Herding Behavior and Stock Returns: An Exploratory Investigation

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I. INTRODUCTION

Modern asset pricing theory says that, at all times, market prices equal fundamental value and that asset returns in the cross-section reflect relative exposures to systematic non-diversifiable risk. Despite three decades of data analysis, empirical support for this theory remains thin. For instance, capital asset pricing model betas are at best weakly related to returns (FAMA and FRENCH, 1992) and there is much unexplained volatility in asset prices (SHILLER, 1989). Shareholder trading practices are also difficult to reconcile with equilibrium theory. Why are periods of price turbulence, accompanied by heavy trading volume, followed by periods of relative calm? And why do people trade so much in the first place? A list of reasons includes consumption-saving decisions, portfolio rebalancing, taxes, and speculation «justified» by superior insight or information.[1] At an intuitive level, the last motive seems very powerful. Yet, standard models do not allow that rational people with identical information «agree to disagree» about the proper interpretation of news (see, however, HARRIS and RAVIV, 1992). Certainly, differences in what investors know may also underlie their disagreement but, in theory, these differences do not by themselves explain trading. If rationality is common knowledge, a lack of consensus will only generate trading if there is exogenous noise.[2] In sum, the

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1. HART and KREPS (1986) define speculation as the short-term trading of assets with a view towards beating the market consensus of value – irrespective of whether, objectively, current prices appear high or low relative to fundamentals.
2. See MILGROM and STOKEY (1982). BLACK (1986) notes that noise trading mitigates the problem which arises when rational investors with private information are unwilling to trade because other rational people also have private information. WANG (1994) reviews various theories of volume.

extraordinary volume of securities trading that is observed defines a puzzle of rationality. Possible psychological explanations have to do with investor conformist behavior and overconfidence (DE BONDT and THALER, 1995).

Perhaps because the standard theory fails to explain share turnover, past empirical research on the cross-section of prices and volumes is limited. Theory suggests that, in equilibrium, less liquid companies should earn higher returns (DEMSETZ, 1968). Of course, in practice, equally well-informed people frequently do disagree about the value implications of news. This may be due to individual differences in past experience or in their capacity to evaluate information. Research in behavioral finance (e.g., as reviewed in DE BONDT and THALER, 1995) recognizes this heterogeneity. Noise trader models propose that there are two classes of investors: rational investors and noise traders. In these models, erratic trading causes temporary disparities between market prices and intrinsic values. It creates risk. To the degree that the risk cannot be diversified and that arbitrage is costly, expected returns must rise. Liquidity constraints that discourage uninformed trading curb this non-fundamental volatility and its consequences.

The noise trader approach follows an intellectual tradition which goes back to MACKAY (1841), LE BON (1895), PARETO (1902), KEYNES (1936), and others. It motivated some of the regulatory reforms of the 1930s.[3] In the aftermath of the 1987 crash, policymakers again considered proposals to curb stock market volatility.[4] Whether speculation is harmful is subject to debate. What are the welfare costs? Fluctuations in stock market wealth may alter the macroeconomic propensity to consume. Also, volatility may adversely affect corporate investment spending (FROOT et al., 1991). Much depends on whether irrational market sentiment raises the cost of capital. To repeat, noise forces risk-averse investors to consider the chances of having to sell at a disadvantageous price.[5]

The explosion in trading volume runs parallel to the evolving composition of the investment public. Institutional ownership of equity has increased from 8 percent in the 1950s to about 50 percent currently (BRANCATO, 1991). More than three quarters of the trading volume on the New York Stock Exchange is due to institutions. Logically, money managers may destabilize prices if their strategies are not based on fundamentals and if

3. KEYNES argues, for instance, that casinos «.. in the public interest, be inaccessible and expensive. And perhaps the same is true of stock exchanges ... a transfer tax on all transactions might prove the most serviceable reform available, with a view to mitigating.. speculation..» (The General Theory, 1936, pp. 159–160).

4. The remedies outlined by the Brady Commission appear to be built upon a belief that volatility can be curbed by reducing market liquidity, e.g., with high margin requirements. These ideas run counter to modern finance theory. MERTON H. MILLER states the argument as follows: «The lower the transactions costs, the more liquid the market, and .. the more economical it is for investors to adjust their portfolios. Yet perversely, .. current regulatory .. proposals .. rest on the assumption that unregulated securities markets supply too much liquidity» (Wall Street Journal, October 19, 1990).

5. In contrast, DOW and GORTON (1994) and PAGANO (1989) offer models in which noise trading is a public good and Pareto-improving. Whereas lemon problems can cause markets to fail, churning can open them up.

they all like or all dislike the same stocks at the same time. This type of herding is plausible for several reasons, e.g., the homogeneity of the information signals received by the investment community; the similarity in interpretation of news items because of mental frames that are socially and professionally shared; incentive systems that encourage money managers to mimic each other's trades; and notions of prudence and fiduciary duty that depend on external validation and that make a security appear more attractive if it is traded by other investors.

The purpose of this research is to evaluate the cross-sectional relationship between expected returns, trading practices, volatility, and standard measures of investment risk (beta, market value, and the market-to-book ratio). Ceteris paribus, does high trading volume raise share prices? Does it increase price volatility? Does the identity of investors (individual investors vs. banks, insurance companies, mutual funds, or money management companies) matter to the level of prices? Do regulatory restrictions qualify our conclusions? We employ price and volume data for individual U.S. firms over twenty years (1970–1990). In addition, institutional ownership data are available since 1979. Our analysis is based on monthly returns. This choice is driven by data requirements and convenience. It allows us to focus on issues of asset pricing rather than the financial economics of market micro-structure.

The balance of the paper is organized as follows. Section II reviews past research on shareholder trading practices and stock returns. Section III presents the data and methods. It includes a description of the various samples. Section IV lists the results. Section V summarizes the findings and offers some directions for future research.

II. SHAREHOLDER TRADING PRACTICES AND STOCK RETURNS

Why do prices move so much? Why do people trade so much? These two questions may well be the two most profound puzzles that asset pricing theory must solve. In the past, the relationship between returns, price volatility, and trading volume has been discussed in at least four different contexts: (i) traditional work on market liquidity and liquidity premia,[6] (ii) recent research on market volatility, (iii) on noise trader models, and (iv) on transaction costs and margin requirements. Below, we briefly review some of the recent research. For our purpose, the defining aspect of this work is the conclusion that the identity of investors and their trading practices should influence the dynamics of security prices.

6. The classic reference is DEMSETZ (1968). Several characteristics describe market liquidity, e.g., low transactions costs, quick and accurate price adjustments to information, price continuity, trading continuity, depth of the market, and ease and speed of order execution. For further references and for a simple model of market structure that «captures the essence» of liquidity, see GROSSMAN and MILLER (1988). In empirical work on stock returns and trading activity, JAMES and EDMISTER (1983) find «no evidence» consistent with the presence of a liquidity premium. However, more recent research does report a link between returns and the bid-ask spread.

The research on market volatility owes much to SHILLER (1989). In a series of articles published during the 1980s, SHILLER suggested that the volatility of stock prices is excessive relative to the movements in dividends. Later work broadly supports the hypothesis of excess volatility. Whereas headline news stories often cause little reaction in prices, large price shocks are not easily traced back to identifiable news (ROLL, 1988). SCHWERT (1989) finds that changes in market volatility are only weakly related to macro-economic factors. The volatility studies underscore the need to better understand the psychology of trading. Relevant stylized facts include (i) the positive correlation between volume and price changes; (ii) the positive correlation between volume and absolute price changes; (iii) persistence in volatility and volume shocks, so that turbulent periods alternate with calm periods; (iv) higher price volatility when markets are open than when they are closed.[7]

DE LONG et al. (1990) construct an asset pricing model with both rational and noise traders. Because of the unpredictability of market sentiment and the short horizon of rational investors, the market «has a life of its own.» In equilibrium, prices are lower than they would be without noise, because rational risk-averse investors must be compensated for bearing non-fundamental risk, i.e., the chance that noise traders suddenly turn bearish. In subsequent work, DE LONG et al. (1990) show that rational arbitrage may be destabilizing. Rational traders who act strategically may widen the gap between price and value, e.g., when positive feedback traders chase imaginary price trends.

