The Impact of Trades on Daily Volatility

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This article proposes a trading-based explanation for the asymmetric effect in daily volatility of individual stock returns. Previous studies propose two major hypotheses for this phenomenon: leverage effect and time-varying expected returns. However, leverage has no impact on asymmetric volatility at the daily frequency and, moreover, we observe asymmetric volatility for stocks with no leverage. Also, expected returns may vary with the business cycle, that is, at a lower than daily frequency. Trading activity of contrarian and herding investors has a robust effect on the relationship between daily volatility and lagged return. Consistent with the predictions of the rational expectation models, the non-informational liquidity-driven (herding) trades increase volatility following stock price declines, and the informed (contrarian) trades reduce volatility following stock price increases. The results are robust to different measures of volatility and trading activity. (*JEL* C30, G11, G12)

Stock return volatility is fundamental to finance. Contingent claims pricing, risk management, asset allocation, and market efficiency tests use volatility as a basic building block. Consequently, volatility has been widely studied along several dimensions. Volatility clustering in financial data has been well documented and extensively modeled by the autoregressive conditional heteroskedasticity (ARCH) of Engle (1982) and the generalized ARCH extension of Bollerslev (1986).[1] Shiller (1981), LeRoy and Porter (1981), Roll (1984, 1988), French and Roll (1986), and Cutler, Poterba, and Summers (1989) have all documented a significant amount of volatility that cannot be explained by changes in fundamentals and, thus, may be attributable to mispricing. Schwert (1989) has studied the variation in stock market volatility over time and has analyzed the

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[1] See Bollerslev, Chou, and Kroner (1992) for a review.

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relation between stock return volatility and macroeconomic volatility, economic activity, financial leverage, and stock trading activity. It has also become a stylized fact that volatility is negatively correlated with lagged returns, a phenomenon known as the asymmetric volatility effect.[2] This article studies the time series properties of daily volatility at the individual stock level and examines the impact of trades on asymmetric volatility.

To motivate this study, we first describe the existing hypotheses for the asymmetric volatility effect. The two major hypotheses are the leverage effect and the existence of time-varying expected returns. The former, proposed by Black (1976) and Christie (1982), suggests that a firm's stock volatility changes due to changes in its financial (and operating) leverage. With a negative realized return, the firm value declines, making the equity riskier and increasing its volatility. Schwert (1989) argues that operating leverage causes the negative relation between returns and volatility to be more pronounced during recessions. Thus, both operating and financial leverages cause firms to appear riskier and have higher volatility when stock prices decline. The second hypothesis, proposed by Pindyck (1984), French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992), says that an anticipated increase in volatility raises the required return on equities, thereby causing an immediate stock price decline. In contrast to the leverage-based explanation, this second hypothesis suggests that volatility changes cause stock price changes.

However, both of these hypotheses have been questioned. Papers studying the leverage hypothesis (Schwert 1989) argue that it cannot fully account for the volatility response to stock price changes. The time-varying expected return hypothesis is controversial because it hinges upon a positive correlation between expected return and volatility. Empirically, the expected return volatility relation is an open issue. While French, Schwert, and Stambaugh (1987), Campbell and Hentschel (1992), and Ghysels, Santa-Clara, and Valkanov (2005) find support for positive relation, Breen, Glosten, and Jagannathan (1989) find evidence to the contrary.

It is our contention that the existing hypotheses for the leverage effect could potentially hold for low frequency observations, which is indeed the focus of previous research studying the asymmetric volatility phenomenon, but they are unlikely to be manifested at the daily frequency. Daily leverage changes can be perceived to be transitory and economically small. In addition, expected returns may vary with the business cycle and this variation, if present, is unlikely to be discernible at higher frequencies. For instance, Sims (1984) and Lehmann (1990), among

[2] See, for example, Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993). Graham and Harvey (2005) document that negative returns are associated with higher ex-ante volatility as measured by survey evidence.

others, have emphasized that asset prices should follow a martingale process over short time intervals as systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable information arrival. In this context, Cochrane (2001, p. 26) argues that

> It is not plausible that risk or risk aversion change at daily frequencies, but fortunately returns are not predictable at daily frequencies. It is much more plausible that risk and risk aversion change over the business cycle, and this is exactly the horizon at which we see predictable excess returns.

Nonetheless, this article demonstrates that the asymmetric volatility phenomenon is strong and robust at the daily frequency as well. This calls for new insights in understanding the time series properties of stock return volatility and, especially, its response to stock price changes at the daily level. French and Roll (1986) have argued that trading causes volatility. Thus, the asymmetric volatility phenomenon could be a result of the trading process. In this article, we build on the methodology of Schwert (1990), Jones, Kaul, and Lipson (1994), and Chan and Fong (2000) to extensively study the impact of trading activity on individual stock return volatility at the daily frequency.

The empirical evidence shows that the asymmetric volatility phenomenon in individual stock returns has a strong time-varying component, as the coefficient in the firm-level regressions of daily volatility on lagged return varies with selling activity.[3] More importantly, selling activity entirely captures the negative coefficient in these regressions. We define selling activity as the number of sell transactions or the number of shares sold each day. For reasons outlined below, when the lagged unexpected return is negative, selling activity governs the increase in subsequent volatility; when the lagged unexpected return is positive, selling activity governs the next period volatility decline. This suggests that selling activity is the source of the asymmetric volatility phenomenon. We demonstrate that the relation between selling activity and the following period volatility applies to stocks with negligible or no leverage, thereby strongly supporting the notion that the volatility response to daily stock price changes is not caused by leverage changes but by trading activity. Moreover, our empirical evidence is robust when daily volatility is based on high frequency return observations, as advocated by Andersen, Bollerslev, Diebold, and Ebens (henceforth ABDE) (2001).

We next turn to explain the empirical findings. Friedman (1953) has argued that irrational investors destabilize prices by buying when prices are high and selling when prices are low, whereas rational speculators

[3] The impact of buying activity can be inferred from that of the selling activity.

who buy when prices are low and sell when high counter the deviation of prices from fundamentals and so stabilize asset prices. Thus, rational traders move prices closer to its fundamental value while noise traders move prices away from fundamentals. Cutler, Poterba, and Summers (1990) and De Long, Shleifer, Summers et al. (1990) have argued that positive feedback investment strategies can result in excess volatility even in the presence of rational speculators. In a similar vein, Froot, Scharfstein, and Stein (1992) provide a model where investors herd on the same information even if this information is unrelated to fundamentals. This idea goes back to Keynes who compares professional investors to beauty-contest judges who vote on the basis of contestants' expected popularity with other judges rather than on the basis of absolute beauty. This herding or positive feedback behavior adversely impacts the informational quality of prices and increases volatility about fundamental values. We test whether this herding behavior causes an increase in volatility and whether contrarian trading leads to a decrease in volatility.

Upon decomposing sell trades into contrarian and herding trades, we find that contrarian trades decrease volatility while herding trades increase volatility. Contrarian trades are defined as sell trades when returns are positive and herding trades are sell trades when returns are negative. We demonstrate that when stock price declines, herding trades govern the increase in next period volatility and when stock price rises, contrarian trades lead to a decrease in next period volatility. Hence, trading activity of contrarian and herding investors seems to explain the relation between daily volatility and lagged returns.

To better understand the volatility response to stock price changes, we also turn to the noisy rational expectations models of Hellwig (1980) and Wang (1993). These models predict that volatility increases with non-informational or liquidity-driven trading. To identify informed versus uninformed trades, we employ the model of Campbell, Grossman, and Wang (henceforth CGW) (1993). In this model, risk averse market makers accommodate selling pressure at a price to show that the first-order daily return autocorrelation is related to whether trades are from informed or uninformed investors. The intuition is as follows: A stock price decline is attributable to either (i) a public announcement that causes a reduction in valuation or (ii) an exogenous selling pressure from uninformed liquidity traders. In the former case, there is no reason to expect any further change in prices. In the latter case, the selling pressure of liquidity traders will cause a temporary reduction in prices that will subsequently be reversed. Thus, price changes generated by non-informational sell trades tend to be reversed. More generally, informed (uninformed) trades will result in zero (non-zero) autocorrelation in individual stock returns.

We conjecture that herding trades are uninformed and contrarian trades are informed. Serial correlation tests provide support to our conjecture. In particular, sell trades in the presence of positive unexpected returns (contrarian sell trades) have no impact on the serial correlation in individual stock returns. However, sell trades in the presence of negative unexpected returns (herding sell trades) contribute to a reversal in stock prices.

Indeed, as predicted by Hellwig (1980) and Wang (1994), we show that informed (or contrarian) trades lead to a reduction in volatility while non-informational (or herding) trades lead to an increase in volatility. The asymmetric volatility phenomenon is, thus, explained as follows: When the stock price declines, non-informational liquidity-driven selling activity governs the increase in volatility the next day. When the stock price rises, informed selling activity reduces the next day volatility. To convincingly show that non-informational liquidity-driven trading activity leads to enhanced volatility in individual stock returns following stock price declines, we again turn to the CGW model. The model argues that the trading volume associated with non-informational trading is likely to be higher than that associated with information-based trading. Consistent with the predictions of the model we demonstrate that, conditional on negative unexpected returns, volatility is significantly higher following high trading volume days than it is following low trading volume days.

There is a potential caveat in classifying trades on a given day as herding versus contrarian or informed versus uninformed. These two groups of informed and uninformed agents most likely cluster and trade together. Essentially, our analysis is about whether herding/contrarian or informed/uninformed traders dominate on a given trading day. To further support our story we implement finer classifications of informed and uninformed traders. In particular, we condition the analysis on trade size as well as cumulative past returns. Focusing on the trade size, the idea is that larger (smaller) trade sizes are more likely to originate from informed (uninformed) traders (Easley and O'Hara 1987). Focusing on cumulative past returns, the disposition effect argues that unsophisticated traders are more (less) likely to sell when past returns have been positive (negative).

Indeed, the evidence shows that small uninformed trades increase volatility by more than large uninformed trades, and large informed trades reduce volatility by more than small informed trades. Similarly, uninformed sell trades with high past returns increase volatility by more than uninformed sells with low past returns, and informed sells with high past returns decrease volatility by less than the informed sells with low past returns. Overall, the evidence is consistent with Hellwig (1980) and Wang (1994) in that informed traders generally reduce volatility and uninformed traders generally increase volatility.

