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Abstract

Many studies argue that differences in information across securities explain much of the cross-sectional variation in stock return volatility. We offer an explanation beyond that previously identified in the literature by developing a proxy for differential information. Our proxy follows from our simple model development where the amount of information regarding a firm is positively related to how similar it is to its comparables (i.e., firms in the same industry). We call this measure of differential information the degree of comparability. In all our empirical tests, we consistently find a negative and highly significant relationship between volatility and the degree of comparability (after controlling for other factors the literature has found affect volatility). Moreover, in some tests, the degree of comparability is the most significant factor in explaining volatility.

Relative Valuation, Differential Information, and Cross-Sectional Differences in Stock Return Volatility

Why are some stocks more volatile than others? Many theoretical models argue that differences in information across investors and securities explain much of the variation in stock return volatility.[1] Empirical studies have used different proxies for differential information. For example, Ataise (1985) argues that there is more information on large firms, which dampens their volatility. He finds that the reaction of large firms to earnings announcements is smaller in magnitude than the reaction for small firms.

Banz (1980) suggests that the higher returns earned by small firms may be due to the lower amount of information available about them. Barry and Brown (1984) investigate this possibility and argue that a firm's period-of-listing, or age, is a proxy for the amount of information on the stock. They find that period-of-listing lowers expected returns after controlling for size, beta and interactive effects. They conclude that age explains much, though not all, of the small firm effect.[2] Though higher expected returns do not necessarily imply higher volatility, the relationship is generally positive. Therefore, Barry and Brown's results suggest a negative relationship between the period-of-listing and stock return volatility.

Another popular proxy for differential information across securities is the number of analysts following a firm. Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) extend Kyle's (1985) model to show that as the number of informed investors increases, the stock price will reflect new information more rapidly. Brennan, Jegadeesh and Swaminathan (1993) use the number of analysts as a

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[1]Examples include Grossman and Stiglitz (1980), Kyle (1985), Admati and Pfleiderer (1988), Foster and Viswannath (1990).

[2]Clarkson and Thompson (1990) find that the betas for IPO firms decline significantly as time passes and information increases. In particular, there is an abrupt decline in betas after the first earnings announcement.

proxy for informed investors. They find that stocks followed by many analysts react more quickly to common information than stocks followed by fewer analysts.

Finally, there is a large literature on the contemporaneous positive relationship between trading volume and volatility (e.g., Karpoff (1987)). For example, trading volume has been posited as a proxy for differences in information or opinion across investors (e.g., Admati and Pfleiderer (1988)).

We propose a new measure of differential information across securities. Our measure offers an explanation for cross-sectional differences in volatility beyond that previously identified in the literature. In contrast, variables such as the firm's period-of-listing and the number of analysts following the firm are insignificantly related to volatility in many of our tests. In fact, the number of analysts is positively related to volatility in several tests, implying some indirect support for the herding hypothesis of Scharfstein and Stein (1990).[3]

Our proxy for differential information follows from our simple model development. In the model, investors are presumed to employ two different valuation techniques, absolute valuation (e.g., discounted cash flow analysis) and relative valuation (e.g., the use of price-earnings (PE) ratios of comparable firms--firms in the same industry). Investors take a weighted average of these two valuations to arrive at a price. The weight assigned to the relative valuation component depends on the degree of comparability between the firm being valued and the identified set of comparable firms; the more similar or comparable they are, the more weight put on the relative valuation component. Because this component is presumed to have less volatility than the absolute valuation component (when there is more than one comparable firm), the greater weight assigned to it implies less return volatility, ceteris paribus. Therefore, we use the degree of comparability as a proxy for differential information.

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[3]Another possibility is that analysts may be attracted to high volatility stocks (e.g., Bhushan (1989)). We account for this endogeneity using the two-stage least method (where the number of analysts is affected by volatility).

We conduct three major tests of the relationship between the degree of comparability and volatility, controlling for other factors the literature has found affect volatility; trading volume, size, period-of-listing, number of analysts and measures of business and financial risk. In the first series of tests, we do a cross-sectional regression of excess daily stock return volatility on the seven factors. Using different specifications, we consistently find a highly significant negative relationship between the degree of comparability and volatility.

We then consider three other ways of measuring volatility for our second series of tests; the first test is based on the ARCH model of volatility developed by Engle (1982). As with the first series of tests, the results show a negative and significant relationship between the degree of comparability and the level of volatility; moreover, though the other variables are also significant, the degree of comparability has the highest level of significance.

The second and third tests of the second test series use Amihud and Mendelson's (1987) volatility decomposition. They identify two volatility components (after prices have fully adjusted): volatility driven by differential information or noise and intrinsic volatility driven by the firm's business and financial risk. This volatility decomposition provides a way to identify a differential information effect in each factor.

With the noise volatility tests, the degree of comparability is negatively related to the volatility measure at high significance levels. As with the ARCH measure, the degree of comparability has the highest level of significance. The significance of the other variables implies that they also have important information components.

We find that all the variables are significantly related to intrinsic volatility. The significance of the degree of comparability, however, is small compared with its significance in the other tests. These results imply that the degree of comparability may not be a pure information effect. Considering the evidence of its significant negative effect on noise volatility and our other measures of volatility, however, the bulk of its negative effect on volatility appears to reflect a differential information effect.

Our third series of tests involve excess stock returns around quarterly earnings announcements. During these announcement periods, the degree of comparability has a significant negative relationship with the magnitude of excess stock returns. In other words, the greater the degree of comparability, the more accurate the market's forecast of the information contained in the earnings announcement. Moreover, there is a significant negative relationship between the magnitude of the excess returns and the number of earnings announcements that comparable firms make (in the same quarter) before the firm's earnings announcement. So, the more announcements made by the comparable firms, the less surprising the firm's own earnings are to the market, ceteris paribus.

In the next section, we develop the simple model of volatility. The data and methodology are discussed in Section II. In Section III we analyze the empirical results and the summary and conclusions are in Section IV.

I. A Simple One-Period Model of Volatility

A. The Model

We begin with a conventional assertion that a stock's price at time t is equal to its expected price based on the information available at time t-1, Ω_{t-1}, and a forecast error:

$$P_{it} = E(P_{it}|\Omega_{t-1}) + \mu_{it} \tag{1}$$

where P_{it} is the logarithm of stock i's actual market price at date t and μ_{it} is an i.i.d. random variable that has a zero mean, finite variance $\sigma^2_{\mu i}$ and is uncorrelated with $E(P_{it}|\ \Omega_{t-1})$.

Consider the following decomposition of Ω_{t-1} into two subsets:

$$\Omega_{t-1} = (\phi_{t-1},\ \theta_{t-1}) \tag{2}$$

where ϕ_{t-1} is the information on comparables and θ_{t-1} represents all other relevant information. Suppose that the market separately forecasts the price based on each information subset and weights the forecasted prices as shown below:

$$E(P_{it}|\Omega_{t-1}) = \omega_{\phi i}E(P_{\phi it}|\phi_{t-1}) + \omega_{\theta i}E(P_{\theta it}|\theta_{t-1}) \tag{3}$$

where $\omega_{\phi i}$ = weight assigned to the forecasted price based on the comparables' information, $\omega_{\theta i} = (1 - \omega_{\phi i})$ = weight assigned to the forecasted price based on other information, $E(P_{\phi it}|\ \phi_{t-1})$ is the expected price based on the comparables' information set and $E(P_{\theta it}|\ \theta_{t-1})$ is the expected price based on the other information set.[4,5] The price based on the comparables is defined as relative valuation whereas the price based on the other information set is defined as absolute valuation (e.g., DCF analysis).[6] These forecasted prices are assumed to be rational:

$$P_{\phi it} = E(P_{\phi it}|\phi_{t-1}) + \mu_{\phi it} \tag{4}$$

$$P_{\theta it} = E(P_{\theta it}|\theta_{t-1}) + \mu_{\theta it} \tag{5}$$

where $P_{\phi it}$ is the true realization of the forecasted price based on the comparables' information, $P_{\theta it}$ is the true realization of the forecasted price based on the other information and $\mu_{\phi it}$ and $\mu_{\theta it}$ are i.i.d. random variables with zero means and finite variances $\sigma^2_{\mu\phi i}$ and $\sigma^2_{\mu\phi i.}$ The error terms are assumed to be independent of each other and are uncorrelated with $E(P_{\phi it}|\ \phi_{t-1})$ and $E(P_{\theta it}|\ \theta_{t-1})$, respectively,

In the interest of simplicity, we use a one-period framework where the weights may vary cross-sectionally but not over the period; specifically, $\omega_{\phi i} = \omega_{\phi i}(\delta_i)$, where δ_i is a measure of how similar the comparable firms are to the firm being valued. There is a montonic positive relationship between $\omega_{\phi i}$ and δ_i. In other words, the more similar the comparable firms are to the firm being valued, the more

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[4]Averaging stock values obtained with different techniques is popular among many investors; its value appeals to the uncertainty surrounding valuation under any one technique (Damodaran (1994) discusses the use of absolute and relative valuation techniques). Moreover, this circumvents the circularity of the market only looking to comparables' multiples to value a firm.

[5]Kaplan and Ruback (1995) find that DCF analysis and comparables' multiples are both useful in valuing a stock. Kim and Ritter (1996) find that multiples such as the market capitalization per employee are more useful in predicting IPO prices than PE and market-to-book ratios.

[6]Comparables can be used in DCF analysis. For example, comparables' betas (sometimes called "pure plays") can be used to estimate the expected return. To the extent that this is true, this information is contained in the comparables' information set.

weight applied to the forecasted price based on the comparables.

