest quintile are significant at the 5% level. By contrast, the portfolio of smallest firms exhibits an insignificantly positive contemporaneous relation. This suggests, but does not confirm, the presence of a positively skewed common factor in small-firm stock returns.

I next use (5b) to construct 'idiosyncratic' returns and volatility estimates for all portfolios except the value-weighted index. I then estimate (2a) for each idiosyncratic return, using an AR(1) correction for the error term. The results are displayed in the final row of Table 5. The idiosyncratic return λ_1 for the smallest quintile is quite large (0.97), but insignificantly different from zero, as are all of the idiosyncratic return λ_1's. This lack of significance is largely a consequence of the standard errors, which are, on average, over three times as large as the standard errors for the excess return λ_1's. More powerful techniques will be required to determine the extent to which a small-firm factor (if one exists) is skewed.

5. Concluding remarks

In this paper I document a strong positive contemporaneous relation between firm stock returns and volatility. (This finding is qualitatively similar to positively skewed returns.) The relation between firm returns and one-period-ahead volatility is much weaker. It is positive at the daily frequency and negative at the monthly frequency. These relations largely explain the finding of Black, Christie, and Cheung and Ng that firm stock returns and changes in volatility are negatively correlated.

Smaller firms exhibit a greater positive contemporaneous relation between returns and volatility than do larger firms. In addition, this contemporaneous relation is much greater for firms that are eventually delisted. Therefore, a survivorship bias has an important effect on the results of earlier empirical work. The behavior of returns near the time that a firm is delisted is responsible for much of the difference between delisted firms and survivors.

Black and Christie hypothesize that variation over time in a firm's financial leverage could explain at least part of the negative correlation between returns and changes in volatility. However, this leverage effect induces a negative correlation between returns and changes in volatility through a negative correlation between returns and future volatility, not through a positive correlation between returns and current volatility. Therefore, the leverage effect (although it may exist) cannot explain the observed relation between returns and changes in volatility.

The leverage effect implies that firms with higher debt/equity ratios should exhibit a stronger negative relation between current returns and future volatility than firms with lower debt/equity ratios. Although I find evidence supporting this implication, I am hesitant to interpret it as support for the leverage effect because firms with higher debt/equity ratios also exhibit a stronger negative relation between returns and *contemporaneous* volatility than do firms with lower debt/equity ratios. Because this latter evidence cannot be explained by the leverage effect, there must be some other unknown force at work linking firm debt/equity ratios with the relation between returns and volatility.

A number of readers have suggested that the positive relation between returns and volatility can be explained by viewing a firm's stock as an option on the assets of the firm. Since an option's price rises when the underlying asset volatility rises, one might think that a stock price should rise when the volatility of the value of the firm (and therefore the volatility of the value of the stock) rises. However, this explanation implies that firms with higher debt/equity ratios should exhibit stronger positive correlations between stock returns and volatility than should firms with lower debt/equity ratios; i.e., the equity of the highly leveraged firm is more 'option-like'. This implication is inconsistent with my results.

At the aggregate return index level, there is a well-known negative contemporaneous relation between returns and volatility. The most important question raised by the results in this paper is why firm-level and aggregate-level returns behave so differently. For example, are idiosyncratic firm returns positively skewed because firm-specific news is generally good? Is there a positively skewed common factor that primarily affects small firms? Explaining these patterns awaits future research.

Appendix

There are two approaches to computing the statistical significance of a given mean coefficient in Table 2. The first approach is to consider the distributions of the individual t-statistics, as in Christie (1982, 1990). However, the error terms in

(1), (2a)–(2b), and (7a)–(7b) are both serially correlated and nonnormal (these features are most pronounced with daily data), so the individual ordinary least-squares t-statistics are not distributed as t's.

The second approach, used in this paper, is to consider the distribution of the individual λ's. For concreteness, consider the estimated λ_0's from firm-by-firm estimation of regression (1). Denote the number of firms by K. I assume that each $\lambda_{i,0}$, $i = 1,\ldots,K$, is drawn from a distribution with a variance var(λ). This assumption cannot literally be correct, because the variance of $\lambda_{i,0}$ should depend on the number of observations for firm i's regression.

Computing the standard error of a given estimate of $\overline{\lambda_{i,0}}$ requires some assumption about the joint distribution of $\lambda_{i,0}$ and $\lambda_{j,0}$, $i \neq j$. Because these statistics are computed over overlapping time periods, aggregate shocks to returns and return volatilities induce dependence between $\lambda_{i,0}$ and $\lambda_{j,0}$.

Denote the correlation between $\lambda_{i,0}$ and $\lambda_{j,0}$ as $\rho_{i,j}$. The variance of the mean $\overline{\lambda_{i,0}}$ is

$$\operatorname{var}(\overline{\lambda_{i,0}}) = \operatorname{var}\left(\frac{1}{K}\sum_{i=1}^{K}\lambda_{i,0}\right) = \frac{\operatorname{var}(\lambda)}{K}\left(1 + \frac{1}{K}\sum_{i=1}^{K}\sum_{i\neq j}\rho_{i,j}\right). \tag{A.1}$$

Denote the mean of all the correlation coefficients $\rho_{i,j}$, $i \neq j$, as $\overline{\rho}$. Eq. (A.1) can then be written as

$$\operatorname{var}(\overline{\lambda_{i,0}}) = \frac{\operatorname{var}(\lambda)}{K}\left[1 + (K-1)\overline{\rho}\right]. \tag{A.2}$$

I estimate var(λ) with the sample variance of λ. To estimate the mean cross-correlation of firms' statistics, I ran (1) on a subset of the firms with seemingly unrelated regressions (SURs). I randomly chose 100 firms with no missing returns over the entire period January 1977 through December 1991. These firms were sorted into ten groups of ten firms; ten SURs were then estimated. The estimated mean cross-correlation of $\lambda_{i,0}$ and $\lambda_{j,0}$, $i \neq j$, is 0.0293. The corresponding estimated cross-correlations for (2a), (2b), (6), (7a), and (7b) are 0.0324, 0.0313, 0.0095, 0.0139, and 0.0133, respectively.

Given these estimated cross-correlations and the sample variances of the distributions of the coefficients of (1), (2a), (2b), (6), (7a), and (7b), the estimated standard errors for these coefficients can be computed. They are reported in parentheses below the mean estimated coefficients.

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