Who is a noise trader? LEE et al. (1989) interpret the average discount on closed-end mutual funds as a proxy for noise trader sentiment. The main group of investors in closed-end funds are small *individual* investors. Much of the research on size-related asset pricing anomalies points in the same direction, since small firms are mostly held by individual investors.

On the other hand, the business press often singles out *institutional* investors as noise traders. CUMMINS et al. (1980) and BADRINATH et al. (1989) discuss the restrictions that stem from both common law and the Employee Retirement Security Act of 1974 (ERISA) and that narrow the investment choices of pension funds. Under ERISA, institutional managers are fiduciaries who are required to perform their duties «with the care, skill, prudence, and diligence ..that a prudent man.. would use.» In practice, investment decisions depend on external validation since «a prudent investment» is defined by what other professionals in the field consider appropriate. Thus, ERISA virtually writes herding behavior into law. DEL GUERCIO (1996) raises the same issue and presents data suggesting that bank managers are more sensitive to prudent-man laws than are mutual funds. In a broader context, BRENNAN (1993), SCHARFSTEIN and STEIN (1990) and TRUEMAN (1988, 1994) also describe herding and noise trading as phenomena that are driven by reputational concerns and by legal or other sanctions on deviant behavior.

7. These and other stylized facts are surveyed by KARPOFF (1987) and SHILLER (1989).

Herding may yet occur for a series of different reasons. DEVENOW and WELCH (1996) present a useful survey of rational herding. ARONSON (1992) discusses the psychology of conformity, ranging from mere compliance to the internalization of beliefs and values. Possible herding mechanisms include (i) the basic human need to create a meaningful self-image (ELLUL, 1965; SUNSTEIN, 1995); (ii) the salience of socially-shared mental frames in ambiguous decision situations (ZALLER, 1992); (iii) payoff externalities in information acquisition (FROOT et al., 1992; HIRSHLEIFER et al., 1994); and (iv) informational cascades (BANERJEE, 1992; BIKHCHANDANI et al., 1992).

The empirical research that studies noise trading and herding is modest but growing. Noise may produce a transitory component in stock prices which is reversed over the long term. DUFFEE (1992) finds that the serial correlation of monthly returns changes with trading volume. Large transitory price shocks tend to coincide with unusual volume. BADRINATH et al. (1989) report that companies that attract institutional interest tend to be larger, with better past price performance, and with lower price volatility than other companies.[8] GRINBLATT et al. (1995) document the tendency of mutual funds to buy past winners and to buy and sell the same stocks at the same time (in excess of what is expected by pure chance). However, in a study of pension funds, LAKONISHOK et al. paint an image that «pension managers herd relatively little in their trades in large stocks .. which is where over 95% of their trading is concentrated» (1992, p. 24). Evidently, it may also be that institutional investors pursue a limited set of investment styles and strategies that, in the end, largely offset one another.

Finally, past research examines the links between asset prices and trading behavior in the context of financial regulation. Throughout history, there has been suspicion about the performance of unregulated, highly liquid markets (GALBRAITH, 1990; NEAL, 1990; WHITE, 1990). At various times, taxes and margin requirements on credit-financed security purchases have been proposed to curb volatility. Optimistic speculators are always tempted to use leverage, causing upward price pressure. If prices go up, the speculators may borrow more, driving prices even higher. The pyramiding process is reversed if there is a price decline that leads to margin calls and a liquidation of positions. High margin requirements may reduce these domino effects.[9] STIGLITZ (1989) and SUMMERS and SUMMERS (1989) argue in favor of high short-term capital gains taxes and transaction taxes. The taxes have a lock-in effect since taxes are only paid when capital gains are realized. Small deviations between price and value are no longer economically viable arbitrage opportunities. In principle, reduced market liquidity should raise the liquidity premium. On the other hand, a cut in noise trading also cuts the noise trader risk premium. The empirical evidence on transaction taxes and margin requirements is

8. Further somewhat mixed evidence on portfolio tilting appears in ARBEL et al. (1983), KANG and STULZ (1995), LAKONISHOK et al. (1991), and SHILLING and MALPEZZI (1996).

9. In a more detailed model, KUPIEC and SHARPE (1991) suggest that the impact of binding margin requirements depends on general market conditions (bullish vs. bearish).

mixed. Whereas HARDOUVELIS (1988) concludes that high margin requirements reduce volatility, HSIEH and MILLER (1990) and others contend that the results are spurious.[10]

III. DATA AND METHODS

Our purpose is to investigate whether the average level and the volatility of stock returns are influenced by shareholder trading practices and shareholder identity. To maintain comparability with earlier work, our methods mirror FAMA and FRENCH (1992). Below, we first describe the sample selection methods. Next, we detail the empirical hypotheses and testing procedures. Finally, we characterize the sample.

A. *The Sample*

We use three types of data: (i) daily and monthly stock returns for stocks listed on the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX), provided by the *Center for Research on Security Prices* at the University of Chicago; (ii) annual accounting numbers and trading volume data, provided by COMPUSTAT; (iii) quarterly reports of the number of institutional investors and their holdings provided by the O'Neil database, a publication of William O'Neil Co. (September 1979–June 1991). The following sample selection criteria are employed:

1. For every security, in July of year t, we require a time series of monthly returns for at least 36 months from years t–2 through t+1. Depending on data availability, between 24 and 60 months of prior to July of t are used to estimate (pre-ranking) CAPM-betas.
2. We require the following Compustat annual data items for year t–1: #24 (closing price); #25 (common shares outstanding); #28 (common shares traded); #60 (common equity). We include firms that eventually disappeared because of merger, bankruptcy, or other reasons.[11]
3. Securities that are part of the S&P 40 Financial Index are excluded. Similar to FAMA and FRENCH (1992), we also drop companies with negative book values.[12]

For the tests with institutional holdings, data limitations force us to rely on more limited samples. For a firm to be included, quarterly institutional holdings must be available in the O'Neil database for each quarter between 1980 and 1990.[13] Firms that disappear –

10. SCHWERT and SEGUIN (1993) offer a useful review of all the theoretical and empirical arguments, as well as further references.
11. Although not required, the following descriptive data items are also extracted: #6 (assets); #12 (sales); #18 (income before extra-ordinary items and discontinued operations); #26 (dividends per share); and #27 (cumulative adjustment factor) and #74 (deferred taxes).
12. The number of such firms varies annually (between 1 and 55). The average is 16 firms.
13. The universe of institutions followed by O'Neil changes over time. In 1980, there were two major

say, because of acquisition – are excluded. Because of the merger wave of the 1980s, this screen excludes several large firms. In addition, the companies must be listed on the NYSE or AMEX for the entire 1980–1990 period. A total of 425 firms satisfies all requirements for inclusion.

The O'Neil database divides institutional investors into four groups: advisors (money managers), mutual funds, banks and insurance companies. The number of advisors and mutual funds followed by O'Neil increased steadily during the 1980s. The number of insurance companies and banks stayed relatively constant.[14]

B. Hypotheses

What is the relationship between trading behavior and expected returns? In the context of the cross-sectional return models studied by FAMA and FRENCH, required returns (R) systematically vary with beta (β), firm size (MV), and the book-to-market ratio (BM):

$$R_i = \alpha + \gamma_1 \beta_i + \gamma_2 MV_i + \gamma_3 BM_i + \gamma_4 V_i + \gamma_5 X_i + \gamma_6 Z_i + \varepsilon_i \tag{1}$$

We add two sets of variables. The first set has to do with the size of the investor base and share turnover (V). The second set of variables has to with the motives for trading. Specifically, we try to measure non-informational trading, e.g., trading that is motivated by the fact that the company belongs to the S&P index (X). (Z defines additional control variables.) Since our analysis follows methods originally developed in FAMA-MACBETH (1972), equation (1) is estimated monthly between 1970 and 1990. Our tests examine the statistical significance of the estimates of j (j = 1, .., 6) averaged over 240 months. The t-statistics compare the average estimated slope to the time-series standard error, so that

$$\bar{\hat{\gamma}}_j = \sum_{t=1}^{T} \frac{\hat{\gamma}_{jt}}{T} \quad and \quad t\left(\bar{\hat{\gamma}}_j\right) = \frac{\bar{\hat{\gamma}}_j}{s\left(\hat{\gamma}_{jt}\right) / \sqrt{T}} \tag{2}$$

where T is the number of months for which equation (1) is estimated.