We substitute the expressions for the expected values in equations (4) and (5) into equation (3) and then substitute equation (3) into equation (1). If we define $P_{it} = \omega_{\phi it}P_{\phi it} + \omega_{\theta it}P_{\theta it}$, then these substitutions provide the following expression for the error term:

$$\mu_{it} = \omega_{\phi_i}\mu_{\phi it} + \omega_{\theta_i}\mu_{\theta it} \tag{6}$$

The total forecast error, or excess return, is a weighted average of the forecast error from the relative valuation, $\mu_{\phi it}$, and the forecast error from the absolute valuation, $\mu_{\theta it}$. With the assumed independence of $\mu_{\phi it}$ and $\mu_{\theta it}$,

$$\sigma^2_{\mu i} = \omega^2_{\phi i}\sigma^2_{\mu\phi i} + \omega^2_{\theta i}\sigma^2_{\mu\theta i} \tag{7}$$

where $\sigma_{\mu i}$ is the excess return volatility, $\sigma_{\mu\phi i}$ is the volatility of the forecast error from the relative valuation and $\sigma_{\mu\theta i}$ is the volatility of the forecast error from the absolute valuation. Because absolute valuation is typically considered more difficult than relative valuation, asserting $\sigma_{\mu\phi i} < \sigma_{\mu\theta i}$ is plausible (though this assumption is not necessary as shown below). As the number of comparable firms that are imperfectly correlated grows, $\sigma_{\mu\phi i}$ becomes smaller. We illustrate this point below.

Without loss of generality, suppose that ϕ_{t-1} is composed entirely of the weighted average P/E ratio for the firm's comparables.[7]

$$E(P_{\phi it}\,|\,\phi_{t-1}) = \left[\sum_{j=1}^{N_i} w_j E[PE_{jt}]\right] \tag{8}$$

where w_j is the weight assigned to comparable firm j, $E[PE_{jt}]$ is the expected price/earnings ratio in period t, given the information available in t-1, for comparable firm j and N_i is the number of

[7]The PE ratio for the comparables is assumed to be exogenous. We illustrate the point using the PE ratio because it is the most popular multiple used in comparables' valuation but the point is easily made with any other multiple (e.g., price/book, price/sales, etc.).

comparables.[8,9] If we define the true realization of the forecasted price based on the comparables' information as the weighted average of the true realization of the comparables' PE ratios (i.e., $P_{\phi it} = \sum w_j PE_j$), then $\mu_{\phi i} = \sum w_j(PE_j - E(PE_j))$. These expressions lead to the following expression for $\sigma_{\mu\phi i}$,

$$\sigma_{\mu\phi i} = \sqrt{\sum_{m=1}^{N_i} w_m^2 \sigma_{PE_m}^2 + \sum_{m \neq j=1}^{N_i} \sum_{j \neq m=1}^{N_i} w_m w_j \rho_{mj} \sigma_{PE_m} \sigma_{PE_j}} \tag{9}$$

where σ_{PEm} is the volatility of the unexpected change in the PE ratio for comparable firm m, σ_{PEj} is the volatility of the unexpected change in the PE ratio for comparable firm j, and ρ_{mj} is the correlation coefficient between the unexpected change in the PE ratio for firms m and j. The correlation coefficients can be interpreted as comparability measures.

Comparability measures likely differ within the industry. In the relative valuation in equation (8), the weight (w_j) assigned to each comparable firm j's PE ratio should depend on how similar it is to firm I; less similar firms should be assigned lower weights. This similarity should also affect the correlation coefficient between firms m and j; the more similar these firms are to each other, the higher should be the correlation coefficient (or comparability measure). Discussions with analysts reveal that similarity in equity capitalization, or size, is arguably the most important factor in assessing comparability within an industry. Therefore, we use size differences for the comparability measure,

$$\rho_{mj} = \frac{1}{[1 + |S_m - S_j|]} \tag{10}$$

[8]Of course, the PE ratio must be multiplied by the firm's earnings to get the stock price estimate. However, the firm's earnings are not part of the comparables' information set and many practitioners view valuation in terms of multiples (e.g., IBM is selling at 15 times earnings). Therefore, the relative and absolute valuation are in terms of the multiple applied to earnings (from a DCF perspective, the appropriate "multiple" to apply to current earnings for a constant growth firm is [(1+g)DPR]/(r - g); where DPR is the dividend payout ratio, r is the cost of equity and g is the expected growth rate in dividends).

[9]This type of forecasting does occur in practice; for example, Value Line forecasts PE ratios.

where S_m is the log of the equity value of comparable firm m and S_j is the log of the equity value of comparable firm j.[10] Equation (10) shows that the greater the difference in size between firm m and firm j, the lower the correlation coefficient (i.e., the less similar, or comparable, firms m and j are to each other). Note the comparability bounds, $0 < \rho_{mj} \leq 1$.

We now illustrate the construction of a size-weighted number of comparables. This number is used to compute two weights. First, the weight assigned to each of the comparable firms in the relative valuation estimation (i.e., w_j in equation (8)). Second, the weight assigned to each firms' relative valuation component, $\omega_{\phi it}$.

Consider the case of firm i and N_i comparable firms,

$$N_i^* = \sum_{j=1}^{N_i} \left[\frac{1}{[1 + |S_i - S_j|]} \right] \qquad \textbf{(11)}$$

If every comparable firm j is the same size as firm i, then the size-weighted number of comparables equals the number of comparables, $N_i^* = N_i$.[11] The larger the size differences between firm I and its comparable firms, the lower is N_i^*. The weight for each comparable firm j is then defined as follows:

$$w_j = \frac{\dfrac{1}{[1 + |S_i - S_j|]}}{N_i^*} \qquad \textbf{(12)}$$

If every comparable firm j is the same size as firm i, then the weight for each firm j collapses to (1/N).[12]

With N_i^* defined, we now propose a functional form for the weight assigned to the relative

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[10]Our point can apply to other ways of estimating comparability. For example, as a robustness check, we estimated the results shown below using the log of total sales instead of the log of equity value. The results are qualitatively similar to those discussed below.

[11]As with the PE ratios, the equity values are exogenous variables.

[12]It is not necessary to make a distinction between comparable firm m and j for the computation of the w's and N_i*.

valuation component, $\omega_{\phi i}(\delta_i)$. We call this measure the degree of comparability:[13]

$$\omega_{\phi i}(\delta_i) = LOG\left(1 + \left(\frac{N_i^*}{N_i}\right)\right) \quad \textbf{(13)}$$

The ratio (N_i^*/N_i) is an index of comparability between firm i and all its comparable firms. As this ratio rises, more weight ($\omega_{\phi i}(\delta_i)$) is assigned to the relative valuation component in equation (3). As $N_i^* \rightarrow N_i$, $\omega_{\phi i}(\delta_i) \rightarrow .301$. This weighting is consistent with the assumption that the market considers information beyond that provided by the comparables.[14]

B. Simulation Analysis

To show the intuition behind the model, we begin with a preliminary simulation analysis that focuses on the volatility of the relative valuation forecast error, $\sigma_{\mu\phi i}$. Suppose the weight assigned to each comparable firms' PE ratio, as shown in equation (8), is the same and the correlation coefficients (or comparability measures) between the comparable firms are the same (i.e., $w_m = w_j$ and ρ_{mj} is constant $\forall$ m, j). Figure 1 shows there is a negative relationship between N_i and $\sigma_{\phi i}$ for a range of constant correlation coefficients. The drop is more precipitous the lower the correlation coefficient and this suggests that there is a greater benefit (i.e., greater reduction in $\sigma_{\mu\phi i}$) to having more comparables when they are less similar to each other. If the comparables are highly similar, then the addition of another firm to the "portfolio" of comparables provides relatively less additional information (and therefore less of a reduction in $\sigma_{\mu\phi i}$).

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[13]This measure is not to be confused with ρ_{mj}, the comparability measure for firms m and j. The degree of comparability, $\omega_{\phi i}(\delta_i)$, is a gauge of how similar *all* the comparable firms are to firm I.

[14]We use the LOG (base 10) function to illustrate a "monotonic" (with some noise) decrease in $\sigma_{\mu i}$ as $\omega_{\phi i}(\delta_i)$ rises in our simulation analysis below. More generally, any weighting scheme where $\omega_{\phi i}(\delta_i) \rightarrow .5$ as $N_i^* \rightarrow N_i$, leads to a "monotonic" decrease in $\sigma_{\mu i}$ as $\omega_{\phi i}(\delta_i)$ rises. If we allow $\omega_{\phi i}(\delta_i)$ to rise above .5 as $N_i^* \rightarrow N_i$, then there is still a negative relationship between $\sigma_{\mu i}$ as $\omega_{\phi i}(\delta_i)$ until N_i^* is close to N_i; at this point, it can turn positive. We therefore consider different specifications for $\omega_{\phi i}(\delta_i)$ in our empirical tests. The empirical results are qualitatively similar under different specifications as noted in the next section.