The contribution of this article is to provide a trading-based explanation for the daily asymmetric volatility at the individual stock level. The daily asymmetric volatility may be a different phenomena from weekly or monthly volatilities and other explanations cannot be ruled out at those lower frequencies. For instance, at the weekly frequency, Bekaert and Wu (2000) provide an explanation based on leverage as well as volatility feedback. Wu (2001) develops a model of asymmetric volatility and estimates it at the weekly and monthly frequency to show that both leverage and volatility feedback are important. Li (2003) develops a general equilibrium representative agent (with Epstein-Zin preferences) model to show that asymmetric volatility may be too strong to be justified by the leverage and volatility feedback effects with conventional preference parameters. Duffee (2002) presents a balance sheet explanation for asymmetric volatility. This explanation also applies at lower frequencies since balance sheet changes can at best be measured at a quarterly frequency.

The rest of the article proceeds as follows. The next section discusses the data. Section 2 presents the empirical evidence about the volatility response to daily stock price changes and runs robustness checks. Section 3 analyzes the source of individual stock return volatility and Section 4 concludes.

1. Data

The data are obtained mainly from the transactions databases, ISSM (1988 through 1992) and TAQ (1993 through 1998), and consist of a total of 2232 different NYSE-listed stocks over the period January 1988 through December 1998. The average (median) number of firms in the sample each year is 1326 (1344). Details about sample selection and filtering rules for this data set can be found in Chordia, Roll, and Subrahmanyam (2000, 2002). The total number of buyer- and seller-initiated trades for each stock is obtained by signing all trades each day using the Lee and Ready (1991) algorithm.[4] The total number of trades each day for each stock is the sum of all buy and sell trades as well as all the unsigned trades. Similarly, the total number of shares bought or sold for each stock each day is computed by adding up all the shares corresponding to the individual buy and sell transactions plus the shares that correspond to the unsigned trades. The daily frequency is a natural habitat for this work because our explanation for the asymmetric volatility is partly based on CGW (1993) who apply their theory to daily data, and because several other papers that use trading variables (Jones, Kaul, and Lipson 1994; Chan and Fong 2000; Chordia, Roll, and Subrahmanyam 2001) resort to daily observations.

[4] We will refer to buyer (seller) initiated trades as buy (sell) trades.

All the results in this article are obtained using a time series of individual stock returns calculated using prices that are the midpoint of the bid-ask spreads. The midpoint prices are obtained from the closing NYSE quotes each day for each stock over our sample period. The midpoint returns eliminate the impact of the bid-ask bounce on the individual stock volatility and are essential for this study of the impact of trading on volatility. In any case, our main conclusions are unchanged when the CRSP daily individual stock returns are used instead of the midpoint returns.

Table 1 summarizes the cross-sectional statistics of the individual firm time-series means. The mean (median) daily return is 0.06% (−0.01%). The average first-order serial correlation is 0.04, whereas the sum of the first twelve serial correlations is −0.03. Indeed, Jegadeesh (1990) shows that stock returns possess negative serial correlation due to the bid-ask bounce. In this study, however, the AR(1) coefficient is positive. The use of the bid-ask midpoint return eliminates the bid-ask bounce effect, resulting in the positive coefficient.

The average (median) number of trades per day is 99 (78) and the average (median) number of shares traded each day is 167,000

Table 1
Summary statistics on individual returns

	Mean	SD	Median	Minimum	Maximum	AR_1	$AR_{1:12}$
R	0.06%	2.47%	−0.01%	−14.91%	17.41%	0.039	−0.032
Transactions							
NT	0.099	0.077	0.078	0.014	0.890	0.639	4.771
NB/*NT*	0.465	0.169	0.470	0.043	0.923	0.234	1.813
NS/*NT*	0.481	0.169	0.479	0.053	0.938	0.220	1.667
Shares							
NT	0.167	0.109	0.116	0.010	4.611	0.311	1.921
NB/*NT*	0.470	0.229	0.467	0.013	0.981	0.093	0.447
NS/*NT*	0.482	0.230	0.477	0.014	0.983	0.085	0.383

		Transactions			Shares		
Cross correlations	*r*	*NT*	*NB*/*NT*	*NS*/*NT*	*NT*	*NB*/*NT*	*NS*/*NT*
Transactions							
NT	0.103	1.000					
NB/*NT*	0.318	0.153	1.000				
NS/*NT*	−0.312	−0.107	−0.865	1.000			
Shares							
NT	0.054	0.574	0.073	−0.063	1.000		
NB/*NT*	0.342	0.077	0.641	−0.548	0.017	1.000	
NS/*NT*	−0.340	−0.044	−0.551	0.639	−0.012	−0.898	1.000

This table presents summary statistics on daily returns and trading data for a total of 2232 individual stocks. *r* is the return, *NB* is the number of buys, *NS* is the number of sells, and *NT* is the total number of trades. "AR_1" is the first-order autocorrelation, and "$AR_{1:12}$" is the sum of the first 12 autocorrelation coefficients. All the statistics are first computed for individual stocks and then averaged across stocks. The sample period is 1988–1998.

(116,000). The average number of buy (sell) trades normalized by the total daily trades is 0.47 (0.48). The normalized buys or sells when measured in terms of trades can be as high as 93% and as high as 98% when measured in terms of shares pointing to the presence of extreme trade imbalances. Note that the ratio of buys to total trades and sells to total trades does not add to one because of the unsigned trades. This is true regardless of whether we measure the buys and sells in terms of the number of transactions or in terms of shares bought or sold. There is considerably higher serial correlation in the number of trades than in the number of shares traded. The number of buy or sell trades also has much higher serial correlation than the number of shares bought or sold. This is reminiscent of the Admati and Pfleiderer (1988) suggestion that noise traders (who trade smaller quantities) are more likely than the informed traders (who trade larger quantities) to bunch their trades. Indeed, the number of transactions (shares traded) is a trading measure biased in favor of small (large) investors.

The midpoint returns are positively (negatively) correlated with buys (sells) consistent with the fact that buys (sells) lead to increase (decrease) in the stock price. The number of buys and sells as a fraction of the total trades are negatively correlated with each other regardless of whether they are measured in terms of the number of trades or in terms of the number of shares traded. The correlation between the normalized number of buy trades and the normalized number of shares bought is 0.64 as is the correlation between the normalized number of sell trades and the normalized number of shares sold. We will present all results for the number of shares bought and sold as well as for the number of daily buy and sell transactions.

2. Results

We estimate the daily stock volatilities using a procedure similar to that used by Schwert (1990), Jones, Kaul, and Lipson (1994), and Chan and Fong (2000). The daily return on individual stocks is first regressed on its own 12 lags, day-of-week dummies, and normalized sell-initiated transactions using the specification

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k}\ D_{kt} + \sum_{k=1}^{12} \beta_{i,k}\ R_{i,t-k} + \gamma_i \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the return on stock i on date t, D_{kt} are day-of-week dummies, $NS_{i,t}$ is the number of sell transactions or the number of shares sold in stock i on date t, and $NT_{i,t}$ is the total number of trades or the total number of shares traded in stock i on date t. We will explain later why we use the control variable $NS_{i,t}/NT_{i,t}$ in regression (1).

The absolute value of the residual from Equation (1) is the volatility measure in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i \ M_t + \sum_{k=1}^{12} \rho_{i,k} \ |\epsilon_{i,t-k}| + \varphi_i \ NT_{i,t} + \left(\delta_{i,0} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}}\right) \epsilon_{i,t-1} + \eta_{i,t}, \qquad (2)$$

where M_t is the Monday dummy. Since volatility is persistent, 12 lags of the volatility are used as independent variables in Equation (2). Further, as documented by numerous researchers (Lamoureux and Lastrapes 1990), volatility is related to trading volume. The total number of trades or the total number of shares traded is used as an explanatory variable to proxy for the trading volume. The coefficient $\delta_{i,0}$ in Equation (2) with $\delta_{i,1}$ set to zero has traditionally been used to study the impact of stock price changes on future volatility. Specifically, a negative $\delta_{i,0}$ stands for the asymmetric volatility effect since it suggests that an increase in lagged unexpected return [as measured by the residual from Equation (1)] reduces volatility, but a decrease in the lagged unexpected return increases volatility.

Table 2 summarizes the results aggregated by size quintiles as well as across all stocks. The coefficient estimates in Table 2 are averages across the individual stock regressions. In what follows, δ_0 (δ_1) denotes the mean value of δ_{i0} (δ_{i1}). The test statistic corrects not only for the cross-correlations in residuals of Equation (2), as shown by Jones, Kaul, and Lipson (1994), but also for the serial correlation and heteroskedasticity in the individual stock regressions. Formal details are provided in the Appendix.

It follows from Table 2 that when $\delta_{i,1} = 0$ in Equation (2) for all individual stocks, δ_0 is negative in each of the size quintiles as well as across all stocks. That is, asymmetric volatility appears to be strong at the daily frequency. We contend that if the asymmetric volatility phenomenon is related to leverage changes or time-varying expected returns, it is unlikely to be manifested in daily returns. Later, we will directly test and reject the leverage hypothesis for daily returns. Also, returns are expected to vary with the business cycle and not at the daily frequency. The existence of the asymmetric volatility phenomenon at the daily frequency calls for further investigation of the time series properties of stock return volatility, which we pursue below.

