Following the Pied Piper: Do Individual Returns Herd around the Market?

William G. Christie and Roger D. Huang

Do equity returns indicate the presence of herd behavior on the part of investors during periods of market stress? To test this proposition, the cross-sectional standard deviation of returns, or dispersion, is used to capture herd behavior. When individual returns herd around the market consensus, dispersions are predicted to be relatively low. In contrast, rational asset pricing models predict an increase in dispersion because individual returns are repelled away from the market return when stocks differ in their sensitivity to market movements. The results for both daily and monthly returns are inconsistent with the presence of herding during periods of large price movements. For example, during extreme down markets, when herding is expected to be most prevalent, the magnitude of the increase in the dispersion of actual returns is mirrored by the increase in the dispersion of predicted returns that are estimated from a rational asset pricing model.

One popular explanation for the variability of equity returns attributes price changes to the influence of investor herds, which many observers perceive as forming spontaneously and behaving irrationally. In an asset pricing context, the belief that herd behavior reflects the irrational response of investors rather than the outcome of rational decision making is of particular concern because it implies that prices may be driven away from their equilibrium values. Under this premise, investors are exposed to the unpredictable whims of herds and may be forced to transact at inefficient prices.

The academic literature includes many models of herd behavior, or cascades, in financial markets. Scharfstein and Stein proposed a model in which managers ignore their own private information and herd on the investment decisions of others.[1] Trueman demonstrated that individual analysts may herd toward earnings forecasts issued by other analysts.[2] Banerjee developed a model of herd behavior that is not affected by the incentive problems inherent in principal–agent relationships.[3] Bikhchandani, Hirshleifer, and Welch used a model of informational cascades to explain conformity and short-lived phenomena such as fads and fashions.[4] Froot, Scharfstein, and Stein showed that "speculators with short horizons may herd on the same information."[5] Welch explained how sequential issues of IPOs can lead investors to ignore their private information and herd on the decisions of earlier investors.[6]

The empirical support for herd behavior is mixed. Shiller and Pound provided survey evidence on herding among institutional investors.[7] They found that institutional investors place significant weight on the advice of other professionals on their buy and sell decisions in volatile stocks. Another recent empirical study found only weak evidence of herding decisions by institutional investors among small stocks and no evidence of herding among large stocks.[8]

The experimental evidence in social psychology on the behavior of individuals in groups suggests that individuals abide by the group decision, even when they perceive the group to be wrong.[9] In a market setting, herds are characterized by individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions. Thus, herd formation

William G. Christie is an assistant professor of management and Roger D. Huang is a professor of management at Owen Graduate School of Management, Vanderbilt University in Nashville.

suggests that investors are drawn to the consensus of the market, implying that individual returns would not stray far from the market return.

This paper focuses on the price implications of herding by investigating whether equity returns reveal the presence of herd behavior. To measure the potential influence of herding on prices, we first considered how herd behavior may manifest itself in return data. Under the traditional definition of herd behavior, an intuitive measure of its market impact is dispersion, defined as the cross-sectional standard deviation of returns. Dispersions quantify the average proximity of individual returns to the mean. They are bounded from below at zero when all returns move in perfect unison with the market. As individual returns begin to vary from the market return, the level of dispersion increases.

Our objective was to test for the presence of herd behavior when herds are most likely to form. Because individuals are more likely to suppress their own beliefs in favor of the market consensus during periods of unusual market movements, herd behavior would most likely emerge during periods of market stress. A natural candidate for these periods are those trading intervals characterized by large swings in average prices. Because the presence of herds implies that investors are willing to suppress their own beliefs in favor of the market consensus, security returns will be swept along with the market. We exploited this implication of herd behavior by testing whether dispersions are significantly lower than average during periods of extreme market movements.

Predictions concerning the behavior of dispersions during periods of market stress also emerge from rational asset pricing models. These models typically relate individual returns to some common factor(s), of which the market return is the most prominent observable factor. During periods of market stress, rational asset pricing models predict that large changes in the market return would translate into an increase in dispersion, because individual assets differ in their sensitivity to the market return. In other words, dispersion in factor sensitivities will repel individual returns away from the market. Thus, herd behavior and rational asset pricing models offer conflicting predictions for the behavior of dispersions during periods of market stress.