For the full simulation analysis, we allow the equity capitalizations (S_i, S_j, S_m) and consequently the weights (w_j's), correlation coefficients (ρ_{mj}'s) and volatilities ($\sigma_{\mu\phi i}$ and $\sigma_{\mu i}$) to vary stochastically. Specifically, the value of firm i and comparable firms m and j are the absolute value of a draw from a standard normal distribution multiplied by the LOG of 10,000. To avoid biasing the simulation results by choosing an arbitrarily high level of $\sigma_{\mu\theta i}$ compared with $\sigma_{\mu\phi i}$, we assume that $\sigma_{\mu\phi i} = \sigma_{\mu\theta i}$ when there is just one comparable firm. To maintain the ceteris paribus conditions, we set the volatility of the unexpected change in the comparable firms' PE ratios equal to the volatility of the absolute valuation forecast error (i.e., $\sigma_{PEm} = \sigma_{PEj} = \sigma_{\mu\theta i} = .2$). The variable N_i varies from 1 to 30 and the simulation is conducted 12,000 times.[15]

Figure 2 and Panel A of Table 1 show a *positive* relationship between the degree of comparability, $\omega_{\phi i}(\delta_i)$, and the volatility of the relative valuation forecast error, $\sigma_{\mu\phi i}$.[16] Intuitively, $\omega_{\phi i}(\delta_i)$ is high when the comparable firms are similar in size to firm I--and therefore likely similar in size to each other--and this implies a high ρ_{mj} $\forall$ m, j. These high correlation coefficients cause a lesser reduction in $\sigma_{\mu\phi i}$ than when the comparable firms are more varied in size. In other words, the volatility of the relative valuation forecast error can be lower with many dissimilar comparable firms (which implies a low value for $\omega_{\phi i}(\delta_i)$) than with many similar comparable firms (which implies a high value for $\omega_{\phi i}(\delta_i)$). The key behind this result is the assumption that $\sigma_{PEm} = \sigma_{PEj}$ $\forall$ m,j. When we allow for the σ_{PE}'s to vary stochastically, the positive relationship between $\omega_{\phi i}(\delta_i)$ and $\sigma_{\mu\phi i}$ is reduced.[17] Nevertheless, although the assumptions are stacked against the primary prediction of an inverse relationship between

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[15]Of course, cross-sectional differences in, for example, business or financial risk also affect the σ's and these effects are controlled for in our empirical tests.

[16]There is a negative relationship between N_i^* and $\sigma_{\mu\phi i}$, and between N_i and $\sigma_{\mu\phi i}$ as shown in Panels B and C of the Table 1 regression results.

[17]As noted earlier, we assume constant volatilities to appeal to the ceteris paribus conditions.

$\omega_{\phi i}(\delta_i)$ and $\sigma_{\mu i}$, the prediction still follows. When the comparable firms are similar, there is more weight assigned to the relative valuation component. Because $\sigma_{\mu\phi i}$ is always less than $\sigma_{\mu\theta i}$ whenever $N_i > 1$, the greater weight assigned to this less uncertain valuation implies less overall volatility (i.e., lower $\sigma_{\mu i}$).

The inverse relationship between $\omega_{\phi i}(\delta_i)$ and $\sigma_{\mu i}$ is illustrated in Figure 3 and Panel D of Table 1. Panel E of Table 1 shows there is also a negative relationship between $\sigma_{\mu i}$ and N_i^* but this relationship is much weaker than the relationship between $\omega_{\phi i}(\delta_i)$ and $\sigma_{\mu i}$. As shown in Panel F of Table 1, the negative relationship between $\sigma_{\mu i}$ and N_i, though significant, is weaker still.

II. Data and Methodology

A. Data

Our sample covers the 1990-94 period. During this period, the economy went through a recession and then recovered. To check the results' robustness to how comparables are defined, we use two different definitions. First, comparable groups of firms are defined by the same 4-digit SIC code and, second, by the Value Line Investment Survey (Value Screen Version) 4-digit industry code. COMPUSTAT and the NYSE/AMEX and NASDAQ CRSP tapes are used to gather the relevant accounting and stock market data. Information on earnings expectations and the number of analysts making the forecasts is taken from I/B/E/S.

The number of comparable firms is estimated at the beginning of each year. To be included in the sample of comparable firms, the firm must have price and shares outstanding data available on CRSP (as of the beginning of January) or COMPUSTAT (as of the end of December of the preceding year).[18] The firm must also have at least 20 days of trading activity during the year. For the sample with the Value Line definition of comparables, we also exclude firms in the "industry" entitled "Unclassified" because they cannot be considered comparables. For the SIC code industries with more than 250 firms,

[18]Supra 10.

we use the 250 largest firms. Over the 5-year sample period there is an average of 6,978 firms in the SIC code sample and 1,517 firms in the Value Line sample.

To be included in our regression tests, the firm must have at least five years' of historical operating earnings (we use this to measure the firm's business risk). The firm also cannot have a missing value for short-term and long-term debt in Compustat. These requirements reduce our average sample size each year to 4,567 firms in the SIC sample and 1,354 firms in the Value Line sample. To guard against the possibility that these screens bias our results, we estimate the results using the median coefficient of variation of operating earnings for the firm's industry when the firm does not have the sufficient historical information to compute this statistic. We also assume that a missing value in the short-term or long-term debt category implies zero debt. The results are qualitatively similar to those reported in the next section.

For the sake of brevity, Table 2 provides some basic descriptive statistics on the sample using the SIC code comparable firm definition. Each year, the statistics are computed and then are averaged over the five-year period. The average ratio of (N_i*/N_i) is 0.42 (median = 0.43) with an average standard deviation of 0.08. On average, there are 58.39 firms in an SIC code industry (median = 28). Of course, the size-weighted number of comparables, N_i*, is lower than the number of comparables N_i, with an average of 26.36 and a median of 11.87.

Analyst coverage averages 2.91 analysts (median = 0) when firms not included in I/B/E/S are presumed not to have any analysts following them ($ANAL_i$ is the variable name for this sample). For the subsample of firms included in I/B/E/S, the number of analysts ($ANAL_i$' is the variable name for this sample) following a firm average 7.51 (median = 4).

Firms' debt-equity (D_i/S_i) ratios average 13.70; this average is much higher than the median of 0.36, implying the existence of outliers. Nevertheless, the outliers do not drive our results. We find qualitatively similar results when they are trimmed from the data set. Debt is the sum of the book value of short and long-term interest-bearing debt measured at the end of the preceding calendar year. The market value of equity is measured at the beginning of the calendar year.[19]

We estimate the business risk with the coefficient of variation of the firm's operating earnings (CV_{EBITi}) using annual data from the preceding five years. This variable has an average value of 2.70. Total dollar trading volume per month (VOL_i) averages $28,335,348 with a median of $1,014,913.[20]

The average period of firm listing (POL_i), (or age, defined as the number of days listed on CRSP), is 8,929.03 days and the median is 5,311 days. Though some firms do trade before CRSP begins in 1926, we think the starting date is suitable for two reasons. First, the bulk of our firms start trading after 1926 (73% in 1990). Second, Barry and Brown (1984) show that the period-of-listing effect on returns is strongest for small (i.e., young) firms.

Table 3 shows the average correlation coefficients for each variable (expressed in natural logs) posited to affect volatility. These correlation coefficients and levels of significance are the result of estimating the correlation coefficients and levels of significance for each year and then averaging them over the 1990-94 period.

The degree of comparability, $LN(1 + N_i^*/N_i)$, is insignificantly related to the debt-equity ratio and the coefficient of variation of operating earnings, consistent with the suggestion that this variable is not a proxy for business or financial risk.[21] Moreover, $LN(1 + N_i^*/N_i)$ is negatively correlated with

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[19]We also conduct the tests with end of year values and the results are qualitatively very similar.

[20]Jones, Kaul and Lipson (1994) report that number of transactions is the facet of volume that drives volatility during their sample period. These data, however, are only available for NASDAQ-NMS firms and the bulk of our sample is listed on the NYSE or AMEX. Moreover, the high positive correlation (reported by Jones et al.) between trading volume measured in terms of number of shares (or dollar values of shares) and the number of transactions suggests that our measure is a good proxy for the effect observed by Jones et al.

[21]In the previous section, we use the $\omega_{\phi i}(\delta_i)$ expression for the degree of comparability. In this section, we use the $LN(1 + N_i^*/N_i)$ expression for the degree of comparability to highlight the natural log transformation of each variable.

$LN(POL_i)$, $LN(S_i)$, $LN(1+ANAL_{it})$ and $LN(ANAL'_{it})$ and all these correlations are significant. These estimates suggest that the negative relationship between volatility and $LN(1 + N_i^*/N_i)$ that we report in subsequent tests is not the result of a serendipitous positive correlation with variables that previous studies have found negatively related to volatility.

$LN(POL_i)$, $LN(S_i)$, $LN(1+ANAL_{it})$ and $LN(ANAL'_{it})$ all have a significant negative correlation with $LN(CV_{EBITi})$, implying that these variables are not solely proxies for differential information. Interestingly, all these variables are positively and significantly related to $LN(1+D_i/S_i)$ and this works against their negative correlation with volatility. One explanation for this phenomenon could be the negative and significant correlation (-0.415) between $LN(1+D_i/S_i)$ and $LN(CV_{EBITi})$. This interpretation is consistent with the notion that firms with higher levels of business risk maintain lower debt ratios to mitigate the possibility of incurring high bankruptcy costs.

The only variable that has a significant positive relationship with volatility and a significant negative relationship with the degree of comparability is $LN(VOL_i)$; the correlation coefficient between $LN(VOL_i)$ and $LN(1 + N_i^*/N_i)$ is -0.191. If trading volume is a proxy for differences of opinion across investors, then this finding makes sense; differences of opinion should be smaller when there is more information (i.e., when $LN(1 + N_i^*/N_i)$ is higher).