We move to the second specification where $\delta_{i,1}$ is not restricted to zero across any of the stocks. In the presence of normalized sell trades in Table 2, δ_0 becomes positive and δ_1 is significantly negative. When all the stocks are aggregated, the average coefficient on the lagged normalized sell trades (δ_0) is 0.03 with a test statistic of 6.72 and δ_1 is -0.10 with a test statistic of -8.38. Table 2 also presents the results when the number

Table 2
Asymmetric volatility

	Number of transactions			Number of shares		
Size	δ_0	δ_1	$\bar{R}^2$ (%)	δ_0	δ_1	$\bar{R}^2$ (%)
1.	−0.017		18.42	−0.006		14.39
	(−4.85)			(−1.71)		
	0.005	−0.050	18.53	0.038	−0.094	14.59
	(0.85)	(−3.82)		(7.95)	(−11.08)	
2.	−0.018		19.96	−0.008		14.06
	(−4.21)			(−1.69)		
	0.011	−0.063	20.10	0.041	−0.102	14.25
	(1.66)	(−4.23)		(9.09)	(−9.56)	
3.	−0.015		19.90	−0.009		13.75
	(−4.10)			(−2.04)		
	0.032	−0.100	20.04	0.039	−0.101	13.91
	(4.12)	(−5.61)		(6.43)	(−8.65)	
4.	−0.014		17.06	−0.013		12.14
	(−3.69)			(−2.88)		
	0.049	−0.135	17.23	0.040	−0.113	12.33
	(6.86)	(−8.46)		(8.76)	(−8.56)	
5.	−0.009		16.24	−0.013		13.07
	(−2.11)			(−2.41)		
	0.084	−0.200	16.40	0.043	−0.118	13.20
	(7.70)	(−7.69)		(5.20)	(−5.13)	
All	−0.015		18.61	−0.009		13.59
	(−4.66)			(−2.34)		
	0.031	−0.099	18.75	0.040	−0.104	13.77
	(6.72)	(−8.38)		(13.38)	(−12.28)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k}\ D_{kt} + \sum_{k=1}^{12} \beta_{i,k}\ R_{i,t-k} + \gamma_i \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i\ M_t + \sum_{k=1}^{12} \rho_{i,k}\ |\epsilon_{i,t-k}| + \varphi_i\ NT_{i,t} + \left(\delta_{i,0} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}}\right) \epsilon_{i,t-1} + \eta_{i,t},$$

where M_t is the Monday dummy, NS is the number of sells, and NT is the total number of trades. Results are presented for both the number of transactions and the number of shares as trading variables. The table reports only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals $\eta_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size "All" reports the means of coefficients across all the stocks. The sample period is January 1988 through December 1998 and the total number of stocks is 2232.

of shares is used instead of the number of trades as a measure of trading activity. Once again, δ_0 (δ_1) is significantly positive (negative).

A negative δ_1 suggests that the asymmetric volatility effect is time varying; it varies with selling activity. We demonstrate that the higher the selling activity on date $t-1$ with positive (negative) unexpected returns, the lower (higher) the volatility on date t. Thus, in the presence of negative unexpected return, selling activity increases the next day volatility, and with positive unexpected return, selling activity leads to a decrease in the next day volatility. A negative δ_1 along with a positive δ_0 suggests that the well-documented negative coefficient in the regression of volatility on lagged return, or the asymmetric volatility effect, is entirely attributable to the interaction between selling activity and return. Later, we will demonstrate that existing rational expectations theories imply that δ_1 should indeed be negative.

Observe in Table 1 that selling activity is contemporaneously associated with stock price declines. One may argue that selling activity in Equation (2) simply captures negative returns and, thus, explains the asymmetric volatility phenomenon. However, note that $NS_{i,t}/NT_{i,t}$ in Equation (1) orthogonalizes the unexpected returns and the selling activity in Equation (2).[5] Thus, we can safely interpret the results to state that it is the selling activity that captures the negative coefficient in the firm-level regressions of volatility on lagged return.

In the regression where sell trades are included, Table 2 summarizes that both δ_0 and the absolute value of δ_1 increase monotonically with the firm size. With the number of shares sold as a measure of selling activity in Table 2, δ_0 and the absolute value of δ_1 of the largest stocks is higher than those of the smallest stocks. Moreover, the decline in δ_1 and the increase in δ_0 are more dramatic when trading activity is measured by trades and is more likely to be driven by individual investors (as opposed to institutional investors). This may suggest that selling activity of individual investors triggers more asymmetric volatility response to price changes in the largest stocks. In other words, a given amount of selling activity as a percentage of the total trading activity in the largest quintile of stocks increases the next day's volatility by more than a similar selling activity in the smallest stocks.

We do not provide a detailed discussion of the impact of buy trades on asymmetric volatility because the normalized buy and sell trades should add up to one (if we would be able to sign all trades) and we should be able to infer the impact of buy trades on volatility. Thus, the impact of buy trades on volatility can be ascertained from the results of Table 2 by considering the approximate identity, $(NS_{i,t}/NT_{i,t}) + (NB_{i,t}/NT_{i,t}) \approx 1$. The results for buy trades are available from the authors upon request.

Before searching for an explanation for the impact of lagged selling activity on future volatility (i.e., the negative coefficient δ_1), we first check the robustness of our results.

[5] These results are unchanged whether or not $NS_{i,t}/NT_{i,t}$ is used in Equation (1).

2.1 Robustness tests

In this section, we make certain that our results are robust to the impact of leverage and to the estimate of daily volatilities.

2.1.1 Leverage. Black (1976) and Christie (1982) have argued that a firm's stock volatility changes with financial leverage. With negative realized returns, the equity value declines. The decline in stock prices increases financial leverage, makes the stock riskier, and increases volatility. It should be noted that papers studying the leverage hypothesis agree that leverage alone cannot fully explain the asymmetric volatility phenomenon. Recently, Bekaert and Wu (2000) reject the pure leverage hypothesis. Instead, they suggest that any negative market-wide shock causes an increase in the conditional covariance of the firm with the market, thus, increasing required returns and causing prices to decline. The leverage effect reinforces this price decline. When the market-wide shock is due to a good (bad) news event the initial increase (decrease) in returns is dampened (enhanced) by the higher expected returns in response to the higher volatility caused by the shock. This difference in the response to positive and negative shocks produces the asymmetric response of volatility.

To test the financial leverage hypothesis, we run two tests: (i) we test for the presence of asymmetric volatility in stocks that have little or no leverage and (ii) we directly introduce leverage into Equation (2) and test for its impact on volatility. Financial leverage is measured as long-term debt divided by the sum of market value of equity and long-term debt.

Over our entire sample period of 1988 through 1998, there were 117 stocks with less than 1% leverage. If financial leverage causes asymmetric volatility then for these 117 stocks there should be no asymmetric volatility, that is, δ_0 should be indistinguishable from zero in Equation (2). Panel A of Table 3 summarizes that not only is $\delta_0 \neq 0$ but the asymmetric volatility effect is entirely captured by selling activity. When selling activity, in terms of sell orders or in terms of shares sold, is included in regression (2), δ_1 is significantly negative and δ_0 becomes positive. That is, during the sample period January 1988 through December 1998, financial leverage has no impact on volatility at the daily frequency. Even though these 117 stocks have no financial leverage, it is possible that the results are obtained because of the impact of operating leverage. Since operating leverage becomes important during recessions, we have checked for robustness after eliminating the recessionary period during the early 1990s. Our conclusions remain unchanged when using only the period 1993–1998 for the daily volatility regressions in Equation (2).

We now consider only those firms that have financial leverage, that is, the sample consists of stocks other than the above 117 that had little or no

Table 3
Asymmetric volatility and leverage effect

Number of transactions				Number of shares			
δ_0	δ_1	δ_2	$\bar{R}^2$ (%)	δ_0	δ_1	δ_2	$\bar{R}^2$ (%)
Panel A: stocks with no leverage							
−0.016			22.22	−0.010			17.43
(−2.16)				(−1.34)			
0.024	−0.090		22.41	0.037	−0.100		17.60
(1.22)	(−2.11)			(2.79)	(−3.40)		
Panel B: stocks with leverage							
−0.014			18.20	−0.010			13.43
(−4.46)				(−2.57)			
−0.012		0.046	19.82	−0.008		0.012	14.20
(−4.18)		(1.99)		(−2.10)		(0.56)	
0.041	−0.115	0.043	19.97	0.044	−0.109	0.016	14.38
(8.42)	(−10.48)	(1.78)		(13.93)	(−13.21)	(0.74)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k}\ D_{kt} + \sum_{k=1}^{12} \beta_{i,k}\ R_{i,t-k} + \gamma \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i\ M_t + \sum_{k=1}^{12} \rho_{i,k}|\epsilon_{i,t-k}| + \varphi_i\ NT_{i,t} + \delta_{i,0}\ \epsilon_{i,t-1} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}} * \epsilon_{i,t-1} + \delta_{i,2}\ L_{i,t-1} + \eta_{i,t},$$

where M_t is the Monday dummy, NB is the number of buys, NS is the number of sells, NT is the total number of trades, and L is the market leverage (ratio of long-term debt to market capitalization). Results are presented for both the number of transactions and the number of shares as trading variables. Panel A uses a sample of 117 stocks that had less than 1% leverage during the sample period. Panel B uses the remaining stocks in the sample. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $\eta_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected t-statistics are reported in parantheses below the coefficients. The sample period is January 1988 through December 1998.

financial leverage over the sample period. We estimate the following equation,

$$\begin{aligned} |\epsilon_{i,t}| =& \phi_i + \psi_i M_t + \sum_{k=1}^{12} \rho_{i,k}|\epsilon_{i,t-k}| + \varphi_i NT_{i,t} \\ &+ \left(\delta_{i,0} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}}\right)\epsilon_{i,t-1} + \delta_{i,2} L_{it-1} + \eta_{i,t}, \end{aligned} \tag{3}$$

where L_{it-1} denotes the financial leverage of stock i.

Panel B of Table 3 summarizes the results. In the absence of sales, the coefficient on financial leverage is positive [significantly so when sales are measured by the number of transactions in the mean return Equation (1)]. Indeed, volatility seems to increase with leverage. However, the impact of leverage on volatility is not robust to the incorporation of the number of shares traded in Equation (1). Moreover, when sales are added to the volatility equation as in (3), the coefficient on leverage is no longer significant while the coefficient on sales is negative and significant as before, suggesting that it is the selling activity rather than financial leverage that drives the daily asymmetric volatility.

2.1.2 Volatility estimate. In this subsection, we estimate the individual stock daily realized volatility using transactions data following Merton's (1980) insight. Merton has shown that although precise estimates of the mean return requires long spans of data, precise estimates of the variances can be obtained over fixed time intervals provided that the sampling interval approaches zero. If asset prices follow a geometric Brownian motion, then the estimation error in the variance of the return over any time interval is proportional to the length of the interval. Hence, any decrease in the time interval results in a commensurate decrease in the estimation error.

This insight has been used by ABDE (2001) to examine the realized daily equity return volatilities and correlations obtained from transactions data for stocks in the Dow Jones Industrial Index. ABDE sample intraday transactions data at five-minute intervals to obtain high frequency returns. The sampling interval of five minutes is a compromise between sampling at very short intervals to improve the precision of the estimates versus avoiding microstructure frictions that arise at these very short intervals.

Following ABDE, we sample at the five-minute interval to obtain prices. When stocks do not trade at exactly five-minute intervals, we use the trade price closest to the five-minute mark. In addition, we use the prevailing quote midpoint at the five-minute mark to obtain prices. Using the quote midpoint has two advantages: the existence of quote midpoints at each five-minute mark and the elimination of the negative serial correlation in five-minute returns that arises due to the bid-ask bounce when using transaction prices. Continuously compounded returns are obtained from the five-minute prices and the variance of daily returns is the sum of the squared continuously compounded returns over the day. We use the natural logarithm of the daily standard deviation as the dependent variable.