In frictionless markets with rational agents, expected stock returns and return volatility are not influenced by shareholder horizons and identity. It is immaterial who owns the

changes: (i) the number of mutual funds rose from 378 to 547; and (ii) the advisors group was added. To maintain consistency, we use data for all four groups from the 3rd quarter of 1980 to the 4th quarter of 1989.

14. At the end of each quarter, mutual funds, banks, and insurance companies file SEC 13F forms while money managers file SEC N1Q forms. These forms are the source of the data. Because some advisors are affiliated with banks and insurance companies, their holdings are reported twice.

firm or what the motivation is for those who trade its shares. There cannot be any clientele effects. In contrast, the noise trader models predict that, in the cross-section, average stock returns and return volatility increase with noise trader risk. If specific groups of institutional investors can be identified as noise traders, a positive risk premium should be associated with the size of their holdings.

In practice, trading behavior is a function of shareholder identity. For example, it is well-known that the typical individual investor trades much less, relative to the market value of his portfolio, than do institutions. Among institutional investors, the portfolios of money management firms show more turnover than do those of insurance companies. The regulatory framework also varies. Because differences in objectives, strategy, and regulation may matter for asset pricing, we develop some tests with variables that capture shareholders' identity. The O'Neil database allows us to distinguish between mutual funds, advisors, banks, and insurance companies. Depending on our purpose, we use one of three measures of institutional group holdings: the fraction of all institutionally-owned shares held by a group; the number of institutional investors in the group; or the fraction of the firm's shares outstanding held by that group.

Our discussion suggests several (not mutually exclusive) hypotheses:

1. The *capital asset pricing model* predicts that $\gamma_1 > 0$ and that all other estimates $(\gamma_2,..,\gamma_6)$ are statistically indistinguishable from zero.
2. FAMA and FRENCH (1992) find that $\gamma_1 = 0$, $\gamma_2 < 0$ and $\gamma_3 < 0$. Since their empirical model ignores the effects of trading behavior, it is predicted that $\gamma_4 = \gamma_5 = 0$.
3. *Herding and incomplete information models* assume that the investor base for each firm is limited. Any investor only pays attention to a subset of all traded securities because of information gathering costs. The costs are asset-specific and depend on company visibility, e.g., news media coverage and analyst reports (MERTON, 1987). Standards of prudence, tradition, regulation, and law reinforce the psychological benefits of herding. Past turnover statistics measure whether a company attracts investor interest. It is predicted that well-known firms earn lower equilibrium returns, $\gamma_4 < 0$.
4. The *noise trader approach* argues that non-informational trading adds an element of risk so long as it is non-diversifiable, e.g., if it affects market indexes. X also measures institutional trading that is not a reaction to news, e.g., the flow of funds in-and-out of mutual funds. Either way, it is predicted that $\gamma_5 > 0$.
5. In contrast to noise trader models, *liquidity models* maintain that investors always prefer more trading opportunities to less, no matter the trading motive. Thus, in this case, both γ_4 and γ_5 should be below zero.

The noise trader approach predicts that excessive trading destabilizes prices and adds volatility. A positive correlation between volume and later volatility would be consistent with the prediction. We measure current volatility by the standard deviation of daily returns and we run monthly regressions as follows:

$$\sigma_i = \alpha_* + \lambda_1 \beta_i + \lambda_2 MV_i + \lambda_3 BM_i + \lambda_4 V_i + \lambda_5 X_i + \lambda_6 DE_i + \eta_i \tag{3}$$

It is important to know more about the determinants of return volatility irrespective of whether volatility is priced. To maintain comparability with equation (1), we use similar variables on the right-hand-side: beta, size, and book-to-market ratio. DE_i represents the debt-to-equity ratio, an attempt to control for leverage effects (CHRISTIE, 1982).

If trading becomes more costly and, ceteris paribus, is reduced, both volatility and expected returns may fall. This is the intertemporal prediction of HARDOUVELIS (1988), STIGLITZ (1989) and others. It is an empirical question of whether the rational or the noise traders curtail their trading more. HSIEH and MILLER (1990) take the position that periods with higher margin requirements are associated with higher asset price volatility. We study the cross-section of R_i and σ_i for various institutional regimes and we check whether the relationship changes.

C. Details

We now offer a few details on the methods that are used to estimate beta, volatility, and share turnover.

We annually estimate a pre-ranking *beta* for each firm, using monthly returns for the previous five years. Following FAMA and FRENCH (1992), we annually rank all companies by market value at the end of June and we form decile size portfolios. Within each size portfolio, all firms are ranked a second time by their pre-ranking betas. This method leads to 100 size-beta portfolios in each year. For the 100 size-beta portfolios, we compute portfolio returns for the subsequent twelve months (starting in July). The portfolio returns are equally-weighted averages of all returns. These procedures are repeated for the period between July 1970 and June 1990. In the end, we have 240 monthly returns for each size-beta portfolio. To estimate post-ranking betas, we regress the portfolio returns on the contemporaneous return for the value-weighted NYSE market portfolio. The full-period post-ranking portfolio betas are assigned to each individual firm within the size-beta portfolio.

We also create for each company a time-series with monthly observations of return *volatility*. The calculation is based on daily returns. We find the standard deviation of returns relative to the average daily return for the month.

We compute *share turnover* (trading volume) annually. For each firm, we divide the annual number of shares traded in the *previous* year by the number of shares outstanding at the end of the previous fiscal year.

D. Sample Characteristics

Table I describes the sample firms over the period from 1970 through 1989. The sample size ranges from 1'472 to 1'892 firms. The number of firms included in the S&P Index ranges between 302 and 408. Although not shown in Table I, a comparison of median and average market values of equity reveals that there are many more small firms in the sample than there are large firms. The volume statistics listed in Table I are the values reported in the *New York Stock Exchange Fact Books*. They are the total annual trading volume on the NYSE divided by the total number of outstanding shares. We also report year-by-year average total returns for all large company stocks, as well as the annualized monthly standard deviations of the index of large company stocks. Both sets of statistics are reported by *Ibbotson Associates*.

IV. RESULTS

A. Decile Portfolios

Before discussing the regression results, we first describe decile portfolios of firms ranked by market value (*MV*) and share turnover (trading volume) (*V*). If we rank on both variables, we first rank on turnover, next on market value.[15] The decile portfolios are produced each year to allow for changes in turnover and size over time. By construction, there are an equal number of firms in each decile portfolio. (Leftover firms between the 5th and 6th decile are removed.) Portfolio characteristics are computed for the entire sample period.

Table II reports median values of FAMA-FRENCH variables for decile portfolios ranked by volume. The securities have turnover ratios that span a wide range, with the median turnover ratios ranging from 7 to 113 percent. Stocks with high *V* tend to be larger firms with higher betas and higher assets-to-book equity ratios than stocks with low *V*. High-volume stocks yield below-average returns with above-average volatility. These results agree with JAMES and EDMISTER (1983). We also present the characteristics of the subset of S&P-500 stocks included in the full sample. Although it is often assumed that S&P stocks are heavily traded, the range of their turnover ratios is just as wide as for the full sample. There are approximately 35 stocks in each turnover decile in each year. The stocks in decile ten have trading volume that is dramatically higher than those in decile nine. High-volume S&P stocks yield below-average returns. These companies tend to be smaller than average, with higher than average betas.