B. Monthly Excess Return Tests

We conduct three major empirical tests. For the monthly excess return test listed below, we use a two-stage least squares estimation procedure:

$$LN(\sigma_{it}) = \beta_0 + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi}) + \beta_5 LN(S_i) + \beta_6 LN(VOL_{it}) + \beta_7 LN(1+ANAL_{it}) + \epsilon_i \tag{14}$$

$$LN(1+ANAL_{it}) = \alpha_0 + \alpha_1 LN(S_i) + \alpha_2 LN(\sigma_i) + \left(\sum_{x=1}^{5} \alpha_{x+2} IND_x\right) + \alpha_8 LN(INST_i) + \mu_i \tag{15}$$

This method recognizes that the number of analysts following firm I in month t ($ANAL_{it}$) may depend on firm I's excess return volatility in month t (σ_{it}) plus the stock value (S_i), institutional ownership ($INST_i$) and six industry dummy variables, where the sixth is captured in the intercept (Bhushan (1989)).[22] Bhushan posits that analysts may be attracted to high volatility stocks and thus his theory predicts a positive and significant coefficient estimate for α_2. His theory also predicts positive and significant coefficient estimates of α_1 and α_8.

We estimate the number of analysts where we use the full sample and presume that no I/B/E/S data on the firm implies there are no analysts following the stock (here, we use $LN(1+ANAL_{it})$). Second, we use the subsample of firms for which there are analysts following the stock (where we use $LN(ANAL_{it}')$). The number of analysts is estimated by the number of annual earnings forecasts reported each month by I/B/E/S.

The results are estimated over the 1990-1994 period. For each year, the total number of trading days is split evenly into 12 "monthly" samples and the cross-sectional regressions are performed each month. Average coefficient estimates and the t-statistics are computed from the time-series variation of the 60 coefficient estimates for each variable (e.g., Fama and MacBeth (1973)).

The degree of comparability is estimated with the natural log function to be consistent with the natural log transformations of the other variables. We also estimate the results without log transformations of all the variables and with LOG transformations of all the variables. Qualitatively, the results are similar with regard to the sign and significance of the degree of comparability variable. Value Line provides information on institutional ownership and thus we use this sample to estimate the two-stage least squares model. Qualitatively, the results are similar to the simple OLS results.

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[22]The 2-digit Value Line code matches the 2-digit SIC code. Note: We also estimated equation (14) using OLS with 4-digit SIC code industry dummy variables as an additional check on any industry effects not captured with the operating earnings volatility. The results are qualitatively similar to those discussed in the next section.

Therefore, for the rest of our tests, we present OLS results for the sample where the SIC codes are used to define the comparable firms because this is the largest sample where the results have the broadest implications.

C. Annual Volatility Tests

For these tests, we use the same methodology as for the monthly tests. The difference is that we estimate volatility over the entire year using alternative methods of estimating volatility. Our first test uses the ARCH model of volatility (Engle (1982)). For the independent variables measured monthly in the preceding tests, we use their average values for each year in these tests.

The second and third volatility measures are based on the simple model of price behavior described in Amihud and Mendelson (1987). They make a distinction between intrinsic value (V_t) and the observed price (P_t) by allowing for both market-structure and information noise and imperfect price adjustments to value changes as shown below

$$P_t - P_{t-1} = g(V_t - P_{t-1}) + \mu_t \tag{16}$$

where V_t and P_t are in logarithms and g is the price adjustment coefficient ($0 < g < 2$). The last term μ_t is a noise term, the magnitude of which is determined by the information-related factors (such as noisy information) and market-structure related factors (such as the bid-ask spread). If we define v^2 to be the variance of the intrinsic value process and σ^2 to be the variance of the noise term, the observed return

$$Var(R_t) = v^2 + 2\sigma^2 + \left(\frac{g}{2-g} - 1\right)v^2 + \left(\frac{2}{2-g} - 2\right)\sigma^2 \tag{17}$$

variance can be decomposed into three components:

If prices adjust slowly to information ($g < 1$), the price-adjustment effect will be negative and lead to lower observed return variances, whereas market overreaction to news ($g > 1$) will have the opposite impact. Concurrently, a higher (lower) bid-ask spread will lead to more (less) noise and higher (lower) return variances.

To estimate these components of the variance, we use a return interval of 20 days. The price adjustment coefficient approaches one for this longer return interval. Though the use of 20 days is arbitrary, Damodaran (1993) considers many other possible intervals and finds the 20-day period reasonable. With this definition of the return interval, the variance components can be estimated as functions of the covariance and variance in 20-day interval returns:

$$\sigma^2 = -Cov(R_{20t}, R_{20t-1}) \tag{18}$$

$$v^2 = \frac{Var(R_{20t}) + 2Cov(R_{20t}, R_{20t-1})}{20} \tag{19}$$

where v^2 is an estimate of the daily variance arising from the underlying business and financial risk; σ^2, as discussed above, is noise induced by imperfect information and market-structure effects.

As with the monthly tests, the coefficient estimates are averaged over time and the t-statistics are formed based on the time-series standard errors. Despite the small sample size of five years, the significance levels are high for most of the variables.

D. Quarterly Earnings Announcement Tests

In our final series of tests, we examine excess returns around quarterly earnings announcements. If the degree of comparability is a good proxy for differential information, then the pre-announcement prices of firms with a high level of this variable should more accurately forecast the information contained in the earnings announcement, ceteris paribus. Therefore, the announcement should be less of a surprise for these firms and this should be manifested in the (lower) magnitude of the excess returns around the announcement.

For each quarter over the 1990-93 period, we conduct the following cross-sectional regression:

$$LN(CAR_{i,21})^2 = \alpha + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi}) + \beta_5 LN(S_i)$$

$$+ \beta_6 LN(VOL_{i,21}) + \beta_7 LN(1+ANAL_{it}) + \beta_8 LN\left(1+\frac{EPS_i-E(EPS_i)}{EPS_i}\right)^2 + \beta_9 LN(1+PREVEANN_{it}) + \epsilon_i \quad \textbf{(20)}$$

where $CAR_{i,21}$ is the cumulative abnormal return for firm I in the 21-day period surrounding the quarterly earnings announcement (event days -10 to +10 where day 0 is the announcement date). We then average the coefficient estimates over the sixteen quarters (we do not have this data available for 1994) and, as in the previous tests, use the time-series variation to estimate the t-statistics. The market model is used to estimate the excess returns and the market-model parameters are calculated for event days -210 to -31. $VOL_{i,21}$ is the total dollar trading volume in the 21-day period.

The number of analysts is computed as the number of quarterly earnings forecasts made just before the earnings per share (EPS_i) are announced. The expected earnings are computed using two different methods; first, we use a naive forecast based on the earnings from the same quarter of the previous year; here, we use $LN(1+ANAL_{it})$ for the number of analysts. Second, we use the average of analysts' forecasts made just before the announcement date (as contained in the I/B/E/S consensus tapes) and we use $LN(ANAL_{it}')$ for the number of analysts.

Our final variable ($PREVEANN_i$) is a counter variable that is equal to the number of earnings announcements made by comparable firms just before the earnings announcement date for firm I (within the same quarter). This variable provides some additional evidence on the relevance of information furnished by the comparable firms. More earnings announcements by comparable firms that precede the announcement (in the same quarter) of firm I's earnings should reduce the forecast error of the information contained in firm I's announcement. Thus, the magnitude of the stock price reaction to the earnings announcement should be smaller with a larger $PREVEANN_i$.

III. Empirical Results

We first present the results of the OLS estimation of equation (14) with the SIC code comparable firm definitions (Panels A and B) and the Value Line comparable firm definitions (Panels C and D) in Table 4. In Panel A, the degree of comparability has a highly significant negative coefficient estimate (-1.531, t = -15.496). The other variables also have significant effects, except $LN(1 + ANAL_{it})$. This insignificant estimate suggests that the number of analysts following a firm is a poor proxy for differential information once we have controlled for the other factors posited to affect volatility (or that the attraction of analysts to highly volatile stocks offsets their volatility dampening effects). With the subsample of firms for which there are annual earnings forecasts in I/B/E/S (where we use $LN(ANAL_{it}')$), the results are shown in Panel B. Qualitatively, these results are the same as in Panel A.

In Panel C, the degree of comparability, $LN(1+N_i^*/N_i)$, has an even higher level of significance (-1.287, t = -26.460). Most of the other variables' significance is lower, though they remain highly significant.[23] The exception is $LN(1+ANAL_{it})$; it has a negative and significant effect on volatility (-0.062, t = -10.959). However, when we use the subsample with $LN(ANAL_{it}')$, the other coefficient estimates and t-statistics are similar to Panel C but the number of analysts has a positive and significant effect on excess return volatility (0.029, t = 2.034). This evidence provides some indirect support for the herding hypothesis of Scharfstein and Stein (1990) or suggests analysts may be attracted to highly volatile stocks (Bhushan (1989)).

As suggested above, the number of analysts may be an endogenous variable influenced by volatility. Therefore, we use a two-stage least squares estimation procedure for the Value Line sample and the results are shown in Table 5. Equations (1) and (2) in the table correspond to equations (14) and

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[23]We also estimate the results with $LN(N_i^*)$ and $LN(N_i)$ as proxies for differential information. As predicted by the simulation analysis, both these variables have a negative and significant relationship with volatility but the significance levels are lower than with $LN(1+N_i^*/N_i)$.