Our empirical evidence shows that dispersions increase significantly during periods of large absolute price changes. These results, which are consistent with the predictions of rational asset pricing, are detected using both daily and monthly returns and are present for both positive and negative movements in average prices. This failure to detect herd behavior may reflect the tendency of herds to form around indicators other than the average consensus of all market participants. Rather, individuals may rely on other cues and herd around the returns of firms that share common characteristics. A widely recognized method for categorizing such firms is by Standard Industrial Code (SIC) classification. If individual security returns herd around their industry average during periods of market stress, a significant reduction in dispersions within industries should be observed. We estimated dispersions within various industry-based portfolios and found that, without exception, significant increases in dispersions occur during periods of market stress when dispersions are estimated using the average industry return.

Our results also show that dispersions increase much more dramatically during up markets relative to down markets. To test whether this asymmetry is consistent with the presence of herding in down markets, we estimated the dispersion of predicted returns that arise from a rational asset pricing model. We found that the actual and the predicted dispersions are virtually identical, consistent with the hypothesis that the muted increase in dispersion during down markets is based on rational pricing rather than herding.

DEFINING EQUITY RETURN DISPERSIONS

The dispersion of equity returns, S, is measured by the following expression:

$$S = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}}, \tag{1}$$

where r_i is the observed return on firm i and $\bar{r}$ is the cross-sectional average of the n returns in the portfolio.[10] By quantifying the degree to which asset returns tend to rise and fall in concert with the portfolio return, this measure captures the key attribute of herd behavior. Dispersions are predicted to be low when herd behavior is present, but low dispersions by themselves do not in turn guarantee the presence of herding. For example, the lack of new information during a trading interval would generate low dispersion, even in the complete absence of herd formation. Therefore, we cannot search for periods of low dispersions *ex post* and attribute them to the influence of herds.

Equity return dispersions bear a resemblance to standard measures of volatility but differ in that expression (1) uses the portfolio return in place of the expected return of the individual assets. For dispersions to correspond more closely to the volatility of a portfolio, the portfolio return should be replaced with the expected return for each of the individual securities. For example, we could set the expected return of each security to zero in considering short time intervals such as daily returns. The measure then collapses to the average volatility of the individual assets in the portfolio at a point in time, but it still differs from the volatility of the portfolio.[11]

HERD BEHAVIOR DURING MARKET STRESS

During periods of abnormally large average price movements, or market stress, the differential predictions of rational asset pricing models and herd behavior are most pronounced. Specifically, because individual securities differ in their sensitivity to the market return, rational asset pricing models predict that periods of market stress induce increased levels of dispersion. In contrast, the herding of individual returns around the market translates into a reduced level of dispersion.

To differentiate between the two hypotheses, we isolated the level of dispersion, S_t, in the extreme tails of the distribution of market returns and tested whether it differs significantly from the average levels of dispersion that exclude the outermost market returns. These tests were performed using the following regression:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t, \qquad (2)$$

where

D_t^L = 1 if the market return on day t lies in the extreme lower tail of the return distribution

D_t^L = 0 otherwise,

and

D_t^U = 1 if the market return on day t lies in the extreme upper tail of the return distribution

D_t^U = 0 otherwise.

The α coefficient denotes the average dispersion of the sample excluding the regions covered by the two dummy variables. Rational asset pricing models predict significantly positive coefficients for β_1 and β_2, and negative estimates of β_1 and β_2 would be consistent with the presence of herd behavior.

Data

We used daily and monthly returns from the Center for Research in Securities Prices (CRSP) at the University of Chicago. The sample comprises firms with shares CRSP classifies as ordinary common. The daily data for NYSE and Amex firms extend from July 1962 to December 1988, and the monthly data for NYSE firms extend from December 1925 to December 1988. Portfolio returns were equally weighted, and dispersions were calculated using Equation 1.

To test for herding within industries, the level of dispersion was also calculated for industry portfolios. Firms were assigned to one of 12 industry groups based on their two-digit SIC classification. The formation of industry portfolios followed the grouping technique first proposed by Sharpe and used by Breeden, Gibbons, and Litzenberger.[12] To ensure that monthly portfolios contained at least 25 securities in any particular month, we excluded finance and real estate, construction, service, and leisure industry sectors. The daily tests retained all 12 industry groups.

Table 1 provides the average level of dispersion, its associated standard deviation, and the average number of firms used to compute these statistics for the entire sample and by industry. For the daily data, the average level of dispersion is 2.90 percent a day across all stocks, with a standard deviation of 0.59 percent. Across industries, the level of dispersion ranges from a low of 1.60 percent for utilities to 3.24 percent for petroleum. These two industries also have the lowest and highest standard deviations of dispersion, respectively. The low level and variability of dispersion for utilities may reflect the regulated nature of that particular industry.