To get a sense of how the above results compare with portfolios ranked by other criteria, Table III reports statistics for portfolios ranked by market value and by the percentage of institutional holdings. The medians in the top panel indicate that small

15. As it happens, the results are similar for the reverse method.

companies have higher betas and higher volatility but, during the 1970–89 period, similar returns to large companies. The bottom panel teaches us that high institutional ownership is associated with high turnover and, by comparison, lower betas.

In order to evaluate possible interactions between market value and turnover, we form ten size portfolios within each turnover decile. Table IV lists characteristics for 40 turnover-size portfolios (the 1st, 4th, 7th, and 10th size portfolio within each trading volume portfolio). The various panels of figure 1 depict similar data for the 2nd, 4th, 6th, 8th, and 10th size deciles within each turnover decile. Table IV shows that firms of all sizes are evenly scattered throughout the turnover deciles. Betas increase with V and decrease with MV. High-V stocks have lower book-to-market ratios than low-V stocks, particularly if the company is small. The volatility data in Table IV are average annual cross-sectional medians of standard deviations of daily returns computed for each month of the year. Definitely, smaller firms offer returns that are much more volatile than larger firms. For large companies, there is a strong positive co-movement between turnover and volatility, even within the subsample of S&P-index stocks (not shown in Table VI).[16]

Figure 1 (panel A) pictures the relationship between median annual returns and turnover, also seen in Table IV. Annual returns are compounded monthly returns. Controlling for size, stocks which trade less often earn higher returns. This negative relation between past turnover and average annual returns is robust to the portfolio formation procedure. The drop in expected returns is especially prominent for small companies. Overall, the decile statistics support the herding hypothesis which predicts that returns are lower for stocks that are more visible and therefore more socially acceptable.

Although not presented in Table IV, the inverse link between returns and trading volume is also observed for a sample of S&P stocks only. Thus, it seems likely that the negative relation is more than a liquidity or transaction cost effect. One further robustness check asks whether the link between returns and the level of trading volume also applies to portfolio returns and *changes* in trading volume (ΔV), say, over the previous two years. Perhaps ΔV measures the popularity flow of a company – which itself may be related to performance. People may want to buy a stock that is going up in price. It is the case that large changes in volume are associated with higher return volatility. However, there is no consistent relation between ΔV and returns.

B. The Cross-Section of Expected Returns

We now discuss the FAMA-FRENCH regressions with the standard explanatory variables (β, MV) as well as trading volume (V) and a S&P index variable (X). In addition, we use

16. Another aspect of the data that Table IV omits is that ranking by size does not amount to a finer sort by turnover. In other words, within each turnover portfolio, the trading volumes for different size portfolios are indistinguishable.

either the natural logarithm of the book-to-market value of equity ratio (*BM*), or both the natural logarithm of the asset to market value of equity ratio (*AM*) and the natural logarithm of the asset to book value of equity ratio (*AB*). These cross-sectional regressions are estimated monthly over the period between July 1970 and June 1990.

Each time, we report the average coefficients and the FAMA-MACBETH t-statistics.

Table V compares our own findings to those reported in FAMA and FRENCH (1992). While the sample periods and firms differ, the estimates are surprisingly similar in both sign and magnitude. Clearly, β is inadequate in explaining average return differentials between firms. (Note, however, the 1975–80 subperiod.) While size and book-to-market ratios perform somewhat better, the results are less than convincing for most subperiods.

Does high turnover push up stock prices and lower expected returns? The results in Table VI strongly indicate that this happens. As predicted, the sign of the coefficient on turnover is consistently negative. Although the negative risk premium – or discount – persists over time, its magnitude varies somewhat. It is more negative during the 1980s. With the FAMA-FRENCH variables included as control variables, the discount on turnover is –.584% per month or about *minus* 7 percent per year on a stock with a turnover of 100%. On a stock with average trading volume of about 30 percent, a doubling reduces average annualized returns by about 2 percent.

The S&P variable (X) controls for non-informational index trading. X is a dummy variable that is set equal to one if the stock is in the S&P 500 Index and that is zero otherwise.[17] The coefficient on X is positive, indicating that S&P stocks outperformed non-S&P stocks by about 6% per year, all else equal. This result plainly contradicts the view that S&P stocks are more liquid and hence earn lower returns. (The result even holds for the 1970–1975 subperiod.) The relationships between R, V, and X appear to strengthen after index arbitrage began in the early 1980s: the relationship between returns and turnover becomes somewhat more negative while the link between returns and S&P listing becomes significantly positive. The negative premium on V supports the arguments of DEMSETZ (1968) who proposes that decreased trading activity increase transaction costs. Because risk-adjusted returns *after* transactions costs are equated in equilibrium, inactive stocks pay a liquidity premium. The negative relationship also agrees with DUFFEE's (1992) results that trading volume shocks cause return reversals. If noise traders use positive feedback strategies and if trading volume measures the volume of noise trader activity, large transitory components may be induced in stock prices.

If turnover is merely a proxy for market liquidity, then adding another liquidity measure to the regression may affect the slope coefficients on V and X. Consistent with

17. The S&P universe is important in asset management for reasons other than index trading. The S&P consists of large well-known companies with highly liquid securities. Thus, investors can purchase substantial dollars amounts of equity in S&P-firms without accumulating a high percentage ownership and without causing price pressure. Further, the S&P index also serves as a formal or informal benchmark in performance evaluation.

prior literature, we obtain from the *Center for Research in Security Prices* the date of the first month of each security's listing on the stock exchange. This variable allows us to estimate the age of the firm. However, this variable is only weakly related to returns and the results discussed above hardly change.

How does the January phenomenon affect expected returns? Table VII presents the premia for each month. Certainly, the turnover discount is far more negative in January than in other months and the S&P discount is more positive. For a stock with a turnover of 100%, the average return in January is reduced by –2.2%. It is also interesting to note that the risk premium on beta is positive in January, and that all FAMA-FRENCH variables have significant explanatory power in January. However, removal of the January data does not extinguish the discount on V or the premium on X during other months. The magnitude of the coefficients is slightly reduced but their statistical significance remains. In contrast, the FAMA-FRENCH variables do lose, on average, their explanatory power during months other than January. Judging by month, the turnover premia are significantly negative in January, March, July and September. The results suggests a quarterly pattern, possibly explained by window dressing, i.e., the periodic rebalancing of portfolios by money managers.

Finally, we consider whether the results are influenced by regime shifts. For instance, the S&P 500 futures contracts started trading in April 1982. Also, during the 1970–1990 period, there were five different regimes for initial margin requirements and four regimes for the length of the holding period that determines whether taxpayers qualify for low long-term capital gains taxes. Our tests do not detect systematic and reliable differences between subperiods, except in the case of the S&P futures contract. After April 1982, the coefficient on V becomes more negative (from –.49 to –.73) and the coefficient on X becomes more positive (from .43 to .62). All coefficients are strongly significant.

C. The Cross-Section of Volatility

Does high trading volume increase stock return volatility? The liquidity hypothesis answers «no.» High volume reduces transaction costs and, in rational markets, all price changes reflect changes in intrinsic value, at least within a transaction cost band. However, it may still be that the dynamics of the information process is such that, in fact, high turnover and high volatility accompany the arrival of important news, so that there is correlation without causation. A negative link, if it were present, would seem to contradict noise trader models since market sentiment creates an additional source of volatility – besides news about fundamentals.[18]

18. CHRISTIE and HUANG (1994) ask a related but different question: whether the cross-sectional standard deviation of returns depends on market conditions. They find that cross-sectional clustering is reduced during periods of market stress (i.e., large average price changes). The authors suggest that this finding contradicts the notion of herding and supports rational pricing models.