The daily realized volatilities are computed over the period January 1993 through December 1998 for 238 of the largest stocks in our sample.[6] We focus on the largest stocks because these are most likely to

[6] In a previous version, we had focused on twelve large well-known firms belonging to twelve different industries, which were the largest in terms of market capitalization as of December 31, 1995. They were (i) General Electric, (ii) American Telephone and Telegraph, (iii) Exxon, (iv) Coca-cola, (v) Merck, (vi) International Business Machines, (vii) Walmart, (viii) American International Group, (ix) Phillip Morris, (x) General Motors, (xi) Du Pont, and (xii) Proctor and Gamble. The results remain essentially the same.

trade frequently enough to provide returns at five-minute intervals. Volatilities calculated using transaction prices are higher than those calculated using the quote midpoints. For instance, the mean (median) daily standard deviation of GE is 1.47% (1.40%) when calculated using transactions prices and 1.22% (1.12%) using quote midpoints. This difference in volatilities when using quote midpoints versus transactions prices underscores the importance of the bid-ask bounce in high frequency transaction prices.

The results of the volatility regressions are summarized in Table 4. Panel A summarizes results when the volatilities are obtained using returns from transaction prices and panel B summarizes results when volatilities are obtained using quote midpoint returns. Since the results are similar in both panels, let us focus on the results in panel B with volatilities obtained from midpoint returns. With $\delta_1 = 0$, δ_0 is strongly negative, consistent with the notion of asymmetric volatility. With sell trades (measured either as transactions or shares) in the regression, δ_0

Table 4
Asymmetric volatility with intraday volatility estimate

Number of transactions			Number of shares		
δ_0	δ_1	$\bar{R}^2$ (%)	δ_0	δ_1	$\bar{R}^2$ (%)
Panel A: standard deviation from transaction prices					
−1.067		52.74	−1.177		50.22
(−9.54)			(−7.62)		
1.088	−4.777	52.83	0.311	−3.279	50.27
(2.91)	(−4.90)		(1.46)	(−4.90)	
Panel B: standard deviation from midpoint returns					
−1.003		42.58	−1.297		38.57
(−8.70)			(−7.31)		
4.020	−10.910	42.74	1.871	−6.963	38.69
(11.68)	(−12.77)		(7.43)	(−10.40)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} \; D_{kt} + \sum_{k=1}^{12} \beta_{i,k} \; R_{i,t-k} + \gamma_i \; \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. Volatility, $\sigma_{i,t}$, estimated using intraday data, is used in the following regression:

$$\sigma_{i,t} = \phi_i + \psi_i \; M_t + \sum_{k=1}^{12} \rho_{i,k} \; \sigma_{i,t-k} + \varphi_i \; NT_{i,t} + \left(\delta_{i,0} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}}\right)\epsilon_{i,t-1} + \eta_{i,t},$$

where M_t is the Monday dummy, NS is the number of sells, and NT is the total number of trades. Results are presented for both the number of transactions and the number of shares as trading variables. Panel A uses log of standard deviation calculated using transaction prices while panel B uses log of standard deviation calculated using midpoint returns. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $\eta_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected test statistics are reported in parantheses below the coefficients. The sample consists of 239 stocks and the sample period is January 1993 through December 1998.

becomes positive, while δ_1 is significantly negative. Overall, when selling activity is measured in terms of the number of shares sold, the mean δ_1 is -7.0 with a test statistic of -10.40 while the average $\delta_0 = 1.8$ with a test statistic of 7.4.

These results are qualitatively similar to those summarized in Table 2, pointing to their robustness to alternative computations of the volatility. Note also that, based on the high-frequency data, the average-adjusted R^2 is 38% or higher, that is, more than twice as high as in Table 2. Indeed, by shrinking the sampling interval to five minutes, we measure volatilities far more precisely.

In sum, the asymmetric volatility effect at the daily frequency is not a result of the leverage effect and is robust to the alternative methods of computing volatility. In particular, asymmetric volatility exists in individual stock returns at the daily frequency and is captured by selling activity.

3. An Explanation

In this section, we discuss our empirical evidence about the volatility response to stock price changes and the impact of sell transactions on future volatility within the context of existing models.

3.1 Contrarian and herding trades

Friedman (1953) points out that irrational investors destabilize prices by buying when prices are high and selling when prices are low. Rational speculators who buy when prices are low and sell when prices are high counter the price deviations from fundamentals and stabilize asset prices. Thus, noise (rational) traders move prices away (close) from (to) fundamentals. Shiller (1981), LeRoy and Porter (1981), Roll (1984, 1988), French and Roll (1986), and Cutler, Poterba, and Summers (1989) document a significant amount of stock return volatility that cannot be explained by changes in fundamentals. Black (1986) argues that excess volatility may arise due to the trading activity of irrational or noise traders. Also related is the work of Cutler, Poterba, and Summers (1990) and De Long, Shleifer, Summers et al. (1990). They argue that positive feedback investment strategies can result in excess volatility even in the presence of rational speculators. In a similar vein, Froot, Scharfstein, and Stein (1992) provide a model in which investors herd on the same information even if this information is unrelated to fundamentals. This herding or positive feedback behavior adversely impacts the informational quality of prices and increases uncertainty about fundamental values. A common denominator for all these studies is the implication that herding behavior enhances volatility and contrarian behavior depresses volatility.

We now test whether herding behavior causes an increase in volatility and whether contrarian trading leads to a decrease in volatility.

Here is how we define herding and contrarian trading behavior. The residual from the regression Equation (1), $\epsilon_{i,t}$, is the unexpected return of stock i on date t. Sell trades in the presence of positive (negative) unexpected returns will be designated contrarian (herding) trades. Formally, the contrarian trades are denoted as $NS_{it}/NT_{it} * (\epsilon_{it} \geq 0)$, where $(\epsilon_{it} \geq 0)$ is a dummy variable that is equal to one when the unexpected return is non-negative and zero otherwise. The herding trades are denoted as $NS_{it}/NT_{it} * (\epsilon_{it} < 0)$, where $(\epsilon_{it} < 0)$ is a dummy variable that is equal to one when the unexpected return is negative and zero otherwise. The notion is that the sell trades in the presence of decreasing prices are designated as herding trades and sell trades in the presence of rising prices are designated as contrarian trades.

We assess the impact of contrarian and herding sell trades on volatility using the following specification:

$$|\epsilon_{i,t}| = \phi_i + \psi_i \; M_t + \sum_{k=1}^{12} \rho_{i,k} |\epsilon_{i,t-k}| + \varphi_i \; NT_{i,t}$$
$$+ \left(\delta_{i,0} + \delta_{i,1} \underbrace{\frac{NS_{i,t-1}}{NT_{i,t-1}} * (\epsilon_{i,t-1} \geq 0)}_{\text{Contrarian}} + \delta_{i,2} \underbrace{\frac{NS_{i,t-1}}{NT_{i,t-1}} * (\epsilon_{i,t-1} < 0)}_{\text{Herding}} \right) \epsilon_{i,t-1} + \eta_{i,t}. \quad (4)$$

This specification separates the impact of sell trades by conditioning on positive and negative unexpected returns. Thus, we expect that $\delta_{i,1} + \delta_{i,2} < 0$. However, we are able to put more structure on $\delta_{i,1}$ and $\delta_{i,2}$. Recall that we expect the herding trades to increase volatility and the contrarian trades to decrease volatility. Both $\delta_{i,1}$ and $\delta_{i,2}$ are expected to be negative; $\delta_{i,1}$ should be less than zero because contrarian sell trades with $\epsilon_{i,t-1} \geq 0$ reduce volatility and $\delta_{i,2}$ should be less than zero because herding sell trades with $\epsilon_{i,t-1} < 0$ increase volatility. The following table summarizes our hypotheses about herding and contrarian sell trades and we will show that the results are consistent with the coefficient signs as shown in this table:

Unexpected returns	Sell trades	Volatility
+	Contrarian	Decreases
−	Herding	Increases

The results are summarized in Table 5 with selling activity measured in terms of trades and shares. It is evident that δ_2 is significantly negative

Table 5
Asymmetric volatility on positive and negative shock days

	Number of transactions				Number of shares			
Size	δ_0	δ_1	δ_2	$\bar{R}^2(\%)$	δ_0	δ_1	δ_2	$\bar{R}^2(\%)$
1.	−0.017			18.42	−0.006			14.39
	(−4.85)				(−1.71)			
	0.012	0.028	−0.143	18.71	0.042	−0.066	−0.131	14.72
	(1.93)	(1.99)	(−8.46)		(9.88)	(−5.59)	(−11.10)	
2.	−0.018			19.96	−0.008			14.06
	(−4.21)				(−1.69)			
	0.015	0.035	−0.166	20.27	0.042	−0.060	−0.144	14.37
	(2.44)	(2.42)	(−8.76)		(10.13)	(−5.45)	(−10.43)	
3.	−0.015			19.90	−0.009			13.75
	(−4.10)				(−2.04)			
	0.037	0.016	−0.229	20.25	0.040	−0.078	−0.125	13.98
	(4.98)	(0.99)	(−9.90)		(6.89)	(−6.58)	(−8.30)	
4.	−0.014			17.06	−0.013			12.14
	(−3.69)				(−2.88)			
	0.054	0.008	−0.294	17.45	0.044	−0.076	−0.164	12.43
	(7.46)	(0.46)	(−13.56)		(11.05)	(−6.30)	(−9.80)	
5.	−0.009			16.24	−0.013			13.07
	(−2.11)				(−2.41)			
	0.086	0.002	−0.403	16.58	0.045	−0.075	−0.170	13.27
	(8.80)	(0.11)	(−12.27)		(5.36)	(−4.72)	(−6.74)	
All	−0.015			18.61	−0.009			13.59
	(−4.66)				(−2.34)			
	0.035	0.020	−0.229	18.94	0.042	−0.070	−0.144	13.87
	(8.02)	(2.62)	(−17.12)		(16.31)	(−10.97)	(−15.22)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k}\ D_{kt} + \sum_{k=1}^{12} \beta_{i,k}\ R_{i,t-k} + \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i\ M_t + \sum_{k=1}^{12} \rho_{i,k} |\epsilon_{i,t-k}| + \varphi_i\ NT_{i,t} + \left[\delta_{i,0} + \delta_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}} * (\epsilon_{i,t-1} \geq 0) + \delta_{i,2} \frac{NS_{i,t-1}}{NT_{i,t-1}} * (\epsilon_{i,t-1} < 0)\right] \epsilon_{i,t-1} + \eta_{i,t},$$

where M_t is the Monday dummy, NS is the number of sells, and NT is the total number of trades. Results are presented for both the number of transactions and the number of shares as trading variables. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $\eta_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size "All" reports the means of coefficients across all the stocks. The sample period is January 1988 through December 1998.

across every size quintile. When the stock price declines, volatility increases and the increase is attributed to herding sell trades. Moving to contrarian traders, we show that, with sales measured in terms of transactions, δ_1 is statistically insignificant across all size quintiles except for the second size quintile. However, when selling activity is measured in terms of shares, representing the actions of large traders, both δ_1 and δ_2 are significantly negative across all size quintiles. A negative δ_1, when selling activity is measured in terms of shares, suggests that the contrarian selling activity of large investors leads to a decrease in volatility of individual stock returns. Note also that δ_2 is larger in absolute terms than δ_1, suggesting that selling activity has a larger impact on volatility when conditioned on negative unexpected returns.