(15) in the paper. The influence of volatility on the number of analysts is mixed but the positive effect of size is palpable in the equation (2) results. With the number of analysts defined as $LN(1+ANAL_{it})$ or $LN(ANAL_{it}')$, $LN(S_i)$ positively affects the number of analysts with a significance level that is much higher than the other variables. Nevertheless, nearly all the other variables are highly significant.

The equation (1) results are similar to the results shown in Panels C and D of Table 4; the negative coefficient estimates for $LN(1+N_i^*/N_i)$ are highly significant. $LN(1+ANAL_{it})$ has a negative and significant effect on volatility whereas $LN(ANAL_{it}')$ is positively related to volatility. The significance of $LN(1+ANAL_{it})$, however, is lower than in Panel C of Table 4 and the significance of $LN(ANAL_{it}')$ is higher. Though this may cast further doubt on the relevance of the number of analysts following the firm, the size and significance of the other variables are very similar to the OLS results. Therefore, we present the remaining results using OLS with the SIC code industry definitions because, as noted earlier, this is the largest sample where the results have the broadest implications.

Table 6 presents the annual volatility test results. For the sake of brevity, we limit the results' presentation to the full sample where the number of analysts is defined as $LN(1+ANAL_{it})$. With Engle's (1982) ARCH estimates of volatility in Panel A, the degree of comparability has a negative coefficient estimate and its significance is higher than for any other variable (-1.860, $t = -11.756$). The only insignificant variable is the number of analysts following the firm (0.013, $t = 0.583$).

Amihud and Mendelson's (1987) estimates of noise volatility are shown in Panel B. The degree of comparability has a negative coefficient estimate and, as with the ARCH measure of volatility, its significance level is higher than any other variable. Number of analysts is the only insignificant variable. In Panel C, we use the Amihud and Mendelson definition of intrinsic volatility. All the variables are significantly related to this measure of volatility with the same signs as in previous tests (the number of analysts has a negative effect). These estimates imply that none of the variables represents a pure information effect. However, there is a highly significant negative relationship between the degree of comparability and noise volatility (and the other measures of volatility) and, in comparison, the negative relationship between the degree of comparability and intrinsic volatility is relatively small in significance. These points suggest that the bulk of the negative relationship between the degree of comparability and volatility reflects a differential information effect.

Table 7 shows the results of the tests with the squared excess returns estimated in the 21-day period surrounding quarterly earnings announcements. In Panels A and B, we use the naive earnings expectation and in Panels C and D, we use the average analysts forecasts (where we can use $LN(ANAL_{i,21}'))$. Every time, the degree of comparability has a negative and highly significant coefficient estimate. This suggests that the greater the similarity in size between the firm being valued and the firms in the same industry (i.e., the higher $LN(1 + N_i^*/N_i)$ is), the less surprised the market is by the information released in the firm's quarterly earnings announcement, ceteris paribus. In Panels A and C, this suggestion receives additional support with the negative and significant coefficient estimates of $LN(1+PREVEANN_i)$. That is, the more earnings announcements (in the same quarter) made by firms in the same industry before the earnings announcement of firm I, the more accurate the market's forecast of the information contained in the announcement. Interestingly, $LN(POL_i)$ is insignificantly related to $LN(CAR_{i,21})^2$ in all the results. The other variables have a sign and significance similar to previous tests except the number of analysts. The estimated coefficient associated with $LN(1+ANAL_{i,21})$ is negative and significantly related to the excess return volatility in Panels A and B but $LN(ANAL_{i,21}')$ has insignificant coefficient estimates in Panel C and D.

IV. Summary and Conclusions

This paper proposes a new measure of differential information across securities that explains cross-sectional differences in stock return volatility beyond that previously identified in the literature. We develop a simple model where investors are presumed to use two different valuation techniques, absolute valuation (e.g., discounted cash flow analysis) and relative valuation (e.g., the use of PE ratios of comparable firms--firms in the same industry). Investors take a weighted average of the two valuations to arrive at a price. The relative valuation component is presumed to have less volatility than the absolute valuation component (when there is more than one comparable firm) and the weight assigned to it depends on the degree of comparability between the firm being valued and the comparable firms; greater comparability, or similarity, implies a greater weight. Greater weight assigned to the less volatile relative valuation component implies less excess return volatility, ceteris paribus. Thus, the degree of comparability is our measure of differential information.

We run three major tests of the relationship between the degree of comparability and volatility, controlling for the other factors the literature has linked to volatility: number of analysts following a stock, period-of-listing, size, trading volume and measures of business and financial risk. Our first test involves a cross-sectional regression of excess daily stock return volatility on the seven factors. Using different specifications (including a two-stage least squares framework), we consistently find a highly significant negative relationship between the degree of comparability and volatility. All other variables are significant except the number of analysts; this variable is often insignificant and in some tests is positively related to volatility.

Our second series of tests involve different measures of volatility; Engle's (1982) ARCH measure of volatility, and Amihud and Mendelson's (1987) measures of intrinsic volatility and noise driven volatility. Again, the coefficient estimate of the degree of comparability is negative and significantly related to each measure of volatility. With the ARCH and noise measures of volatility, the degree of comparability has the highest level of significance among all the variables.

Finally, we examine the magnitude of stock price reactions to quarterly earnings announcements. If the degree of comparability is a good proxy for differential information, then the pre-announcement prices of firms with a high level of this variable should more accurately forecast the information contained in the earnings announcement, ceteris paribus. As with every other test, the degree of comparability coefficient estimate is negative and highly significant. Moreover, there is a negative and significant relationship between the number of earnings announcements made by comparable firms before the firm's earnings announcement (within the same quarter) and the magnitude of the firm's stock price reaction to its earnings announcement. Therefore, the more earnings announcements made by comparable firms, the less surprising the firm's own earnings are to the market, ceteris paribus.

BIBLIOGRAPHY

Admati, Anat R. and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, Review of Financial Studies, 1, 3-40.

Amihud, Yakov and Haim Mendelson, 1987, Trading mechanisms and stock returns: An empirical investigation, Journal of Finance, 42, 533-553.

Atiase, R.K., 1985, Predisclosure information, firm capitalization and security price behavior around earnings announcements, Journal of Accounting Research, 21-36.

Banz, Rolf W., 1981, The relationship between return and market value of common stock, Journal of Financial Economics, 9, 3-18.

Barry, Christopher B. and Stephen J. Brown, 1984, Differential information and the small firm effect, Journal of Financial Economics, 283-294.

Bhushan, Ravi, 1989, Firm characteristics and analyst following, Journal of Accounting and Economics, 11, 255-274.

Brennan, Michael J., Narasimhan Jegadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, Review of Financial Studies, 6, 799-824.

Clarkson, Peter and Rex Thompson, 1990, Empirical estimates of beta when investors face estimation risk, Journal of Finance, 45, 431-453.

Damodaran, Aswath, 1993, A simple measure of price adjustment coefficients, Journal of Finance, 48, 387-400.

__________, 1994, Damodaran on Valuation, Wiley, New York, NY.

Engle, Robert F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, Econometrica, 50, 987-1007.

Fama, Eugene F. and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, Journal of Political Economy, 81, 607-636.

Foster, F. Douglas and S. Viswanathan, 1990, A theory of interday variations in volumes, variances and trading costs in securities markets, Review of Financial Studies, 3, 593-624.

__________, 1993, The effect of public information and competition on trading volume and price volatility, Review of Financial Studies, 6, 23-56.

Grossman, Sanford J. and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, American Economic Review, 70, 393-408.

Holden, Craig W. and Avanidhar Subrahmanyam, 1992, Long-Lived Private Information and Imperfect Competition, Journal of Finance, 47, 247-270.

Jones, Charles M., Gautam Kaul and Marc L. Lipson, 1994, Transactions, volume and volatility, Review of Financial Studies, 7, 631-651.

Kaplan, Steven N. and Richard S. Ruback, 1995, The Valuation of Cash Flow Forecasts: An Empirical Analysis, Journal of Finance, 50, 1059-1093.

Kim, Moonchul and Jay R. Ritter, 1996, Valuing IPOs, working paper, KyungHee University and University of Florida.

Kyle, Albert S., 1985, Continuous auctions and insider trading, Econometrica, 1985, 53, 1315-1335.

Roll, Richard, 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, Journal of Finance, 39, 1127-1139.

Scharfstein, David S. and Jeremy C. Stein, 1990, Herd behavior and investment, American Economic Review, 80, 465-479.