The results in Table VIII show that, in the cross-section of companies, high-turnover securities tend to be more volatile in price. The coefficient on past trading volume is positive and strongly significant. (The result survives even if we use the *change* in turnover.) Further, if a firm is part of the S&P index, its stock is on average more volatile than if it is not. The coefficient on X is positive in all subperiods except for 1980–1985. Ceteris paribus, the stocks of companies with large equity capitalization and with high book-to-market ratios are more volatile than other stocks. Since CHRISTIE (1982), it is well-established that financial leverage is a determinant of stock return volatility. We confirm this result.

Robustness tests, not shown in Table VIII, detect no monthly seasonality in the relationship between trading volume and volatility. Regime shifts relating to margin requirements, capital gains taxes, and the introduction in 1982 of the S&P futures contract do not matter much either.

D. Returns, Volatility, and Institutional Holdings

Two types of tests are performed with the sample of firms for which we have institutional ownership data. As mentioned above, there are four types of institutions investors listed in the O'Neil database: Mutual funds, advisors, banks, and insurance companies. First, we form decile portfolios of firms ranked by the fraction of institutionally-held shares held by each institutional group. This ranking is repeated for each quarter between the 1st quarter of 1980 and the 4th quarter of 1989. We list the average median volume and beta for each decile portfolio. Second, we estimate FAMA-FRENCH cross-sectional regressions. Once again, we examine the average slope coefficients and the associated t-statistics.

Table IX shows that, during 1980–1989, trading volume and beta vary systematically with the fraction of institutionally-held shares held by each institutional group. If mutual funds or money management companies control a high percentage of the institutionally-held shares, volume and beta tend to be high. Just the opposite is true for banks, with insurance companies falling somewhere in between. Thus, we confirm our earlier suspicion (and the results of previous studies) that institutional investors do not act in one single block.

Finally, Table X teaches us that expected returns and volatility depend on the number of mutual funds that own a company (at the end of the previous quarter). Since many mutual funds are indexers, and since management has little control over in- and outflows of funds, these results strongly support the noise trader hypothesis. It is, after all, quite plausible that many clients of mutual funds are positive feedback traders, always chasing last year's winners. Finally, Table X also shows that, if «more conservative» banks and insurance companies own a security, its volatility (in the cross-section of assets) tends to be lower. Surprisingly, none of the findings with trading volume and the S&P dummy variable change once institutional ownership data are included.[19]

V. CONCLUSION

Herding may be understood in a number of ways. It may be interpreted as rational learning (see, e.g., DEVENOW and WELCH, 1996), it may be driven by rational concern to stay in the good graces of other people (see, e.g., SCHARFSTEIN and STEIN, 1990), it may relate to notions of prudence and accountability, and so forth. It could also be superstitious and largely irrational, as MACKAY (1841), LE BON (1895), or PARETO (1902) believe.

In this paper, we ask whether there is evidence that, in the cross-section of stocks, returns and volatility are influenced by shareholder trading practices. People are human, and cognitive development naturally implies a degree of conformist behavior, particularly when it comes to risky and ambiguous tasks (ARONSON, 1992). Prior beliefs that trading is partly based on emotion, and that many investors experience the same sentiments at the same time, are the traditional building blocks for theories and policy proposals that deplore excessive trading. Noise trader models formalize and refine these old arguments.

We collect trading volume and institutional ownership data, and we use standard methods in empirical asset pricing research. The main hypothesis is that investors, who are reluctant to deviate from accepted norms, find a stock more attractive if many other people already trade it. We find overwhelming evidence of a negative relationship between past trading volume and security returns. This relationship is robust to alternate specifications of control variables. It is relatively stable across time periods and it is not exclusively a January phenomenon. The results are consistent with the notion that herds offer «protection in numbers.» They may also arise in the context of a rational model with non-trivial information costs (e.g., MERTON, 1987). The data may further be interpreted as consistent with the neglected stock anomaly (ARBEL et al., 1983), or as evidence of a liquidity premium that is separate from size and book-to-market effects. All these theories imply that, ceteris paribus, investors are willing to pay somewhat more for a security that many other people also choose to trade.

Our finding that the inclusion of a stock in the S&P index raises its expected return is less easily rationalized. Certainly, S&P stocks are highly liquid and it is not difficult to obtain company information. Perhaps the finding is specific to our sample period – a consequence of the extraordinary growth of the money management industry during the 1970s and the 1980s. Yet, the result is exactly what noise trader models predict. S&P stocks are commonly traded for non-informational reasons, e.g., as part of a package that mirrors the index. This behavior adds an element of risk that, in equilibrium, should be priced. Interestingly, following the introduction of trading of the S&P futures contract in 1982, the average premium on S&P stocks increased further.

19. The results in table X appear robust. For instance, they do not change in any meaningful way if we use the number of mutual funds (or advisors, etc.) that own the company at the end of the second-to-last quarter (rather than the last quarter).

We find that price volatility is higher for companies with large share turnover and for companies that belong in the S&P index. A negative link would have undermined noise trader theories but the apparent positive link may still occur for many reasons, rational and irrational. If an investor has a short horizon and believes that other traders are less than fully rational, he has no choice but to pay more attention to the daily news. This is KEYNES' beauty contest.

Tests with institutional ownership variables produce conflicting results. However, there is no doubt that mutual funds, advisors, banks, and insurance companies differ greatly in the stocks that they select, particularly when it comes to turnover or beta. Because institutional investors do not constitute one single block, it may be misguided to look for a link between aggregate institutional ownership, returns, and volatility. However, depending on the type of investor, trading patterns can make a difference (see, e.g., DEL GUERCIO, 1996, or GRINBLATT et al., 1995). Apparently, in our sample, if the number of mutual funds that hold a company (or the change in that variable) goes up, expected returns go up. Again, this is consistent with noise trader models, since it is well-known that many mutual funds are indexers that buy and sell stocks depending on the flow of investor funds. It is important to observe that return volatility is also positively related to mutual fund ownership. In the case of the insurance companies, the link with volatility is negative, and so is the return premium.

We end with the ritual cry for further work. It would be interesting to examine the link between past performance and the perceived attractiveness of strategies, e.g., value vs. growth investing. In our context, it may well be that trading volume somehow proxies for the winner/loser effect, since it is known that volume goes up for past winners, and slows down to a trickle for losers (LAKONISHOK and SMIDT, 1986). A second topic for further research is the role of trading volume and the S&P dummy variable in the FAMA-FRENCH regressions. Did we unwittingly discover two new asset pricing factors? We suspect that many readers – including those who are sympathetic to the role of investor psychology – will be tempted to put forward alternative interpretations of the data.

Table I
Characteristics of the Sample and the Sample Period

We show the total number of firms in the sample for each year, as well as the number of firms that are in the S&P-Index. Average trading volume is reported as a fraction of the number of shares outstanding (x 100). Average dividend yield is reported as a fraction of firm share price x 100. Both are measured at the end of the fiscal year. The year-by-year average total return for all large company stocks (R) and the annualized monthly standard deviation of the index of large company stocks (s_t) are taken from the *Stocks, Bonds, Bills, and Inflation 1996 Yearbook* by Ibbotson Associates.