In sum, the selling activity of both large and small traders who herd leads to an increase in volatility, whereas the selling activity of large contrarian investors leads to a decrease in individual stock return volatility. These results provide an explanation for why, in Table 2, the selling activity captures the asymmetric volatility phenomenon. The negative coefficient on the herding selling activity and the negative or zero coefficient on the contrarian selling activity combine to give the negative coefficient on the overall selling activity, thereby explaining the asymmetric volatility phenomenon.

The overall conclusion from contrarian and herding trades is that herding trades generally lead to an increase in volatility while the contrarian trades of large investors lead to a decrease in volatility, possibly because contrarian traders stabilize prices, and the herding traders destabilize prices.

In the following subsection, we seek to put more interpretation on the herding and contrarian traders. In particular, we turn to the market microstructure literature that has focused on informed and uninformed traders. Is it possible that the non-informational, liquidity-driven trading causes an increase in volatility while the informational-based trading reduces volatility? Can we consider the contrarian and herding traders as informed and uninformed, respectively?

3.2 Informed and uninformed trading

We now turn to the noisy rational expectations model of Hellwig (1980) to argue that return volatility increases with uninformed trading. In Hellwig's model, information is aggregated into prices by the actions of risk averse, heterogeneous agents who, individually, have no influence on prices. In Proposition 5.3, Hellwig (1980) provides an expression for the conditional volatility of the underlying asset. In Figure 1, we plot this conditional volatility as a function of the volatility of the supply of the underlying asset and the volatility of the information signal. Supply shocks can be thought of being caused by the trading activities of liquidity traders who are exogenous to the Hellwig (1980) model. Increased volatility of supply of the underlying asset signals increased liquidity trading. Analogously, an increase in the volatility of the information signal points to a decrease in the presence of the informed traders. Figure 1 shows that the conditional return volatility increases with both the volatility of the

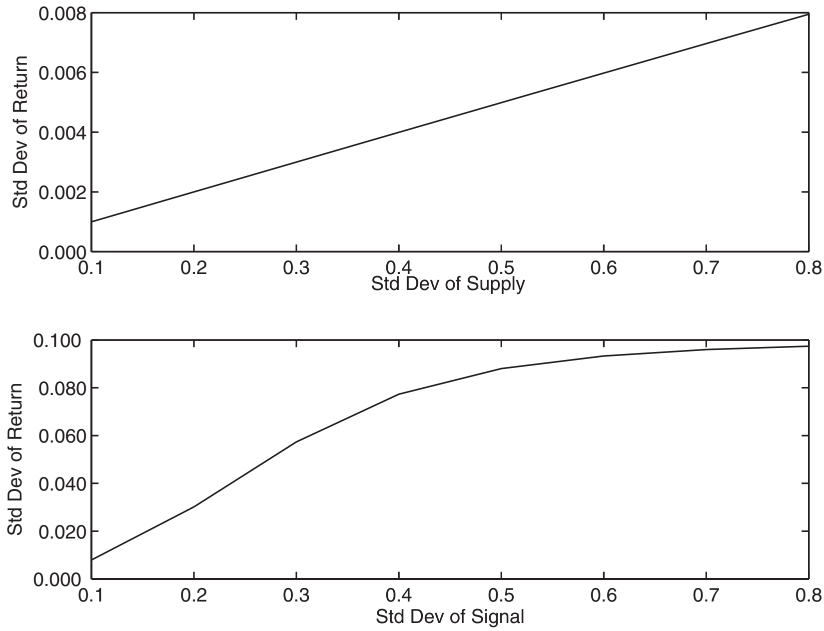

Figure 1
Volatility of returns and uninformed trading
This figure plots the volatility of returns for different levels of uninformed trading based on Hellwig (1980) model. The model parameters are as follows. The payoff is normally distributed with mean of one and a standard deviation of 0.1. The coefficient of absolute risk aversion is set to one. The supply is normally distributed with mean of one and standard deviation that changes in the top panel from 0.1 to 0.8 but is set to constant 0.5 in the bottom panel. The standard deviation of the informed traders' signal is set to a constant 0.1 in the top panel but changes from 0.1 to 0.8 in the bottom panel.

supply and of the information signal, thus, providing a theoretical underpinning to the argument that it is the uninformed or liquidity trading that leads to an increase in volatility.

In general, rational informed investors stabilize prices by taking positions whenever prices deviate from fundamentals, and in doing so they provide a (noisy) signal about their information, thus, moving prices back toward fundamentals. As the number of informed investors increases or as their signals become more precise, their impact on price increases causing a decrease in the deviation of price from fundamental value. If liquidity trading leads to an increase in volatility, then it should be the case that volatility increases as more uninformed investors trade. Wang (1993) also provides a model of asymmetric information and shows in Figure 2 of his paper that the conditional volatility of prices increases with uninformed trading for the most part. The exception is when almost all traders are uninformed.

In sum, both the noisy rational expectations model of Hellwig (1980) and that of Wang (1993) show that volatility increases with liquidity/uninformed trading. Conversely, volatility decreases with informed trading. Consistent with the spirit of the above models, we should find that non-informational trading increases volatility and informed trading decreases volatility. Let us conjecture that the contrarian trades are informed and the herding trades are uninformed. Table 5 summarizes that contrarian (herding) trades decrease (increase) volatility. If our conjecture about the uninformed and informed trades is correct, then the results are consistent with informed (uniformed) trades reducing (increasing) volatility. The question of how to test our conjecture that contrarian (herding) trades are informed (uninformed) is what we address next.

3.2.1 Autocorrelation. To identify informed versus uninformed trading, we turn to the theory of CGW (1993).[7] They have argued that price reversals occur as risk-averse market makers absorb order flow from uninformed or liquidity traders. In their model, a decline in stock prices could occur due to public information or due to liquidity-driven selling pressure. When the price change is due to informational reasons, price reversals are unlikely. However, suppliers of liquidity who accommodate the non-informational sell orders demand higher expected returns and must be compensated for bearing portfolio risk when buying shares that they would otherwise not trade. In fact, liquidity suppliers are attracted by prices that move away from fundamentals in response to the liquidity-driven selling pressure. We do not expect price changes after the public information has been incorporated into prices. On the contrary, price reversals are to be expected following liquidity-driven selling. Of course, if demand curves were perfectly elastic, price reversals would not be obtained. Given downward sloping demand curves (Shleifer 1986), price reversals should proxy for liquidity/uninformed trading and should be related to volatility.

The main result from CGW is that there should be no price change following informed trading. In other words, while price changes should not be related to past informed trading, they will be related to past liquidity trades. Thus, sell and buy trades that lead to price reversals can be classified as non-informational trades. In addition, Hellwig (1980) and Wang (1993) predict that non-informational trades lead to an increase in volatility while informed trades lead to a decrease in

[7] Empirical support for this theory has been provided by Conrad, Hameed, and Niden (1994) as well as Avramov, Chordia, and Goyal (2005). The former examines the role of volume in understanding the source of profitability of reversal trading strategies and the latter adds the dimension of illiquidity.

volatility. In the context of our study, those theories imply the following hypotheses:

Unexpected returns	Sell trades	Volatility	Informed versus uninformed	Serial correlation
+	Contrarian	Decreases	Informed	None
−	Herding	Increases	Uninformed	Negative

Since we conjecture that the contrarian trades are akin to informed trades and the herding trades represent uninformed trades, sell trades in the presence of positive (negative) unexpected returns will be designated informed (uninformed) trades. CGW suggest that exogenous selling pressure from uninformed liquidity traders causes the stock price to temporarily decline. This temporary decline is then reversed as informed traders accommodate the selling pressure.

We now empirically examine the CGW hypothesis about informed and uninformed trades using autocorrelation tests. As shown in the above table, lagged informed trades should not be related to future stock returns, or, put another way, informed trades should not impact the serial correlations in returns. Lagged uninformed trades, on the contrary, will be correlated with future returns and, thus, will have an impact on the serial correlation in returns.

Table 6 summarizes the results for the following autocorrelation regression

$$\epsilon_{i,t+1} = \phi_i + \left(\psi_i \, M_t + \delta_{i,0} \, Turn_{it} + \delta_{i,1} \underbrace{\frac{NS_{it}}{NT_{it}} * (\epsilon_{it} \geq 0)}_{\text{Informed}} + \delta_{i,2} \underbrace{\frac{NS_{it}}{NT_{it}} * (\epsilon_{it} < 0)}_{\text{Uninformed}} \right) \epsilon_{it} + u_{it+1}, \qquad (5)$$

where $Turn_{it}$ represents the turnover of stock i on day t. Turnover has been included in regression (5) to control for the CGW result that turnover contributes to return reversals. If our conjecture that $(NS_{it}/NT_{it}) * (\epsilon_{it} \geq 0)$ represents informed trading and $(NS_{it}/NT_{it}) * (\epsilon_{it} < 0)$ represents uninformed trading is correct, then δ_1 should be statistically insignificant and δ_2 should be different from zero. This is precisely what we find.