The most striking difference between the results for daily and monthly data is that the magnitude of the dispersion measure is considerably higher for the monthly data. This difference reflects the fact that, with monthly data, individual returns have a greater opportunity to stray farther from the mean. For the specific industries, utilities continue to display the lowest level of dispersion (6.63 percent a month). The distribution of dispersions is relatively tight across the remaining industries.

Daily Regression Evidence

Equation 2 was estimated using two criteria to define extreme market movements. The 1 percent (5 percent) criterion restricts D_t^L and D_t^U to 1 (5) percent of the lower tail and 1 (5) percent of the

Table 1. Summary Statistics

Industry	Average Return Dispersion	Standard Deviation of Dispersion	Average Number of Firms
Daily Data			
All industries	2.90%	0.59%	2,292
Petroleum	3.24	1.22	119
Finance and real estate	2.94	0.90	265
Consumer durables	3.17	0.74	370
Basic industries	2.78	0.69	319
Food and tobacco	2.37	0.65	143
Construction	2.77	0.88	86
Capital goods	2.84	0.68	309
Transportation	2.78	0.86	75
Utilities	1.60	0.45	174
Textile and trade	2.92	0.85	241
Services	3.15	1.01	95
Leisure	3.01	1.00	96
Monthly Data			
All industries	9.77%	5.22%	890
Petroleum	8.45	4.80	49
Consumer durables	9.89	5.05	151
Basic industries	9.41	5.46	190
Food and tobacco	8.66	5.64	96
Capital goods	9.07	4.42	132
Transportation	10.96	7.48	69
Utilities	6.63	4.93	100
Textile and trade	9.37	5.41	103

upper tail of the market return distribution. These two criteria were adopted because the definition of an extreme market return is arbitrary. Table 2 provides the regression estimates for the overall sample and the estimates across industries. The first row of Table 2, which contains the estimates of β_1 and β_2 for the entire sample, indicates that the coefficients are positive; the heteroscedasticity-consistent t-statistics confirm the coefficients' reliability. Thus, dispersions are significantly higher than average during days characterized by large swings in average prices. These results are consistent with the predictions of rational asset pricing and contradict the predictions of herd behavior.

The remaining rows of Table 2 contain the estimates across industry portfolios. Under both criteria for extreme market movements, the coefficient estimates are reliably and uniformly positive, and the 5 percent criterion continues to produce smaller estimates than the 1 percent criterion. Therefore, the predictions of rational asset pricing are most apparent when extreme market movements are confined to the upper and lower 1 percent of market returns. In addition, the estimates of β_1 across industries exhibit considerable uniformity, but a much wider distribution is apparent for β_2. This result implies that the increase in dispersion across industries during large market downturns is relatively more uniform than during unusually large upswings in average prices. A comparison of the magnitudes of β_1 and β_2 across industries shows that the heavily regulated utility industry is unique because it exhibits the lowest average dispersion (as indicated by α) and the smallest increases in dispersion during periods of market stress under the 1 percent criterion. The strength of these results in favor of the predictions of rational asset pricing suggests that few follow the tune of the Pied Piper as he attempts to rally investors around either the market or industry returns.

Although the cross-sectional standard deviation of returns is a natural measure for capturing the influence of herd behavior, results based on this measure can be sensitive to outliers. To test for the robustness of our results, we replicated the

Table 2. Regression Coefficients: Daily Dispersions During Periods of Market Stress
(heteroscedastic-consistent t-statistics in parentheses)