Year	# Firms	# S&P	Volume	Yield	R_t	s_t
1970	1'499	302	41	3.6	4.01	21.60
1971	1'605	318	28	3.7	14.31	15.64
1972	1'701	327	36	3.3	18.98	7.80
1973	1'774	333	36	3.2	−14.66	12.15
1974	1'865	339	26	5.0	−26.47	18.74
1975	1'930	344	18	8.1	37.20	24.38
1976	1'903	347	23	5.1	23.84	16.89
1977	1'863	348	27	4.1	−7.18	8.97
1978	1'805	351	27	4.5	6.56	17.92
1979	1'763	355	38	5.1	18.44	15.79
1980	1'735	361	37	4.8	32.42	24.19
1981	1'693	365	46	4.8	−4.91	12.44
1982	1'668	371	40	5.2	21.41	23.38
1983	1'690	376	45	4.5	22.51	12.02
1984	1'665	382	55	3.9	6.27	15.00
1985	1'626	393	46	4.3	32.16	15.85
1986	1'618	406	52	4.0	18.47	21.39
1987	1'613	406	61	4.3	5.23	34.04
1988	1'639	408	65	5.3	16.81	11.69
1989	1'684	406	46	6.7	31.49	16.03

Table II
Medians for Decile Portfolios of Firms Ranked by Trading Volume

Decile portfolios are formed by rankings on turnover. All medians are averaged over the 1970–1989 period. In total, there are 3,421 firms in each decile. The top panel show the median decile values for all companies in the sample. The bottom panel shows the median decile values for all companies in the sample that are in the S&P Index. *V* is share turnover in percent. β represents the FAMA-FRENCH beta. *MV* is the market value of equity in $million. *AM* is the ratio of total assets to market equity. *AB* is the ratio of total assets to book equity. *R* denotes the annual portfolio return x 100 (compounded from monthly returns). σ is the volatility of daily returns calculated in each month averaged over the 12 months in the year. *R* and σ are for the year subsequent to the portfolio ranking.

Decile	*V*	β	*MV*	*AM*	*AB*	*R*	σ
			Medians for All Companies				
Low	7	.77	60	2.35	1.93	14	1.8
2	13	.87	58	2.40	2.01	13	1.9
3	17	.87	77	2.30	1.99	13	1.9
4	21	.90	93	2.20	1.96	12	2.0
5	26	.99	95	2.16	1.96	12	2.1
6	32	.79	100	2.09	1.99	12	2.1
7	39	.99	96	2.16	2.01	10	2.3
8	50	1.06	107	2.16	2.18	15	2.6
9	64	1.11	107	2.12	2.25	15	2.8
High	113	1.15	113	1.91	2.34	9	3.0
			Medians for S&P Companies Only				
Low	11	.60	841	1.49	1.77	20	1.5
2	17	.68	943	1.58	1.87	15	1.5
3	20	.69	1'057	1.46	1.90	14	1.6
4	23	.71	996	1.63	1.96	13	1.6
5	27	.71	994	1.57	1.89	14	1.6
6	33	.76	927	1.68	1.93	13	1.7
7	39	.81	909	1.63	1.97	12	1.8
8	47	.88	716	1.63	1.98	12	2.0
9	62	.98	640	1.75	2.04	11	2.1
High	103	.99	561	1.50	2.02	11	2.4

Table III
Medians for Portfolios of Firms Ranked by Market Value and Institutional Holdings

Decile portfolios are formed by ranking on market value (1970–1989) or by ranking on institutional holdings (1979–1990). Institutional holdings (*IH*) is the fraction of all shares held by institutional investors (mutual funds, advisors, banks, and insurance companies combined.) There are either 3,427 companies in each decile (ranking by market value) or 1,411 (by institutional holdings). The exact sampling criteria are described in the main text. All medians are averaged over the period. Variables are defined in Table II. In the bottom panel, *QR* is the average median quarterly return, found by compounding the monthly returns. *BM* is the book value of common equity *plus* balance-sheet deferred taxes divided by the market value of equity.

Decile	V	β	MV	AM	AB	R	σ
			Firms Ranked by Market Value, 1970–1989				
Low	20	1.30	5	3.58	2.03	10	3.8
2	24	1.24	12	2.81	1.97	8	3.0
3	28	1.11	22	2.58	2.09	11	2.7
4	31	1.12	37	2.37	2.03	10	2.5
5	33	1.09	59	2.02	2.03	11	2.3
6	32	.98	101	2.03	2.04	12	2.1
7	29	.95	175	1.91	2.04	13	1.9
8	32	.87	323	1.73	1.96	11	1.8
9	30	.81	689	1.78	2.06	11	1.7
High	25	.66	2'322	1.40	1.92	11	1.6
Decile	V	β	MV	BM	IH	QR	σ
			Firms Ranked by Institutional Holdings, 1979–1990				
Low	56	1.26	628	2.03	17	4	2.1
2	53	1.20	645	2.08	32	5	1.9
3	57	1.21	770	2.08	38	4	1.9
4	61	1.17	921	1.93	43	5	1.9
5	65	1.15	969	1.99	48	5	1.8
6	61	1.17	990	2.01	53	4	1.8
7	61	1.13	1'034	2.01	57	5	1.8
8	67	1.12	1'039	2.12	61	5	1.8
9	71	1.13	1'003	2.08	66	5	1.8
High	82	1.15	747	2.23	76	5	1.8

Table IV
Medians for Portfolios of Firms Ranked by Trading Volume and Market Value

Decile portfolios are formed by ranking on share turnover first, then on market value. The medians shown below are averaged over the 1970–1989 period. All variables are as defined in Table II. The turnover deciles are the columns in the table; the size deciles are the rows. We show medians for the small company decile (decile #1), the 4th and 7th deciles, and the large company decile (decile #10)

Volume	Low	2	3	4	5	6	7	8	9	High
Market Value										
					Annual Return (R)					
1	13	13	10	9	8	8	9	−1	−1	−9
4	14	13	17	12	11	9	14	11	7	2
7	13	13	16	13	13	12	12	13	9	0
10	14	15	12	10	13	11	8	10	9	7
					Volatility (σ)					
1	3.7	3.8	4.0	3.8	3.9	3.7	3.7	3.5	3.6	3.6
4	2.0	2.2	2.1	2.2	2.3	2.4	2.6	2.7	2.8	3.0
7	1.6	1.5	1.6	1.6	1.8	1.8	2.0	2.1	2.4	2.7
10	1.5	1.4	1.5	1.4	1.5	1.6	1.7	1.8	1.9	2.2
					Beta (β)					
1	1.11	1.11	1.21	1.21	1.30	1.32	1.35	1.32	1.35	1.38
4	.88	.97	1.01	1.02	1.01	1.05	1.11	1.19	1.21	1.23
7	.76	.80	.80	.82	.87	.87	.94	.98	1.01	1.10
10	.51	.60	.60	.60	.66	.66	.69	.71	.76	.96
					Market Value of Equity (MV)					
1	4	3	4	4	4	6	6	7	8	11
4	28	28	39	41	37	38	38	34	39	53
7	157	136	214	253	234	233	272	155	125	154
10	3'992	1'434	1'797	2'948	2'305	2'607	2'103	1'872	1'515	1'114
					Book-to-Market Ratio (BM)					
1	1.87	2.08	1.81	1.74	1.74	1.57	1.50	1.36	1.38	1.23
4	1.36	1.18	1.18	1.24	1.24	1.14	1.15	1.06	.99	.96
7	1.00	.99	1.00	.96	.90	.95	.92	.92	.89	.81
10	.92	.77	.80	.76	.82	.77	.69	.71	.78	.69

Table V
Estimated Fama-French Risk Premia

For every month during the sample period, we run cross-sectional regressions using the methods of FAMA-FRENCH (as pioneered by FAMA-MACBETH). All variables are defined in Table II. We employ the natural logarithms of *MV*, *MB*, *AM* and *AB* rather than their raw values. Each panel shows a separate set of average cross-sectional regression slopes and their associated t-statistics (in brackets). For example, in the top panel, beta is the only explanatory variable. In the bottom panel, *MV*, *AM* and *AB* are the explanatory variables. The FAMA-FRENCH results for 7/1963 to 12/1990, taken from their 1992 paper, are reported in the first column. The second column shows the full period estimates of average slope coefficients for our sample between July 1970 and June 1990. The four 5-year periods results shown in the 3rd through 6th columns are 7/1970 to 6/1975, 7/1975 to 6/1980, and so on. The estimates are reported in percent per month, i.e., multiplied by 100.