Table 6 defines sells in terms of the number of trades and in terms of numbers of shares sold. Under both definitions, δ_1 is statistically indistinguishable from zero for each size quintile and δ_2 is negative for every

Table 6
Autocorrelation patterns on positive and negative shock days

	Number of transactions				Number of shares			
Size	δ_0	δ_1	δ_2	$\bar{R}^2$ (%)	δ_0	δ_1	δ_2	$\bar{R}^2$ (%)
1.	−0.001			0.04	−0.000			0.04
	(−0.98)				(−0.29)			
	−0.006	−0.005	−0.144	0.39	−0.006	−0.014	−0.143	0.39
	(−3.58)	(−0.23)	(−5.43)		(−3.72)	(−0.75)	(−6.51)	
2.	−0.002			0.12	−0.001			0.13
	(−1.42)				(−0.84)			
	−0.005	−0.004	−0.084	0.38	−0.005	0.000	−0.103	0.41
	(−2.05)	(−0.17)	(−2.03)		(−2.36)	(0.01)	(−3.17)	
3.	−0.002			0.05	−0.001			0.04
	(−1.32)				(−0.31)			
	−0.004	0.008	−0.054	0.29	−0.005	−0.024	−0.097	0.33
	(−1.29)	(0.25)	(−1.33)		(−2.21)	(−1.28)	(−3.66)	
4.	−0.004			0.15	−0.002			0.13
	(−2.77)				(−1.03)			
	−0.004	0.033	−0.053	0.39	−0.003	0.022	−0.065	0.38
	(−1.20)	(0.92)	(−1.03)		(−1.20)	(0.89)	(−1.81)	
5.	−0.006			0.32	−0.003			0.25
	(−4.22)				(−2.21)			
	−0.011	−0.023	−0.118	0.53	−0.009	−0.017	−0.121	0.47
	(−2.55)	(−0.44)	(−1.51)		(−2.89)	(−0.59)	(−1.93)	
All	−0.003			0.13	−0.001			0.11
	(−2.30)				(−1.00)			
	−0.006	0.003	−0.088	0.39	−0.005	−0.006	−0.104	0.39
	(−2.31)	(0.12)	(−2.27)		(−2.95)	(−0.41)	(−3.64)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{kt} + \sum_{k=1}^{12} \beta_{i,k} R_{i,t-k} + \gamma_{i,1} \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$\epsilon_{i,t+1} = \phi_i + \left[\psi_i M_t + \delta_{i,0} \, \mathrm{Turn}_{it} + \delta_{i,1} \frac{NS_{it}}{NT_{it}} * (\epsilon_{it} \geq 0) + \delta_{i,2} \frac{NS_{it}}{NT_{it}} * (\epsilon_{it} < 0) \right] \epsilon_{it} + u_{it+1},$$

where M_t is the Monday dummy, Turn is the stochastically detrended turnover using last one year of observations, NS is the number of sells, and NT is the total number of trades. Results are presented for both the number of transactions and the number of shares as trading variables. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $u_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size “All” reports the means of coefficients across all stocks. The sample period is January 1988 through December 1998.

size quintile, significantly so for the smaller size quintiles. Overall, $\delta_2 = -0.088$ with a test statistic of -2.27 when measuring transactions and $\delta_2 = -0.104$ with a test statistic of -3.64 when measuring shares sold. Thus, informed sell trades have no impact on the serial correlation pattern of individual stock returns, whereas uninformed sell trades contribute to the negative autocorrelation in individual stock returns. The negative autocorrelation due to uninformed sell trades is consistent with CGW who argue that price reversals occur as liquidity suppliers absorb non-informational sell trades.

Overall, the informed trades are associated with a zero serial correlation in returns and the uninformed sell trades result in price reversals. The impact of trading activity on the serial correlations is consistent with our volatility results. Uninformed sell trades increase volatility, whereas the informed trades have no impact on the asymmetry in volatility of daily stock returns.

In the next test we, condition on trading volume to further reinforce our contention that uninformed (informed) traders increase (decrease) volatility.

3.2.2 Volatility. To reinforce our empirical evidence about the time series properties of stock return volatility, and especially the asymmetric volatility response to stock price changes, we turn, once again, to CGW. Their model has suggested that information-(liquidity) driven selling will not (will) result in subsequent price change. They use trading volume to distinguish between information and liquidity-based selling activity. Selling activity accompanied with high trading volume is likely to be liquidity driven while selling activity accompanied by low trading volume is likely to be information driven. Thus, if high trading volume is attributed to non-informational trading, then it should lead to a larger increase in volatility as compared to low trading volume that is attributed to informed trading. We now test whether, conditional on negative unexpected returns, high trading volume days are followed by higher volatility. We have already seen that with negative unexpected returns, selling activity leads to an increase in volatility. In this subsection, we check whether conditional on trading volume, negative unexpected returns have an impact on volatility.

We employ Equation (1) to estimate the unexpected returns using both the number of sell transactions and the number of shares sold as a measure of selling activity. Days with negative unexpected returns, $\epsilon_{i,t} < 0$, are subdivided into two groups based on trading volume. Trading volume is proxied by turnover, the number of transactions, or the number of shares traded. The high and low volume classification is based on above/below the historical one-year average or above/below the historical one-year average plus/minus the historical one-year standard deviation. Volatility on the next day, $|\epsilon_{i,t+1}|$, is then calculated for each of these groups and is labeled as V_{Lo} and V_{Hi} for high and low trading volume. Table 7 summarizes the annualized volatilities that are averaged across days and stocks.

The volatility is higher following the high volume trading days regardless of how we measure volume or how we calculate volatility. For

Table 7
Volatility following low and high volume days with negative shocks

	Number of transactions			Number of shares		
Volume	V_{Lo}	V_{Hi}	t-stat	V_{Lo}	V_{Hi}	t-stat
Panel A: based on prior mean						
Turnover	20.55%	23.97%	68.30	19.96%	25.89%	54.03
Transactions	21.77%	23.73%	37.74	18.36%	26.08%	73.09
Shares	21.64%	24.50%	50.77	17.32%	26.89%	63.80
Panel B: based on prior mean ± 1 SD						
Turnover	20.00%	23.59%	73.37	19.46%	25.48%	55.39
Transactions	21.29%	23.33%	39.60	18.02%	25.74%	74.29
Shares	21.18%	24.09%	51.92	16.72%	26.64%	68.09

The daily return on individual stocks is regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{kt} + \sum_{k=1}^{12} \beta_{i,k} R_{i,t-k} + \gamma \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies, NS is the number of sells, and NT is the total number of trades. Days with negative residuals, $\epsilon_{i,t} < 0$, are further subdivided into two groups based on trading volume. Volatility on the next day, $|\epsilon_{i,t+1}|$, is then calculated for each of these groups and is labeled as V_{Lo} and V_{Hi}. The mean equation above uses either the number of transactions (in the left half of the table) or the number of shares (in the right half of the table) for the trading variable. The trading volume is proxied for by turnover, the number of transactions, or the number of shares traded. Finally, high and low volume classification is based on above/below the historical 1-year average (in panel A) or above/below the historical 1-year average plus historical 1-year standard deviation (in panel B). The volatilities are averaged across days and stocks, and the table summarizes the overall annualized averages and the test statistic for the difference in means. The sample period is January 1988 through December 1998, and the total number of stocks is 2232.

instance, when selling activity is defined as number of shares sold in Equation (1) and turnover is used as a measure of trading volume with high volume being defined as being above its previous one-year average, the average annualized volatility following the high volume days is about 26%, whereas the volatility following the low volume days is about 20%. The difference is significant with a p-value < 0.001. This result supports our argument that non-informative, liquidity-driven selling activity (which causes a temporary decline in prices) leads to enhanced volatility in individual stock returns at the daily frequency.

3.3 Finer classification of informed and uninformed trading

Thus far, we have argued that selling transactions accompanied with declining (rising) prices originate from the uninformed (informed) traders. The caveat in classifying trades on a given day as informed or uninformed is that not all the trades on a given day are the same. Different groups of traders trade with each other and on any given day both the informed and the uninformed traders will be present. Thus, our analysis thus far conditions on whether informed or uninformed traders *dominate* on a given day. In this section, we use a finer partition to allow for informed (uninformed) selling when prices are falling (rising). We do this by considering the disposition effect and by considering the size of trades.

3.3.1 Volatility and the disposition effect. The behavioral finance literature is built upon the contention that unsophisticated investors suffer from a number of cognitive biases. One of those biases is the loss aversion, which suggests that investors are reluctant to realize their losses. This reluctance reflects the disposition effect. In the context of selling activity, the disposition effect suggests that uninformed investors are more likely to sell following price advances than following price declines. In our next test, we incorporate past returns to get a finer partition of the informed and uninformed traders.[8] More specifically, we estimate the following regression

$$\begin{aligned}|\epsilon_{i,t}| &= \phi_i + \psi_i M_t + \sum_{k=1}^{12} \rho_{i,k}|\epsilon_{i,t-k}| + \varphi_i NT_{i,t} + \delta_{i,0}\,\epsilon_{i,t-1} \\ &+ \left[\delta_{i,1}^{+} * (R_{i,t-11:t-2} \geq 0) + \delta_{i,1}^{-} * (R_{i,t-11:t-2} < 0)\right] * (\epsilon_{i,t-1} \geq 0) \\ &* \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}} + \left[\delta_{i,2}^{+} * (R_{i,t-11:t-2} \geq 0) + \delta_{i,2}^{-} * (R_{i,t-11:t-2} < 0)\right] \\ &* (\epsilon_{i,t-1} < 0) * \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}} + \eta_{i,t}, \end{aligned} \tag{6}$$

where $R_{i,t-11:t-2} \geq 0$ is a dummy variable equal to one when the cumulative return over time period $t-11$ to $t-2$ is non-negative and zero otherwise. Similarly, $R_{i,t-11:t-2} < 0$ is a dummy variable equal to one when the cumulative return over time period $t-11$ to $t-2$ is less than zero and zero otherwise. We use raw cumulative returns $R_{i,t-11:t-2}$ rather than the unexpected cumulative returns $\epsilon_{i,t-11:t-2}$ because the disposition effect relates to what investors have earned in raw returns before adjusting for expected returns.

Compared to Equation (4), we have now divided $\delta_{i,1}$ into $\delta_{i,1}^{+}$ and $\delta_{i,1}^{-}$ and $\delta_{i,2}$ into $\delta_{i,2}^{+}$ and $\delta_{i,2}^{-}$ by conditioning on past returns.[9] Recall that we have classified sales in the presence of negative (positive) returns as originating from uninformed (informed) traders. We now add more nuance to this classification. Sales in the presence of negative (positive) returns will still be classified as originating from uninformed (informed) traders but these sales could occur when the past returns, $R_{i,t-11:t-2}$, have

[8] Note that we are not making any claims about returns which can be problematic because of aggregation issues. We are only using the disposition effect to get a better classification of informed and uninformed traders.