	1 Percent Criterion			5 Percent Criterion		
Industry	α	β_1	β_2	α	β_1	β_2
All industries	2.87	1.09	1.99	2.83	0.39	1.04
		(6.93)	(12.45)		(7.82)	(19.41)
Petroleum	3.21	0.88	1.54	3.19	0.15	0.77
		(4.58)	(7.44)		(2.31)	(8.69)
Finance and real estate	2.91	1.10	2.03	2.87	0.37	0.99
		(6.14)	(10.89)		(6.33)	(13.85)
Consumer durables	3.13	1.17	2.25	3.09	0.39	1.21
		(7.51)	(11.89)		(7.06)	(18.52)
Basic industries	2.75	1.06	1.85	2.71	0.40	0.97
		(6.45)	(11.87)		(7.71)	(17.29)
Food and tobacco	2.35	0.84	1.29	2.32	0.35	0.74
		(6.03)	(10.12)		(7.39)	(14.77)
Construction	2.74	1.03	2.05	2.70	0.35	1.03
		(5.92)	(11.66)		(6.26)	(16.67)
Capital goods	2.80	1.02	2.05	2.76	0.37	1.06
		(6.51)	(11.89)		(6.95)	(18.33)
Transportation	2.75	1.10	1.93	2.70	0.52	1.04
		(6.21)	(12.52)		(8.08)	(17.79)
Utilities	1.58	0.82	1.14	1.55	0.39	0.59
		(5.83)	(11.61)		(9.73)	(16.25)
Textile and trade	2.89	1.11	1.91	2.85	0.41	1.07
		(7.03)	(9.59)		(7.24)	(16.32)
Services	3.11	1.25	2.37	3.06	0.54	1.24
		(6.95)	(10.84)		(7.88)	(15.50)
Leisure	2.97	1.21	2.14	2.93	0.50	1.04
		(7.04)	(9.24)		(7.21)	(13.18)

tests using mean absolute deviations, S^*, defined as

$$S^* = \frac{\sum_{i=1}^{n} |r_i - \bar{r}|}{n}. \quad (3)$$

The results, which are not reported here, show that the regression coefficients are all positive and significantly different from zero under each of the two criteria. Thus, the results that use this alternative definition preserve the evidence in favor of rational asset pricing.

Monthly Regression Evidence

The use of daily data implicitly assumes that herd behavior is a very short-lived phenomenon. If herds require a longer time horizon to affect market prices, however, the use of daily data unfairly restricts the ability of herd behavior to manifest itself in dispersions during periods of market stress.

The coefficient estimates for monthly returns from Equation 2 are reported in Table 3. Because monthly returns span the period between January 1926 and December 1988, only 756 observations per regression were available. Therefore, the 5 percent criterion produces more reliable estimates because the beta coefficients are each estimated with 38 observations rather than the 8 data points available under the 1 percent criterion. The results indicate that monthly data generate significantly higher levels of dispersion because individual returns are permitted more time to stray from the mean. More importantly, each of the beta coefficients is positive for the entire sample and across different industries. Thus, altering the data frequency fails to elicit price behavior consistent with herd behavior.

Table 3 highlights the asymmetric behavior of dispersion to wide swings in average prices. The estimates for β_2 are between three and six times greater than those for β_1 under the 5 percent criterion; this ratio becomes even more pronounced under the 1 percent criterion. These results suggest that the increase in dispersion is much more aggressive during dramatic up markets than in down markets.[13]

To highlight the asymmetric behavior of dispersion during months of market stress, Table 4 provides the ten largest positive and ten largest negative portfolio returns and their associated dispersions. The results during extreme down markets reveal that the average dispersion of actual returns, 14 percent a month, is only slightly higher than the mean of 9.77 percent for the entire 63-year period. The average dispersion of actual returns for extreme up markets, 39.76 percent, is almost four times larger than the overall average. The higher-than-average dispersion of actual returns during market stress is consistent with the predictions of rational asset pricing. The rationality hypothesis, however, does not predict the asymmetric response of actual dispersions to dramatic price swings of opposite direction.

One characteristic of portfolio returns that may explain the asymmetric behavior of dispersion is the inherent asymmetry in the range of potential portfolio returns. Returns are truncated from below at –100 percent but have unlimited upside potential. The results in Table 4 reflect this asymmetry: The largest monthly decline in returns is approximately half the magnitude of the largest percentage increase in average prices. To control for this discrepancy, we compared the average dispersions across returns of similar magnitudes.

Table 3. Regression Coefficients: Monthly Dispersions During Periods of Market Stress
(heteroscedastic-consistent *t*-statistics in parentheses)