	Regression Periods					
	FAMA-FRENCH	1970–90	1970–75	1975–80	1980–85	1985–90
β	0.15	0.25	−0.16	2.92	−0.01	−0.33
	(0.46)	(0.53)	(−1.64)	(2.49)	(−0.01)	(−0.47)
MV	−0.15	−0.11	0.01	−0.44	−0.20	0.10
	(−2.61)	(−1.63)	(0.19)	(−0.83)	(−0.48)	(0.25)
BM	0.50	0.45	0.47	0.87	0.47	0.01
	(6.17)	(3.02)	(1.05)	(1.63)	(1.15)	(0.03)
β	−0.37	−0.13	−1.86	2.14	−0.82	0.03
	(−1.23)	(−0.27)	(−0.62)	(1.96)	(−0.95)	(0.04)
MV	−0.17	−0.13	−0.10	−0.24	−0.30	0.11
	(−3.43)	(−2.10)	(−0.65)	(−1.94)	(−2.44)	(1.29)
MV	−0.12	−0.04	0.23	−0.25	−0.18	0.13
	(−2.18)	(−0.69)	(1.43)	(−1.97)	(−1.76)	(1.68)
AM	0.34	0.39	0.75	0.15	0.32	0.14
	(4.39)	(2.99)	(2.68)	(0.75)	(1.15)	(0.82)
AB	−0.50	−0.58	−1.37	0.06	−0.40	−0.40
	(−4.38)	(−3.63)	(−3.73)	(0.20)	(−1.16)	(−2.05)

Table VI
Does Herding Behavior Influence the Cross-Section of Returns?

For every month of the sample period, we run FAMA-MACBETH cross-sectional regressions. Variables and sample periods are defined in Tables II and V. V represents share turnover in percent. X is a dummy that equals one if the stock is part of the S&P-Index. We show the average cross-sectional regression slopes and their t-statistics. The estimates are listed in percent per month (i.e., multiplied by 100).

	Regression Periods				
	1970–90	1970–75	1975–80	1980–85	1985–90
	$R_i = \alpha + \gamma_1 \beta_i + \gamma_2 MV_i + \gamma_3 BM_i + \gamma_4 + \gamma_5 X_i + \varepsilon_i$				
β	0.086	−1.525	2.224	−0.456	0.102
	(0.195	−1.727	2.215	−0.553	0.135)
MV	−0.109	−0.043	−0.175	−0.338	0.122
	(−1.844	−0.309	−1.605	−2.720	1.411)
BM	0.284	0.532	0.355	0.111	0.137
	(2.540	2.124	1.398	0.533	0.795)
V	−0.584	−0.494	−0.453	−0.576	−0.814
	(−3.545	−2.201	−0.860	−2.307	−3.667)
X	0.512	0.546	0.299	0.736	0.467
	(5.433	3.917	1.785	3.108	2.376)
	$R_i = \alpha + \gamma_1 \beta_i + \gamma_2 MV_i + \gamma_3 AM_i + \gamma_4 AB_i + \gamma_5 V_i + \gamma_6 X_i + \varepsilon_i$				
β	0.102	−1.485	2.222	−0.463	0.132
	(0.230	−1.688	2.211	−0.561	0.175)
MV	−0.106	−0.034	−0.176	−0.339	0.126
	(−1.795	−0.244	−1.613	−2.722	1.455)
AM	0.296	0.574	0.341	0.110	0.159
	(2.695	2.304	1.380	0.532	0.962)
AB	−0.422	−1.102	−0.168	−0.095	−0.322
	(−3.113	−3.534	−0.614	−0.339	−1.688)
V	−0.582	−0.483	−0.476	−0.574	−0.794
	(−3.522	−2.148	−0.904	−2.310	−3.490)
X	0.504	0.528	0.309	0.738	0.439
	(5.313	3.839	1.860	3.123	2.155)

Table VII
The Seasonality of Risk Premia

For every month between July 1970 and June 1990, we run FAMA-MACBETH cross-sectional regressions. The variables are defined in Tables II, V, and VI. We list the average cross-sectional regression slopes and their t-statistics for all months, all months of January, all months of February, etc. We also report our findings for all months *but* January. The cross-sectional regressions are as follows:

$$R_i = \alpha + \gamma_1 \beta_i + \gamma_2 MV_i + \gamma_3 BM_i + \gamma_4 V_i + \gamma_5 X_i + \varepsilon_i$$

	β	*MV*	*BM*	*V*	*X*
All Months	0.086	–0.109	0.284	–0.584	0.512
	(0.196	–1.848	2.545	–3.553	5.444)
January	5.923	–0.937	2.700	–2.191	1.342
	(1.973	–3.027	4.691	–2.482	4.719)
February	0.819	–0.395	0.149	0.135	0.648
	(0.644	–1.660	0.368	0.284	1.748)
March	0.679	–0.236	0.355	–0.956	0.908
	(0.438	–1.816	1.523	–2.442	2.628)
April	–1.052	–0.100	0.194	–0.094	0.526
	(–0.755	–0.714	0.681	–0.380	1.579)
May	–1.044	–0.186	0.054	–0.074	0.833
	(–1.016	–1.414	0.255	–0.184	3.010)
June	–1.526	–0.179	–0.385	–0.125	0.240
	(–1.250	–1.231	–1.181	–0.244	0.788)
July	–0.513	–0.206	0.218	–1.257	0.811
	(–0.344	–1.152	0.632	–2.401	1.915)
August	1.484	0.525	0.686	–0.214	–0.176
	(1.374	2.593	2.199	–0.666	–1.045)
September	–0.747	–0.214	–0.020	–1.114	0.124
	(–0.712	–1.952	–0.058	–2.779	0.583)
October	–3.558	0.169	–0.321	–1.369	0.612
	(–2.959	1.026	–1.061	–1.578	1.757)
November	0.170	0.279	–0.114	0.273	0.037
	(0.165	1.197	–0.312	0.433	0.107)
December	0.401	0.174	–0.113	–0.025	0.237
	(0.487	1.039	–0.380	–0.051	0.994)
All Months	–0.444	–0.033	0.064	–0.438	0.436
Excluding January	(–1.180	–0.607	0.660	–2.795	4.468)

Table VIII
The Cross-Sectional Determinants of Volatility

For every month between July 1970 and June 1990, we run cross-sectional regressions. The variables are defined in Tables II and V. We list the average cross-sectional regression slopes and their t-statistics. V is share turnover in percent. X is a dummy variable that equals one if the stock is part of the S&P-500 Index. *DE* represents the debt-to-equity ratio. The cross-sectional regressions are as follows:

$$\sigma_i = \alpha_* + \lambda_1 \beta_i + \lambda_2 MV_i + \lambda_3 BM_i + \lambda_4 V_i + \lambda_5 X_i + \lambda_6 DE + \eta_i$$

β	*MV*	*BM*	*V*	*X*	*DE*
		July 1970-June 1990			
.44	–.32	–.07	.63	.12	.04
(34.10	–48.83	–5.92	29.90	10.35	13.51)
		All Months Excluding January, 1970-1989			
.43	–.32	–.08	.62	.11	.04
(33.16	–46.70	–6.16	28.71	9.48	13.08)
		January Only, 1970-1989			
.55	–.36	–.01	.68	.18	.03
(10.02	–15.38	–.23	8.53	4.58	3.43)
		July 1970-June 1975			
.43	–.39	–.19	.48	.10	.04
(15.88	–32.88	–6.34	15.02	6.91	4.65)
		July 1975-June 1980			
.58	–.39	.07	.85	.15	.05
(19.24	–37.29	4.84	20.71	7.91	9.97)
		July 1980-June 1985			
.38	-.22	–.21	.80	–.06	.03
(20.36	–33.55	–16.00	28.29	–4.14	5.13)
		July 1985-June 1990			
.39	–.29	.03	.37	.27	.05
(22.85	–40.51	2.46	13.68	13.64	13.55)

Table IX
Institutional Investors, Trading Volume, and Beta

Decile portfolios are formed in four different ways. We rank each quarter by: (*i*) the fraction of all institutionally owned shares held by mutual funds (*MF*), (*ii*) the fraction held by money managers (*MM*), (*iii*) the fraction held by banks (*B*), and (*iv*) the fraction held by insurance companies (*IC*). For each ranking, we list the average median values of the ranking variable, *V*, and β, by decile. As before, *V* represents annual share turnover in percent (multiplied by 100). β is the FAMA-FRENCH beta. In total, there are 40 quarters between the start of 1980 and the end of 1989.