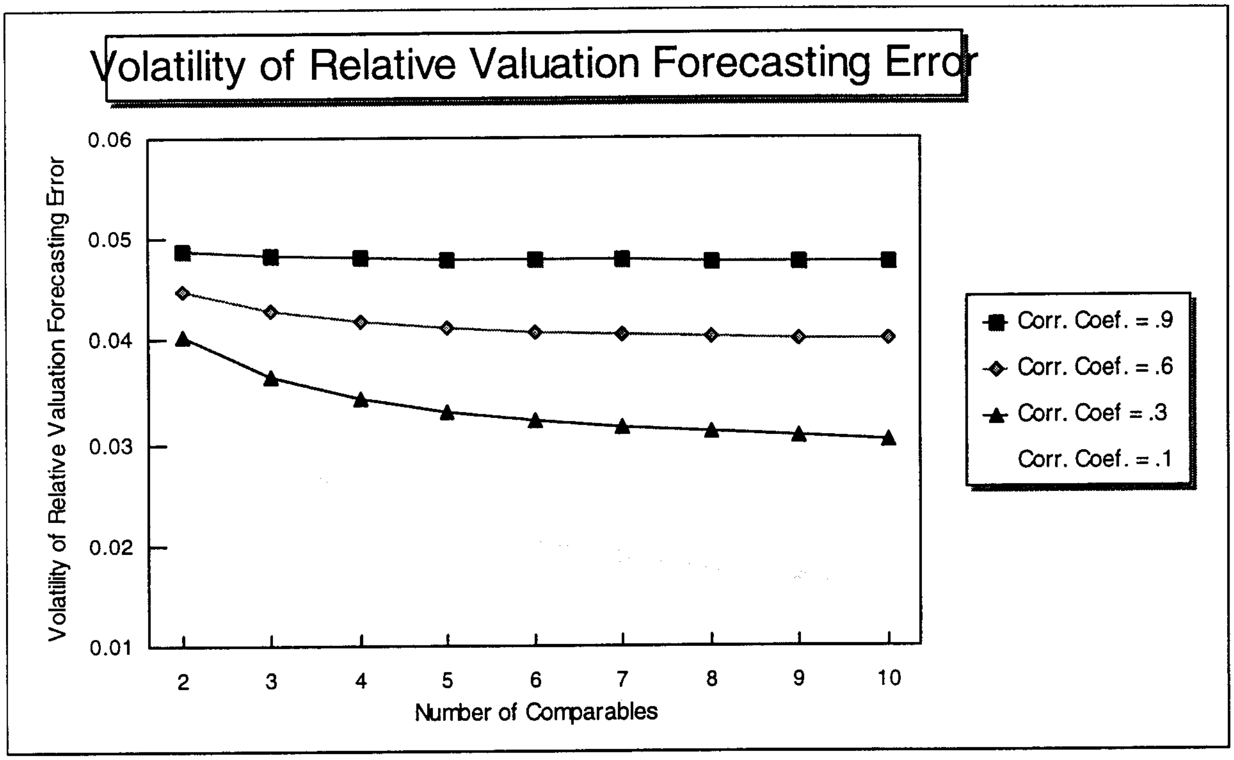

Figure 1. This figure shows how the inverse relationship between the number of comparables and the volatility of the relative valuation forecast error becomes more pronounced as the correlation coefficients decrease.

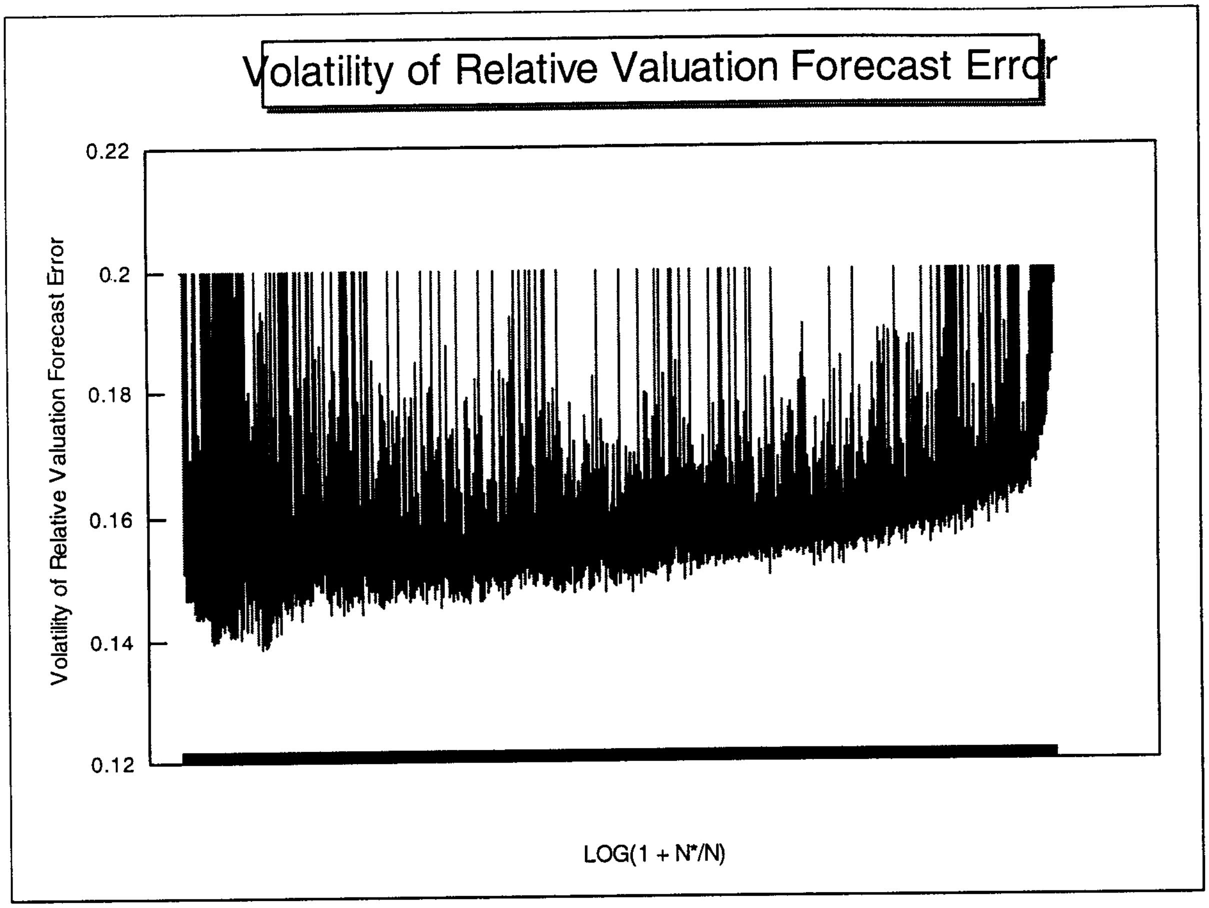

Figure 2. This figure shows the positive relationship between the volatility of valuation based on the comparables' information set and the weight assigned to the comparables' information set.

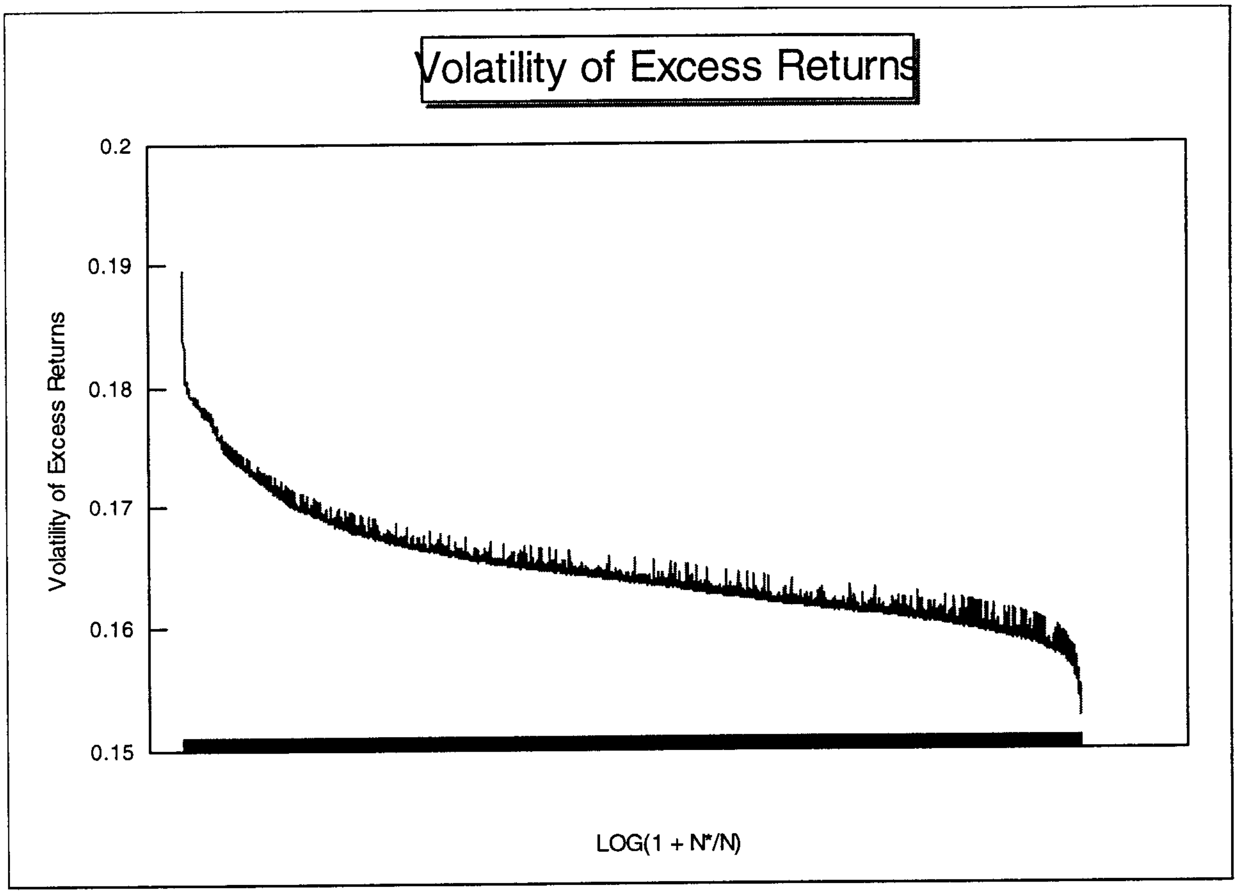

Figure 3. This figure shows the negative relationship between the excess stock return volatility and the weight assigned to the comparables' component of valuation.