	1 Percent Criterion			5 Percent Criterion		
Industry	α	β_1	β_2	α	β_1	β_2
All industries	9.39	4.21	31.75	8.92	3.08	13.72
		(3.50)	(5.80)		(5.47)	(9.21)
Petroleum	8.18	2.77	22.36	7.84	2.53	9.59
		(2.56)	(4.38)		(3.97)	(5.33)
Finance and real estate	8.66	4.03	28.64	8.16	2.50	14.40
		(3.17)	(7.55)		(4.25)	(6.55)
Consumer durables	9.56	2.26	28.91	9.19	2.35	11.70
		(1.62)	(5.27)		(3.31)	(5.39)
Basic industries	9.02	4.48	32.08	8.68	2.95	11.50
		(2.91)	(4.81)		(4.93)	(4.84)
Food and tobacco	8.23	5.11	35.89	7.89	3.12	12.25
		(2.84)	(4.88)		(4.82)	(4.59)
Construction	8.96	2.47	27.20	8.45	2.15	14.18
		(1.71)	(4.08)		(3.53)	(5.20)
Capital goods	8.79	3.11	22.90	8.51	2.19	8.88
		(2.87)	(4.61)		(4.90)	(4.84)
Transportation	10.58	3.73	32.27	9.88	3.34	18.27
		(2.84)	(4.64)		(4.72)	(5.44)
Utilities	6.30	4.68	26.66	5.91	3.27	10.98
		(5.26)	(3.45)		(5.94)	(4.51)
Textile and trade	9.01	4.86	28.94	8.66	3.56	10.65
		(2.58)	(4.69)		(3.98)	(4.90)
Services	9.73	6.42	15.66	9.24	3.80	10.66
		(5.28)	(3.94)		(4.83)	(4.86)
Leisure	9.44	1.35	24.00	9.09	1.81	10.44
		(1.35)	(4.83)		(3.38)	(5.76)

Table 4. Identification of Extreme Portfolio Returns and Their Associated Dispersions

Date	Portfolio Return	Actual Dispersion	Predicted Dispersion
Largest Negative Monthly Portfolio Returns			
September 1931	–31.13%	14.80%	13.37%
March 1938	–28.57	11.75	13.57
May 1940	–26.83	11.49	14.47
October 1987	–26.34	12.52	13.90
October 1929	–21.13	14.84	NA
May 1932	–20.49	21.67	7.47
September 1937	–19.29	9.55	9.59
December 1931	–18.82	18.65	7.37
June 1930	–18.76	12.72	NA
July 1934	–18.69	12.45	7.90
Average		14.04	10.96
Largest Positive Monthly Portfolio Returns			
August 1932	65.82%	58.92%	28.39
May 1933	60.84	59.47	27.62
April 1933	51.62	47.96	24.05
July 1932	43.87	44.70	16.94
September 1939	39.54	53.22	16.49
January 1934	32.04	29.61	14.33
June 1938	30.68	16.90	13.45
January 1975	28.62	22.10	11.75
June 1933	22.56	33.61	10.39
April 1938	21.32	31.10	9.83
Average		39.76	17.32

Note: NA = not available.

The five largest negative mean returns average –26.8 percent and produce a mean dispersion of 13.1 percent. In contrast, the sixth through tenth largest positive mean returns average 27 percent and produce a mean dispersion of 26.7 percent. Thus, the asymmetry is apparent even after controlling for the absolute magnitude of the monthly returns.[14]

Dispersion of Actual versus Predicted Returns

Our hypothesis was that herding emerges during periods of market stress, independent of the direction of the movement in average prices. An alternative hypothesis is that herding responds asymmetrically to extreme market movements. Specifically, the concept of herd behavior may be more relevant on the downside than the upside because few investors have a natural short position. Thus, the relatively modest increase in dispersion during down markets may be a manifestation of herding. To test this hypothesis, we compared the dispersion of actual returns with the dispersion of returns estimated using a rational asset pricing model. If herding is responsible for the dampened increase in dispersion during down markets, the dispersion in predicted returns should be significantly larger than the dispersion in actual returns.

To estimate the dispersion of predicted returns, we used the market model to predict the return for each firm in each of the months of market stress identified in Table 4. The predicted return for firm i in month t is given by

$$E[R_t^i] = \alpha^i + \beta^i R_t^M, \tag{4}$$

where R_t^M is the return of the equally weighted market index in month t and α^i and β^i are computed using the 60 months of data prior to month t. Because this methodology requires five years of historical data, we could not compute the predicted dispersions for October 1929 and June 1930. The dispersion in predicted returns was then computed for each of these days from the standard deviation of predicted returns using Equation 1.

The results are reported in Table 4. For the down markets, the average dispersion of observed returns, 14.04 percent, exceeds the average dispersion of predicted returns, 10.96 percent. The similarity between the actual and predicted dispersions increases with the magnitude of the market decline, implying that the evidence in favor of the rationality hypothesis becomes stronger with the severity of the downturn. We also found that the actual dispersions exceed the dispersions of the predicted returns in extreme up markets. These results are inconsistent with a herding explanation for the asymmetry in dispersion between up and down markets.