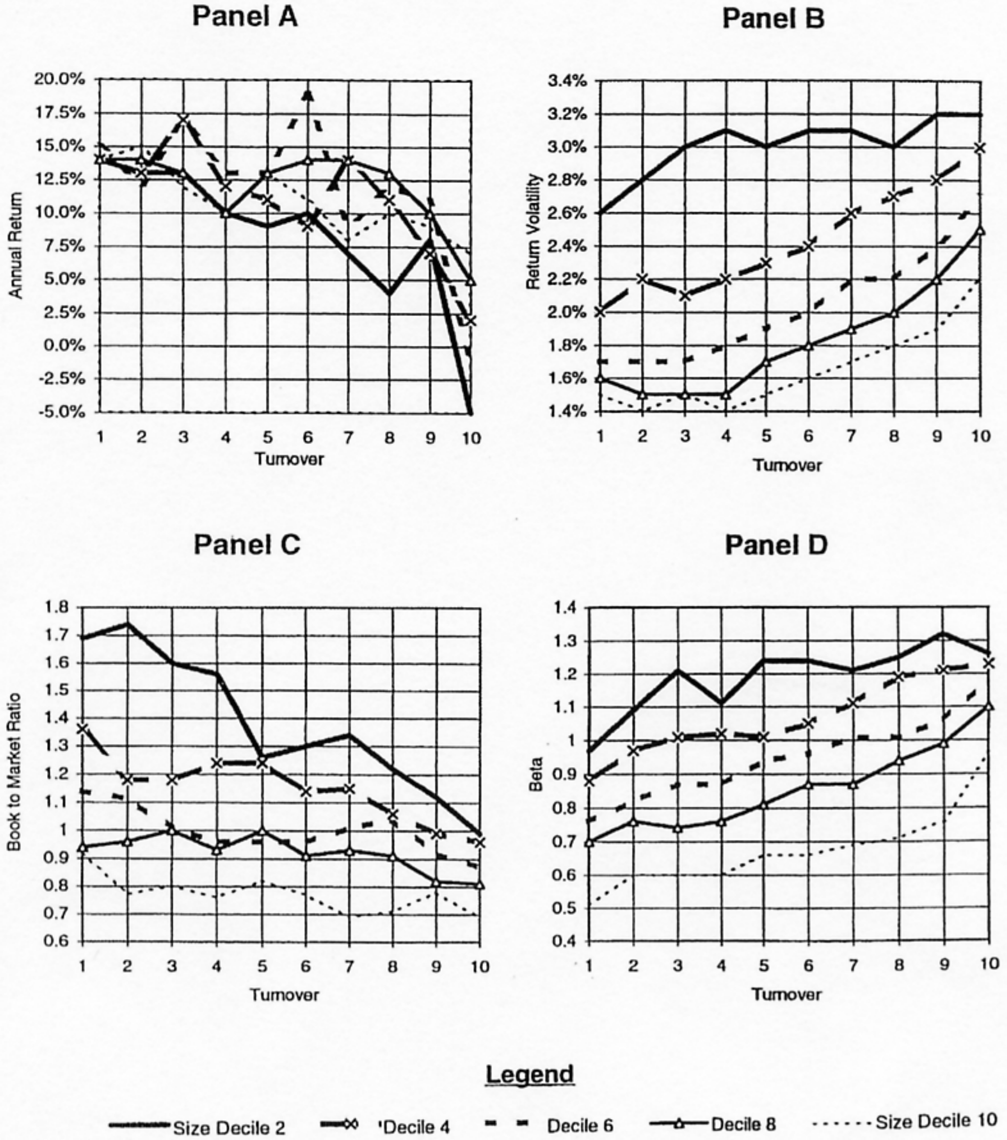
	Mutual Funds			Advisors			Banks			Insurers		
	MF	*V*	β	*MM*	*V*	β	*B*	*V*	β	*IC*	*V*	β
						Medians						
Low	3	40	1.10	19	45	1.18	11	72	1.33	1	60	1.24
2	5	50	1.06	35	52	1.17	18	71	1.30	4	63	1.24
3	7	64	1.11	40	55	1.14	22	67	1.24	5	62	1.24
4	9	60	1.14	43	59	1.15	26	66	1.24	7	61	1.17
5	10	62	1.18	46	69	1.17	29	65	1.20	8	59	1.13
6	12	63	1.20	49	64	1.19	32	72	1.17	9	60	1.16
7	13	63	1.27	81	66	1.18	35	59	1.16	11	61	1.19
8	15	67	1.25	84	65	1.23	39	53	1.13	13	69	1.22
9	18	71	1.30	87	67	1.24	45	47	1.06	16	63	1.23
High	25	73	1.35	64	70	1.26	59	41	1.09	24	53	1.21

Table X
The Cross-Section of Expected Returns and Volatility

For every month between January 1980 and December 1989, we run cross-sectional regressions with R and as the regressands. Variables are defined in Tables II, V, and VI. *#MF* denotes the number of mutual funds that own the security at the end of the previous quarter (divided by 100). *#MM*, *#B*, and *#IC* are defined in a similar way. They denote the number of money managers (advisors), banks, and insurance companies. Each column below shows a separate set of average cross-sectional regression slopes and their associated t-statistics (in brackets). The estimates are reported in percent, i.e., multiplied by 100. We report our findings for the full period and for two subperiods: January 1980–December 1984 and January 1985–December 1989. «na» means «does not apply.»

	Expected Returns			Volatility		
	1980–89	1980–84	1985–89	1980–89	1980–84	1985–89
β	–.33	–.61	–.05	.53	.55	.51
	(–.90	–1.11	–.11)	(31.29	23.39	21.16)
MV	–.28	–.32	–.25	–.05	–.04	–.05
	(–2.37	–1.65	–1.78)	(–5.17	–2.82	–4.26)
BM	.09	–.15	.33	–.09	–.13	–.05
	(.46	–.51	1.26)	(–8.25	–9.25	–3.29)
V	–.55	–.53	–.57	.22	.47	–.02
	(–2.64	–1.41	–3.13)	(7.74	17.07	–.77)
X	.57	.87	.28	–.01	–.09	.07
	(2.84	2.65	1.21)	(–.61	–4.47	3.92)
#MF	2.28	3.07	1.50	.11	.08	.14
	(4.49	4.23	2.15)	(2.84	1.30	3.00)
#MM	.06	.82	–.69	.19	.04	.34
	(.11	.81	–1.26)	(4.00	.48	9.92)
#B	–.26	–1.30	.78	–.17	.15	–.49
	(–.85	–2.88	2.14)	(–4.46	5.10	–13.86)
#IC	–2.97	–4.01	–1.93	–.40	–.77	–.04
	(–1.81	–1.63	–.89)	(–3.55	–4.79	–.27)
DE	na	na	na	.05	.03	.07
				(7.21	3.01	8.18)

Figure 1: Descriptive Statistics of Portfolios of Stocks Ranked by Turnover and Size



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SUMMARY

We collect trading and ownership statistics for U.S. stocks between 1970 and 1989 and we study the cross-section of returns. In rational and frictionless markets, equity returns should not depend on asset turnover nor should they depend on owner identity. Yet, with market imperfections, crowd behavior may affect returns. We examine two types of herding: (i) conventional investing, and (ii) trading for non-informational reasons. Incomplete information models predict that conventional stocks command higher prices. Noise trader models predict that shares that are traded for non-informational reasons are more risky and sell for lower prices. We find evidence that supports both predictions, even if we control for beta, firm size, and the book-to-market ratio.