Table 1
Simulation Analysis

The value of firm i and comparable firms m and j are the absolute value of a draw from a standard normal distribution multiplied by the LOG of 10,000. To avoid biasing the simulation results by choosing an arbitrarily high level of $\sigma_{\mu\theta i}$ (volatility of the absolute valuation forecast error) compared with $\sigma_{\mu\phi i}$ (volatility of the relative valuation forecast error), we assume that $\sigma_{\mu\phi i} = \sigma_{\mu\theta i}$ when there is just one comparable firm. To maintain the ceteris paribus conditions, we set the volatility of the unexpected change in the comparable firms' PE ratios equal to the volatility of the forecast error for the absolute valuation (i.e., $\sigma_{PEm} = \sigma_{PEj} = \sigma_{\mu\theta i} = .2$) and N_i (the number of comparables for firm i) varies from 1 to 30. Based on a random draw of firm values, the correlation coefficients, weights and then the volatilities ($\sigma_{\mu\phi i}$ and $\sigma_{\mu i}$, the volatility of the excess returns) are computed; this simulation is conducted 12,000 times. N^*_I is the size weighted number of comparables and $\omega_{\phi i}$ is the degree of comparability. The t-statistics are in parentheses.

Parameter Estimates

Model	α	β	$\bar{R}^2$
Panel A			
$\sigma_{\mu\phi i} = \alpha + \beta\,\omega_{\phi i} + \epsilon_i$	-0.853	0.297*	0.094
	(-522.026)	(35.375)	
Panel B			
$\sigma_{\mu\phi i} = \alpha + \beta N_i^* + \epsilon_i$	-0.751	-0.054*	0.486
	(-1655.760)	(-106.600)	
Panel C			
$\sigma_{\mu\phi i} = \alpha + \beta N_i + \epsilon_i$	-0.729	-0.062*	0.612
	(-1432.845)	(-137.550)	
Panel D			
$\sigma_{\mu i} = \alpha + \beta\,\omega_{\phi i} + \epsilon_i$	-0.703	-0.422*	0.988
	(-8331.003)	(-973.732)	
Panel E			
$\sigma_{\mu i} = \alpha + \beta N_i^* + \epsilon_i$	-0.776	-0.009*	0.075
	(-2898.950)	(-31.178)	
Panel F			
$\sigma_{\mu i} = \alpha + \beta N_i + \epsilon_i$	-0.783	-0.001*	0.001
	(-2167.883)	(-3.484)	

*Significant at the 1 percent level.

Table 2

Descriptive Statistics

Basic descriptive statistics for each of the variables posited to affect volatility. N_i* is the size weighted number of comparables for firm i. N_i is the number of comparables for firm i. POL_i is the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest bearing debt (short-term and long-term) to market value of equity. The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings (σ_{EBITi}). The total equity value of firm I is S_i. VOL_i is the total dollar trading volume over the period. $ANAL_{it}$ is the number of analysts that make an annual earnings forecast at any point during the year as reported in the IBES tapes; if there is no data for a firm, then no analysts are presumed to follow the firm. $ANAL_{it}$' has the same definition as the previous variable except that only firms with analysts following the firm are included. Each year, the statistics are computed and then averaged over the 5-year period.

Variable	Mean	Median	Standard Deviation
$\frac{N_i^*}{N_i}$	0.416	0.426	0.075
N_i^*	26.351	11.869	32.527
N_i	58.386	28	67.392
POL_i	8,929.039	5,311	7,227.179
$\left(\frac{D_i}{S_i}\right)$	13.703	0.355	320.770
CV_{EBITi}	2.703	0.485	55.260
S_i	9,874,242	41,336.4	4,812
VOL_i	28,335,348	1,014,913	13,110,000
$ANAL_{it}$	2.913	0	3.045
$ANAL_{it}$'	7.505	4	8.301

Table 3
Average Correlation Coefficients for Explanatory Variables

N_i* is the size weighted number of comparables for firm i. N_i is the number of comparables for firm i. POL_i is the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest-bearing debt (short-term and long-term) to market value of equity (where debt is measured at the end of the preceding year and equity is measured at the beginning of the year). The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings (σ_{EBIT}). VOL_i is the average total dollar trading volume over the year. $ANAL_i$ is the average number of analysts that make an annual earnings forecast each month as reported in the I/B/E/S; if the firm is not listed in I/B/E/S, then no analysts are presumed to follow the firm. $ANAL_i$' has the same definition as the previous variable except that only firms with analysts following the firm are included. These correlation coefficients and levels of significance are the result of estimating the coefficients and significance levels for each year and then averaging them over the 1990-94 period.

	$LN(1+N_i^*/N_i)$	$LN(N^*_i)$	$LN(N_i)$	$LN(POL_i)$	$LN(1 + (D_i/S_i))$	$LN(CV_{EBIT})$	$LN(S_i)$	$LN(VOL)_i$	$LN(1 + ANAL_i)$	$LN(ANAL'_i)$
$LN(1+N_i^*/N_i)$	1	0.398	0.234	-0.103	-0.087	0.012	-0.129	-0.191	-0.241	-0.427
	(0)	(0.000)	(0.000)	(0.000)	(0.132)	(0.483)	(0.000)	(0.000)	(0.000)	(0.000)
$LN(N^*_i)$		1	0.957	-0.046	0.006	0.049	0.009	-0.067	-0.181	-0.158
		(0)	(0.000)	(0.388)	(0.242)	(0.120)	(0.364)	(0.004)	(0.000)	(0.000)
$LN(N_i)$			1	-0.046	0.022	0.050	0.030	-0.041	-0.132	-0.049
			(0)	(0.119)	(0.363)	(0.067)	(0.170)	(0.056)	(0.000)	(0.152)
$LN(POL_i)$				1	0.209	-0.212	0.377	0.178	0.217	0.411
				(0)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$LN(1 + (D_i/S_i))$					1	-0.144	0.102	0.058	0.093	0.129
					(0)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$LN(CV_{EBIT})$						1	-0.415	-0.282	-0.322	-0.237
						(0)	(0.000)	(0.000)	(0.000)	(0.000)
$LN(S_i)$							1	0.776	0.627	0.800
							(0)	(0.000)	(0.000)	(0.000)
$LN(VOL)_I$								1	0.606	0.766
								(0)	(0.000)	(0.000)
$LN(1 + ANAL_i)$									1	0.100
									(0)	(0.000)
$LN(ANAL'_i)$										1
										(0)

Table 4

Average OLS Results of Cross Sectional Excess Return Volatility Tests

Regression estimates of the model,

$$LN(\sigma_{it}) = \alpha + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi})$$

$$+ \beta_5 LN(S_i) + \beta_6 LN(VOL_{it}) + \beta_7 LN(1+ANAL_{it}) + \epsilon_i$$

where LN(σ_{it}) is the log of the standard deviation of the daily excess rates of return over the "month" (where a month is equal to 1/12 of the total number of trading days in the year). LN(1+N_i*/N_i) is the degree of comparability. LN(POL_i) is the log of the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest bearing debt (short-term and long-term) to market value of equity (where both variables are measured at the beginning of the year). The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings LN(CV_{EBITi}). LN(VOL_i) is the total dollar trading volume over the month. LN(1+$ANAL_{it}$) is the log of the number of analysts that make an annual earnings forecast during month t as reported in I/B/E/S; if the firm is not included in I/B/E/S, then no analysts are presumed to follow the firm. LN($ANAL_i$') has the same definition as the previous variable except that only firms with analysts following the firm are included. The model is estimated for each month from 1990 to1994. The coefficient estimates reported below are the average values from the 60 monthly regressions. The t-statistics reported in parentheses are formed from the time-series variation in the coefficient estimates. The adjusted R-square is the average value from the 60 monthly regressions.

	Average Coefficient Estimates			
	SIC Code Definition of Comparables		Value Line Definition of Comparables	
Variables	Panel A	Panel B	Panel C	Panel D
Intercept	-0.327* (-3.590)	-0.931* (-7.625)	-2.827* (-16.043)	-2.689* (-10.844)
LN(1+N_i*/N_i)	-1.531* (-15.496)	-1.392* (-13.398)	-1.287* (-26.460)	-1.278* (-26.497)
LN(POL_i)	-0.235* (-31.772)	-0.238* (-37.300)	-0.233* (-30.314)	-0.221* (-31.491)
LN(1+D_i/S_i)	0.252* (10.340)	0.087* (4.889)	0.103* (5.568)	0.060* (3.250)
LN(CV_{EBITi})	0.182* (38.215)	0.177* (37.056)	0.222* (31.823)	0.214* (29.363)
LN(S_i)	-0.542* (-54.563)	-0.524* (-54.317)	-0.491* (-23.169)	-0.545* (-28.295)
LN(VOL_{it})	0.146* (23.766)	0.165* (24.300)	0.255* (10.161)	0.270* (9.790)
LN(1+$ANAL_{it}$)	-0.006 (-0.776)		-0.062* (-10.959)	
LN($ANAL_{it}$')		-0.006 (-0.769)		0.029** (2.034)
Adjusted R^2	.514	.552	.586	.642

*Significant at the 1 percent level. **Significant at the 5 percent level.