[9] While we present results with past returns over the period $t-11$ to $t-2$, our results are robust to using different time periods such as $t-31$ to $t-2$ and $t-61$ to $t-2$.

been either positive or negative. The disposition effect suggests that when past returns are positive, the sales are likely to have a higher preponderance of uninformed traders and when past returns are negative, the sales are less likely to be from the uninformed traders.

The following table summarizes our hypotheses:

Unexpected returns	Sell trades	Past returns	Informed versus uninformed	Volatility	Average coefficients
+	Contrarian	Positive	Less Informed	Decreases less	δ_1^+
+	Contrarian	Negative	More Informed	Decreases more	δ_1^-
−	Herding	Positive	More Uninformed	Increases more	δ_2^+
−	Herding	Negative	Less Uninformed	Increases less	δ_2^-

In terms of the coefficients in Equation (6), we still expect δ_1^+, δ_1^-, δ_2^+, and δ_2^- to be negative but given the conditioning on past returns and its impact on volatility as shown in the above table we expect $\delta_1^- < \delta_1^+$ and $\delta_2^+ < \delta_2^-$. We test for precisely these relationships amongst the coefficients. Table 8 summarizes the results.

Focusing first on the case where sales are measured in terms of number of transactions, we see that overall $\delta_1^- < 0$ and δ_1^+ is positive albeit insignificant at the 5% level. All the coefficients have the expected sign except that δ_1^+ is significantly positive in the two smallest size quintiles. Thus, with positive unexpected returns, the presence of uninformed traders (as suggested by the disposition effect) causes an increase in volatility in the smallest two quintiles. Overall, both δ_2^+ and δ_2^- are negative. As hypothesized, we do find that $\delta_1^- < \delta_1^+$ and $\delta_2^+ < \delta_2^-$. Moreover, using the Wilcoxon–Mann–Whitney ranks test, we find that the differences are significant at the 1% level (with *t*-statistics of 6.22 and −4.17).

With sales measured in terms of shares traded, all the coefficients have the expected signs and as hypothesized $\delta_1^- < \delta_1^+$ and $\delta_2^+ < \delta_2^-$. For instance, for the overall sample $\delta_1^+ = -0.07$ and $\delta_1^- = -0.1$. Once again, using the Wilcoxon–Mann–Whitney ranks test, we show that these differences are significant at the 1% level (*t*-statistics = 3.83 and −2.72). Moreover, except for the size quintile two with negative unexpected returns, these relationships hold in each of the size quintiles.

In sum, the results are consistent with the idea that the disposition effect leads to more (less) selling by uninformed investors after positive (negative) past returns. The finer partitioning of the informed and the uninformed traders once again supports Wang (1994), in that the informed traders generally reduce volatility and the uninformed traders generally increase volatility.

3.3.2 Volatility and the size of trades. In this subsection, we account for trade size to, once again, obtain a finer classification of informed and

Table 8
Asymmetric volatility and disposition effect

	Number of transactions						Number of shares					
Size	δ_0	δ_1^+	δ_1^-	δ_2^+	δ_2^-	$\bar{R}^2$ (%)	δ_0	δ_1^+	δ_1^-	δ_2^+	δ_2^-	$\bar{R}^2$ (%)
1.	0.012	0.037	−0.106	−0.149	−0.012	19.08	0.042	−0.064	−0.109	−0.133	0.004	14.91
	(1.64)	(1.97)	(−5.42)	(−7.21)	(−0.34)		(9.17)	(−5.19)	(−6.09)	(−9.12)	(0.09)	
2.	0.014	0.043	−0.042	−0.163	−0.143	20.50	0.043	−0.058	−0.121	−0.143	−0.160	14.57
	(2.51)	(2.31)	(−1.96)	(−7.09)	(−5.49)		(10.61)	(−4.92)	(−14.57)	(−7.79)	(−7.54)	
3.	0.034	0.021	−0.031	−0.222	−0.189	20.47	0.039	−0.079	−0.086	−0.125	−0.090	14.18
	(4.74)	(0.95)	(−1.20)	(−9.15)	(−6.53)		(7.42)	(−6.16)	(−4.09)	(−6.52)	(−2.68)	
4.	0.053	0.018	−0.022	−0.298	−0.267	17.61	0.044	−0.075	−0.097	−0.164	−0.149	12.56
	(7.42)	(0.81)	(−0.87)	(−9.76)	(−9.32)		(11.35)	(−6.74)	(−7.00)	(−7.04)	(−6.43)	
5.	0.082	0.024	0.015	−0.405	−0.390	16.70	0.044	−0.067	−0.077	−0.166	−0.160	13.40
	(7.24)	(0.84)	(0.52)	(−8.21)	(−8.20)		(5.58)	(−3.53)	(−3.08)	(−4.20)	(−4.12)	
All	0.034	0.030	−0.042	−0.229	−0.180	19.17	0.042	−0.068	−0.101	−0.144	−0.108	14.04
	(7.50)	(1.88)	(−2.53)	(−12.35)	(−10.32)		(17.80)	(−9.50)	(−13.83)	(−9.37)	(−5.13)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following regression.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{kt} + \sum_{k=1}^{12} \beta_{i,k} R_{i,t-k} + \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i M_t + \sum_{k=1}^{12} \rho_{i,k} |\epsilon_{i,t-k}| + \varphi_i NT_{i,t} + \delta_{i,0}\, \epsilon_{i,t-1} + \left[\delta_{i,1}^{+} * (R_{i,t-11:t-2} \geq 0) + \delta_{i,1}^{-} * (R_{i,t-11:t-2} < 0)\right] * (\epsilon_{i,t-1} \geq 0) * \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}}$$
$$+ \left[\delta_{i,2}^{+} * (R_{i,t-11:t-2} \geq 0) + \delta_{i,2}^{-} * (R_{i,t-11:t-2} < 0)\right] * (\epsilon_{i,t-1} < 0) * \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}} + \eta_{i,t},$$

where M_t is the Monday dummy, NS is the number of sells, NT is the total number of trades, and $R_{t-11:t-2}$ is the cumulative return over time period $t-11$ to $t-2$. Results are presented for both the number of transactions and the number of shares as trading variables. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $\eta_{i,t}$ of the second regression. The cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size “All” reports the means of coefficients across all the stocks. The sample period is January 1988 through December 1998.

uninformed traders. Easley and O'Hara (1987) suggest that informed traders are more likely to submit larger orders. Consequently, we estimate the following regression

$$
\begin{aligned}
|\epsilon_{i,t}| = \phi_i + \psi_i M_t + \sum_{k=1}^{12} \rho_{i,k} |\epsilon_{i,t-k}| + \varphi_i NT_{i,t} \\
+ \left[\delta^l_{i,1} * LT_{i,t-1} + \delta^s_{i,1} * ST_{i,t-1}\right] * (\epsilon_{i,t-1} \geq 0) * \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}} \\
+ \left[\delta^l_{i,2} * LT_{i,t-1} + \delta^s_{i,2} * ST_{i,t-1}\right] * (\epsilon_{i,t-1} < 0) * \epsilon_{i,t-1} * \frac{NS_{i,t-1}}{NT_{i,t-1}} + \eta_{i,t}, \quad (7)
\end{aligned}
$$

where LT and ST are dummy variables for large and small trades, respectively. LT is defined to be one if shares traded per transaction on a given day are larger than the moving average calculated over the past year, and zero otherwise, whereas ST = 1 − LT is defined to be one if shares traded per transaction are smaller than the lagged annual moving average and zero otherwise. While sales in the presence of (positive) negative unexpected returns will still be considered as being from the informed (uninformed), we can now add nuances to this classification. Large sell trades are more likely to be from informed, whereas small sell trades are more likely to be from the uninformed.

The following table summarizes our hypotheses:

Unexpected returns	Sell trades	Trade size	Informed versus uninformed	Volatility	Average coefficients
+	Contrarian	Large	More informed	Decreases more	δ^l_1
+	Contrarian	Small	Less informed	Decreases less	δ^s_1
−	Herding	Large	Less uninformed	Increases less	δ^l_2
−	Herding	Small	More uninformed	Increases more	δ^s_2

In terms of the coefficients, we expect all the coefficients to be negative. In addition, we expect $\delta^s_2 < \delta^l_2$ and $\delta^l_1 < \delta^s_1$. Table 9 summarizes the results.

Focusing first on trades where sales are measured as number of shares sold, we find that indeed $\delta^s_2 < \delta^l_2$ and $\delta^l_1 < \delta^s_1$. This relation holds for each of the size quintiles and for the overall sample as well. For instance, for the overall sample $\delta^s_2 = -0.19$ and $\delta^l_2 = -0.1$. Also, $\delta^l_1 = -0.09$ and $\delta^s_1 = -0.02$. Moreover, these differences are statistically significant at the 1% level based on the Wilcoxon–Mann–Whitney ranks test (*t*-statistic = −7.38 and 8.93).

The case with sales measured in terms of transactions also confirms the above results and the differences are once again statistically significant at the 1% level as expected (*t*-statistics= −3.54 and 2.90). Surprisingly, in

Table 9
Asymmetric volatility and informed and uninformed trading on positive and negative shock days