CONCLUSION

Because dispersion quantifies the average proximity of individual returns to the mean, it reveals the presence of herd behavior when individual returns follow the lead of the portfolio returns. Our strategy was to compare the predictions of herd behavior along side those of rational asset pricing models during periods of market stress, or exaggerated price movements. Dispersions were found to increase significantly during periods of large average price changes, implying individual returns do not cluster around either the market or industry returns during periods of market stress. We also examined the hypothesis that herding is an attribute of market stress only during extreme market declines. A comparison of actual dispersion with the dispersion of returns predicted by the market model shows that, consistent with the predictions of the rationality hypothesis, the predicted and the actual dispersions are very similar. Thus, the preponderance of the evidence supports the predictions of rational asset pricing models and suggests that herding is not an important factor in determining equity returns during periods of market stress.[15]

FOOTNOTES

1. David S. Scharfstein and Jeremy C. Stein, "Herd Behavior and Investment," *The American Economic Review*, vol. 80, no. 3 (June 1990):465–79.
2. Brett Trueman, "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, vol. 7, no. 1 (Spring 1994):97–124.
3. Abhijit Banerjee, "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, vol. 107, no. 3 (August 1992):797–817.
4. Sushil Bikhchandani, David Hirshleifer, and Ivo Welch, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, vol. 100, no. 3 (October 1992):992-1026.
5. K.A. Froot, David S. Scharfstein, and Jeremy C. Stein, "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation," *The Journal of Finance*, vol. 47, no. 4 (September 1992):1461–84.
6. Ivo Welch, "Sequential Sales, Learning, and Cascades," *The Journal of Finance*, vol. 47, no. 4 (June 1992):695–732.
7. Robert J. Shiller and John Pound, "Survey Evidence of Diffusing of Interest Among Institutional Investors," *Journal of Economic Behavior and Organization*, vol. 12, no. 1 (August 1989): 47–66.
8. Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny, "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, vol. 32, no. 1 (August 1992), pp. 23–44.
9. A classic reference to this literature is Solomon E. Asch, *Social Psychology* (Englewood Cliffs, NJ: Prentice Hall, 1952).
10. Other studies have used the cross-sectional dispersion of returns in the context of market microstructure issues. Yakov Amihud and Haim Mendelson, in "Market Microstructure and Price Discovery on the Tokyo Stock Exchange," *Japan and the World Economy*, vol. 1, no. 4 (1989): 341–70, used dispersions to measure the noise induced in asset returns through alternative trading mechanisms on the Tokyo Stock Exchange. Specifically, they computed the dispersion in returns across the 50 largest stocks (measured by market value of equity) using both opening and closing transaction prices. Thomas H. McInish and Robert A. Wood, in "A Transactions Data Analysis of the Variability of Common Stock Returns During 1980–1984," *Journal of Banking and Finance*, vol. 14, no. 1 (March 1990):99–112, used dispersion to examine the variability of returns across stocks at the beginning and end of the trading day. Richard W. McEnally and Rebecca Todd, in "Cross-Sectional Variation in Common Stock Returns," *Financial Analysts Journal*, vol. 48, no. 3 (May/June 1992):59–63, used the interquartile range to study cross-sectional variation in stock returns.
11. A formal derivation of the relation between dispersion, average volatility, and the volatility of a portfolio is available from the authors upon request.
12. See William Sharpe, "Some Factors in New York Stock Exchange Security Returns," *The Journal of Portfolio Management*, vol. 8, no. 4 (1982):5–19; and Douglas Breeden, Michael R. Gibbons, and Robert H. Litzenberger, "Empirical Tests of the Consumption-Oriented CAPM," *The Journal of Finance*, vol. 44, no. 2 (June 1989):231–62.
13. This asymmetry is also observed using daily data, although the pattern is not as pronounced.
14. An examination of the specific months experiencing the largest positive and negative average returns in Table 4 also reveals that all but two of these months occur prior to 1940. Indeed, they are concentrated almost exclusively during the Great Depression. The asymmetric response of dispersions to large market movements is not confined to the Great Depression, however. It is also observed when the data are restricted to the post-1945 period. Specifically, the mean dispersion for the ten most negative months in the postwar era is 8.82 percent, and the mean dispersion in the ten most positive months is 12.89 percent. These estimates both lie above the average dispersion of 8.09 percent for the postwar periods and differ from each other at the 1 percent level of significance.
15. We appreciate the helpful comments of the editor, W. Van Harlow III. This research was supported by the Dean's Fund for Faculty Research and the Financial Markets Research Center at the Owen Graduate School of Management, Vanderbilt University.