Table 5

Average Two-Stage Least Squares Results of Cross Sectional Excess Return Volatility Tests With the Value Line Definition of Comparable Firms

Regression estimates of the model,

$$LN(\sigma_{it}) = \alpha + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi})$$

$$+ \beta_5 LN(S_i) + \beta_6 LN(VOL_{it}) + \beta_7 LN(ANAL_{it}) + \epsilon_i \qquad (1)$$

$$LN(ANAL_{it}) = \alpha_0 + \alpha_1 LN(S_i) + \alpha_2 LN(\sigma_i) + \left(\sum_{x=1}^{5} \alpha_{x+2} IND_x\right) + \alpha_8 LN(1+INST_i) + \mu_i \qquad (2)$$

where LN(σ_{it}) is the log of the standard deviation of the daily excess rates of return over the "month"(where a month is equal to 1/12 of the total number of trading days in the year). LN(1+N_i*/N_i) is the degree of comparability. LN(POL_i) is the log of the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest bearing debt (short-term and long-term) to market value of equity (where both variables are measured at the beginning of the year). The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings LN(CV_{EBITi}). LN(VOL_i) is the total dollar trading volume over the month. LN(1+$ANAL_{it}$) is the log of the number of analysts that make an annual earnings forecast during month t as reported in I/B/E/S; if the firm is not included in I/B/E/S, then no analysts are presumed to follow the firm. LN($ANAL_i$') has the same definition as the previous variable except that only firms with analysts following the firm are included. IND_A is a dummy variable for 6 industries as posited by Bhushan (1989) and $INST_i$ is the proportion of institutional ownership in firm I's stock. The model is estimated for each month from 1990 to 1994. The coefficient estimates reported below are the average values from the 60 monthly regressions. The t-statistics reported in parentheses are formed from the time-series variation in the coefficient estimates. The adjusted R-square is the average value from the 60 monthly regressions.

Average Coefficient Estimates

Equation 1			Equation 2		
Variables	Panel A	Panel B	Variables	Panel A	Panel B
Intercept	-3.575* (-8.190)	9.637* (18.969)	Intercept	-4.379* (-129.400)	-3.980* (-139.152)
LN(1+N_i*/N_i)	-1.356* (-24.649)	-1.322* (-39.332)	LN(σ_i)	-0.009 (-1.806)	0.085* (17.831)
LN(POL_i)	-0.203* (-24.224)	-0.170* (-25.852)	LN(S_i)	0.399* (256.386)	0.475* (327.783)
LN(1+D_i/S_i)	0.078* (3.373)	0.041** (2.771)	IND_1	-0.514* (-97.361)	0.189* (13.427)
LN(CV_{EBITi})	0.219* (25.032)	0.166* (30.293)	IND_2	-0.014** (-2.053)	-0.104* (-21.458)
LN(S_i)	-0.428* (-15.581)	-1.793* (-35.498)	IND_3	0.055* (8.436)	-0.124* (-19.829)
LN(VOL_{it})	0.249* (9.709)	0.133* (5.620)	IND_4	-0.012 (-1.208)	-0.049* (-6.913)
LN(1+$ANAL_{it}$)	-0.206** (-2.664)		IND_5	-0.300* (-35.198)	-0.045* (-5.683)
LN($ANAL_{it}$')		2.995* (27.317)	LN(1+$INST_i$)	0.232* (32.047)	0.133* (15.266)
Adjusted R^2	.37	.62		.52	.46

*Significant at the 1 percent level.

**Significant at the 5 percent level.

Table 6

Average Results of OLS Annual Volatility Tests

Regression estimates of the model,

$$LN(\sigma_{it}) = \alpha + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi})$$

$$+ \beta_5 LN(S_i) + \beta_6 LN(VOL_{it}) + \beta_7 LN(1+ANAL_{it}) + \epsilon_i$$

where LN(σ_{it}) is the log of the volatility estimate over the year (using 3 different estimates of volatility in Panels A through C). LN(1+N_i*/N_i) is the degree of comparability. LN(POL_i) is the log of the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest bearing debt (short-term and long-term) to market value of equity (where both variables are measured at the beginning of the year). The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings LN(CV_{EBITi}). LN(VOL_i) is the average total dollar trading volume over the year. LN(1+$ANAL_{it}$) is the log of the average number of analysts that make an annual earnings forecast over the year as reported in I/B/E/S; if the firm is not included in I/B/E/S, then no analysts are presumed to follow the firm. The model is estimated for each year from 1990 to 1994. The coefficient estimates reported below are the average values from the 5 annual regressions. The t-statistics reported in parentheses are formed from the time-series variation in the coefficient estimates. The adjusted R-square is the average value from the 5 annual regressions.

	Average Coefficient Estimates		
Variables	Panel A	Panel B	Panel C
	Engle's (1982) ARCH Estimate of Volatility	Amihud & Mendelson's (1987) Noise Volatility	Amihud & Mendelson's (1987) Intrinsic Volatility
Intercept	-0.243 (-1.324)	-0.567 (-1.878)	-5.043* (-9.015)
LN(1+N*/N)	-1.860* (-11.756)	-1.493* (-12.671)	-1.085* (-4.343)
LN(POL_i)	-0.240* (-9.455)	-0.205* (-7.620)	-0.100* (-3.432)
LN(1+(D_i/S_i))	0.178* (4.073)	0.178* (3.975)	0.141* (5.435)
LN(CV_{EBITi})	0.206* (11.146)	0.213* (9.173)	0.212* (9.171)
LN(S_i)	-0.500* (-7.711)	-0.527* (-7.905)	-0.527* (-6.889)
LN(VOL_k)	0.124** (2.636)	0.168* (3.245)	0.322* (4.813)
LN(1+$ANAL_i$)	0.013 (0.583)	0.023 (1.112)	-0.039** (-2.467)
Adjusted R^2	0.624	0.496	0.390

*Significant at the 1 percent level. **Significant at the 5 percent level.

Table 7

Average Results of Excess Return Volatility Tests Surrounding Earnings Announcements

Regression estimates of the model,

$$LN(CAR_{i,21})^2 = \alpha + \beta_1 LN\left(1+\frac{N_i^*}{N_i}\right) + \beta_2 LN(POL_i) + \beta_3 LN\left(1+\frac{D_i}{S_i}\right) + \beta_4 LN(CV_{EBITi}) + \beta_5 LN(S_i)$$

$$+ \beta_6 LN(VOL_{i,21}) + \beta_7 LN(1+ANAL_{it}) + \beta_8 LN\left(1+\frac{EPS_i - E(EPS_i)}{EPS_i}\right)^2 + \beta_9 LN(1+PREVEANN_{it}) + \epsilon_i$$

where $LN(CAR_{i,21})^2$ is the log of the squared cumulative abnormal return over the 21 day period surrounding the quarterly earnings announcement for firm I. $LN(1+N_i^*/N_i)$ is the degree of comparability. $LN(POL_i)$ is the log of the period-of-listing, or age of the firm as of the beginning of the year. The variable (D_i/S_i) is the book value of total interest bearing debt (short-term and long-term) to market value of equity (where both variables are measured at the beginning of the year). The underlying business risk of the firm is estimated with the log of the coefficient of variation of the firm's operating earnings $LN(CV_{EBITi})$. $LN(VOL_i)$ is the total dollar trading volume over the month. $LN(1+ANAL_{i,21})$ is the log of the number of analysts that make an annual earnings forecast at during the earnings announcement month t as reported in I/B/E/S; if the firm is not included in I/B/E/S, then no analysts are presumed to follow the firm. $LN(ANAL_{i,21}')$ has the same definition as the previous variable except that only firms with analysts following the firm are included. $PREVANN_i$ is a counter variable equal to the number of earnings announcements made by the comparable firms before firm I's earnings were announced. The model is estimated for each quarter from 1990 to 1993. The coefficient estimates reported below are the average values from the 16 quarterly regressions. The t-statistics reported in parentheses are formed from the time-series variation in the coefficient estimates. The adjusted R-square is the average value from the 16 quarterly announcements.

	Average Coefficient Estimates			
	Naive Earnings Expectation		Average Analysts' Earnings Expectation	
Variables	Panel A	Panel B	Panel C	Panel D
Intercept	-5.373* (-18.061)	-5.554* (-17.859)	-5.441* (-12.939)	-5.551* (-12.276)
$LN(1+N_i^*/N_i)$	-1.126* (-13.210)	-1.408* (-14.775)	-1.600* (-11.194)	-1.905* (-12.700)
$LN(POL_i)$	-0.024 (0.920)	-0.004 (-0.161)	-0.039 (-1.125)	-0.013 (-0.347)
$LN(1+D_i/S_i)$	0.102* (4 565)	-0.077* (3.387)	-0.030 (-0.953)	-0.071** (-2.437)
$LN(CV_{EBITi})$	0.191* (21.751)	0.192* (21.079)	0.177* (13.344)	0.176* (13.218)
$LN(S_i)$	-0.575* (-62.278)	-0.581* (-67.537)	-0.581* (-33.629)	-0.600* (-35.825)
$LN(VOL_i)$	0.429* (62.511)	0.433* (66.032)	0.454* (45.227)	0.461* (49.127)
$LN(1+ANAL_{i,21})$	-0.053* (-6.450)	-0.050* (-5.920)		
$LN(ANAL_{i,21}')$			-0.017 (-0.915)	-0.005 (0.234)
$LN(1+(E_i-E(EPS_i))/EPS_i))^2$	0.052* (6.940)	0.052* (6.992)	0.098* (8.832)	0.093* (8.305)
$LN(1+PREVEANN_i)$	-0.060* (-6.880)		-0.078* (-6.000)	
Adjusted R^2	.568	.552	.586	.642

*Significant at the 1 percent level.

**Significant at the 5 percent level.