	Number of transactions						Number of shares					
Size	δ_0	δ_1^l	δ_1^s	δ_2^l	δ_2^s	$\bar{R}^2$ (%)	δ_0	δ_1^l	δ_1^s	δ_2^l	δ_2^s	$\bar{R}^2$ (%)
1.	0.016	−0.003	0.045	−0.144	−0.161	19.36	0.045	−0.097	−0.048	−0.114	−0.153	15.05
	(2.31)	(−0.08)	(2.20)	(−6.55)	(−6.29)		(10.14)	(−6.57)	(−3.33)	(−16.89)	(−10.18)	
2.	0.014	0.044	0.074	−0.166	−0.207	20.61	0.030	−0.056	−0.014	−0.094	−0.169	15.17
	(1.84)	(1.31)	(2.98)	(−6.93)	(−7.97)		(5.53)	(−3.90)	(−0.85)	(−6.78)	(−9.56)	
3.	0.034	0.003	0.062	−0.199	−0.247	20.84	0.041	−0.108	−0.034	−0.091	−0.178	15.16
	(3.73)	(0.15)	(2.84)	(−7.02)	(−8.43)		(8.57)	(−9.74)	(−2.57)	(−4.76)	(−8.50)	
4.	0.048	0.013	0.046	−0.270	−0.305	18.48	0.037	−0.074	−0.012	−0.126	−0.215	13.84
	(5.80)	(0.47)	(1.73)	(−9.17)	(−10.80)		(7.19)	(−5.23)	(−0.65)	(−4.84)	(−9.08)	
5.	0.085	−0.010	0.025	−0.382	−0.416	17.40	0.039	−0.096	0.005	−0.099	−0.225	14.56
	(7.35)	(−0.29)	(0.67)	(−8.03)	(−8.31)		(5.06)	(−4.87)	(0.25)	(−2.84)	(−5.98)	
All	0.036	0.012	0.053	−0.221	−0.257	19.53	0.038	−0.085	−0.022	−0.104	−0.185	14.80
	(6.02)	(0.63)	(2.84)	(−10.64)	(−11.54)		(10.64)	(−9.98)	(−2.06)	(−6.74)	(−10.82)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{kt} + \sum_{k=1}^{12} \beta_{i,k} R_{i,t-k} + \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$|\epsilon_{i,t}| = \phi_i + \psi_i M_t + \sum_{k=1}^{12} \rho_{i,k} |\epsilon_{i,t-k}| + \varphi_i NT_{i,t} + (\delta_{i,1}^l{*}\mathrm{LT}_{i,t-1} + \delta_{i,1}^s{*}\mathrm{ST}_{i,t-1}){*}(\epsilon_{i,t-1} \geq 0){*}\epsilon_{i,t-1}{*}\frac{NS_{i,t-1}}{NT_{i,t-1}} + (\delta_{i,2}^l{*}\mathrm{LT}_{i,t-1} + \delta_{i,2}^s{*}\mathrm{ST}_{i,t-1}){*}(\epsilon_{i,t-1}<0){*}\epsilon_{i,t-1}{*}\frac{NS_{i,t-1}}{NT_{i,t-1}} + \eta_{i,t},$$

where M_t is the Monday dummy, NS is the number of sells, NT is the total number of trades, and LT is a dummy variables for a large trade defined to be one if shares traded per transaction are higher than the moving average calculated over the last 250 days ($ST = 1 - LT$). Results are presented for both the number of transactions and the number of shares as trading variables. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $\eta_{i,t}$ of the second regression. The cross-correlation corrected t-statistics are reported in parenthesis, and cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size "All" reports the means of coefficients across all the stocks. The sample period is January 1988 through December 1998.

the smaller size quintiles as well as for the overall sample, δ_1^s is positive suggesting that small sell trades in the presence of positive unexpected returns actually increase volatility.

To ascertain that our classification of large and small size trades as informed and uninformed, we turn once again to the autocorrelation regressions. More specifically consider the following regression,

$$\begin{aligned}\epsilon_{i,t+1} = \phi_i \; + \Big[\psi_i\, M_t + \delta_{i,0}\,\text{Turn}_{it} + \epsilon_{it} + \epsilon_{it} \\ + \Big(\delta_{i,1}^{l} {*}\text{LT}_{i,t} + \delta_{i,1}^{s} {*}\text{ST}_{i,t}\Big) {*} \frac{NS_{it}}{NT_{it}} {*} (\epsilon_{it} \geq 0) \\ + \Big(\delta_{i,2}^{l} {*}\text{LT}_{i,t} + \delta_{i,2}^{s} {*}\text{ST}_{i,t}\Big) {*} \frac{NS_{it}}{NT_{it}} {*} (\epsilon_{it} < 0)\Big]\epsilon_{it} + u_{it+1}. \qquad (8)\end{aligned}$$

This regression is similar to Equation (5) except that $\delta_{i,1}$ is now split into $\delta_{i,1}^l$ and $\delta_{i,1}^s$ conditional on the average size of trades on a given day. Similarly, $\delta_{i,2}$ is now split into $\delta_{i,2}^l$ and $\delta_{i,2}^s$. We also control for higher order terms of the unexpected returns, ϵ_{it}, to control for non-linearities in the autocorrelation. The reason for this is that large trades are likely to be accompanied by large unexpected returns and this may influence the autocorrelation coefficients if there are non-linearities in the serial correlation patterns of individual stock returns.

The following table depicts our hypotheses.

Unexpected returns	Sell trades	Trade size	Informed versus uninformed	Serial	Average correlation
+	Contrarian	Large	More informed	Zero	δ_1^l
+	Contrarian	Small	Less informed	Zero	δ_1^s
–	Herding	Large	Less uninformed	Less negative	δ_2^l
–	Herding	Small	More uninformed	More negative	δ_2^s

As before, the informed (uninformed) trades should lead to no (negative) serial correlation in returns but now by conditioning on trade size we can say that the less informed and the more uninformed trades should have a lower serial correlation coefficient. In other words, $\delta_1^s < \delta_1^l$ and $\delta_2^s < \delta_2^l$.

The results in Table 10 are consistent with our hypotheses. Focusing on the number of transactions, δ_1^s and δ_1^l are both statistically indistinguishable from zero, whereas δ_2^s and δ_2^l are both significant. Moreover, $\delta_1^s < \delta_1^l$ and this difference is statistically significant with a test statistic of −4.16 based on the Wilcoxon–Mann–Whitney ranks test. However, δ_2^s is statistically indistinguishable from δ_2^l. When focusing on the number of shares sold, δ_1^l is significantly positive, suggesting that large informed trades lead to a continuation in returns. Moreover, $\delta_1^s < \delta_1^l$ and $\delta_2^s < \delta_2^l$ and the

Table 10
Autocorrelation and informed and uninformed trading on positive and negative shock days

	Number of transactions						Number of shares					
Size	δ_0	δ_1^l	δ_1^s	δ_2^l	δ_2^s	$\bar{R}^2$ (%)	δ_0	δ_1^l	δ_1^s	δ_2^l	δ_2^s	$\bar{R}^2$ (%)
1.	−0.008	−0.012	−0.060	−0.103	−0.073	1.46	−0.005	0.007	−0.042	−0.037	−0.039	1.48
	(−4.71)	(−0.36)	(−2.15)	(−2.99)	(−2.16)		(−3.53)	(0.81)	(−1.60)	(−3.53)	(−1.49)	
2.	−0.010	−0.016	−0.048	−0.088	−0.087	1.33	−0.006	0.015	0.002	−0.038	−0.065	1.36
	(−3.70)	(−0.48)	(−1.48)	(−2.12)	(−2.17)		(−2.66)	(2.14)	(0.10)	(−3.50)	(−2.75)	
3.	−0.009	0.070	−0.013	−0.106	−0.109	1.15	−0.006	0.004	−0.032	−0.027	−0.077	1.13
	(−3.56)	(2.44)	(−0.41)	(−2.42)	(−2.94)		(−2.50)	(0.60)	(−1.77)	(−2.34)	(−3.93)	
4.	−0.008	0.115	0.057	−0.099	−0.085	1.10	−0.006	0.006	−0.022	−0.021	−0.056	1.04
	(−2.43)	(2.65)	(1.41)	(−2.49)	(−2.09)		(−2.94)	(0.72)	(−1.22)	(−2.14)	(−3.13)	
5.	−0.014	0.128	0.071	−0.170	−0.179	1.27	−0.006	0.019	−0.002	−0.013	−0.044	1.01
	(−3.15)	(2.28)	(1.30)	(−2.96)	(−2.95)		(−3.61)	(2.77)	(−0.11)	(−0.99)	(−1.75)	
All	−0.010	0.051	−0.004	−0.109	−0.103	1.26	−0.006	0.010	−0.019	−0.028	−0.058	1.21
	(−3.98)	(1.83)	(−0.13)	(−3.37)	(−3.08)		(−3.33)	(2.28)	(−1.59)	(−3.61)	(−3.79)	

The daily return on individual stocks is first regressed on its own 12 lags and day-of-week dummies according to the following equation.

$$R_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} D_{kt} + \sum_{k=1}^{12} \beta_{i,k} R_{i,t-k} + \frac{NS_{i,t}}{NT_{i,t}} + \epsilon_{i,t},$$

where D_{kt} are day-of-week dummies. The residuals from this regression are then used in the following regression:

$$\epsilon_{i,t+1} = \phi_i + \left[\psi_i M_t + \delta_{i,0}\,\mathrm{Turn}_{it} + \epsilon_{it} + \epsilon_{it}^2 + (\delta_{i,1}^l{*}\mathrm{LT}_{i,t} + \delta_{i,1}^s{*}\mathrm{ST}_{i,t}){*}\frac{NS_{it}}{NT_{it}}{*}(\epsilon_{it} \geq 0) + (\delta_{i,2}^l{*}\mathrm{LT}_{i,t} + \delta_{i,2}^s{*}\mathrm{ST}_{i,t}){*}\frac{NS_{it}}{NT_{it}}{*}(\epsilon_{it} < 0)\right]\epsilon_{it} + u_{it+1},$$

where M_t is the Monday dummy, Turn is the stochastically detrended turnover using last one year of observations, NS is the number of sells, NT is the total number of trades, and LT is a dummy variable for a large trade defined to be one if shares traded per transaction are higher than the moving average calculated over the last 250 days ($ST = 1 - LT$). Results are presented for both the number of transactions and the number of shares as trading variables. The table summarizes only the estimates of δ from the second regression. The reported coefficients are the averages across all stocks. The standard errors for means of coefficients are corrected for cross-correlation between residuals, $u_{i,t}$ of the second regression. The cross-correlation corrected test statistics are reported in parenthesis, and cross-correlation and Newey–West corrected test statistics are reported in parenthesis below the coefficients. The results are presented for stocks grouped by size and for all stocks. Size "All" reports the means of coefficients across all the stocks. The sample period is January 1988 through December 1998.

differences are statistically significant with *t*-statistics of −5.87 and −3.58, respectively. Also, the hypothesized relationship holds for each size quintile. This provides strong confirmation for our classification of informed and uninformed trades based on the size of the trades.

Overall, the results are consistent with the notion that trade size can be used to classify informed and uninformed trades. Small uninformed trades increase volatility by more than large uninformed trades. Similarly, large informed trades reduce volatility by more than the small informed trades.

4. Conclusions

This article studies the time series properties of daily volatility at the individual stock level and proposes a trading-based explanation for the asymmetry in volatility phenomenon, that is, that volatility increases (decreases) following stock price declines (increases). Previous research has proposed two major explanations for this phenomenon: leverage effect and time varying expected returns. However, returns are expected to vary at the frequency of the business cycle. We do observe the presence of asymmetric volatility in individual stock returns at the daily frequency. We show the leverage has no impact on asymmetric volatility and, moreover, we also observe asymmetric volatility for stocks with no leverage, suggesting that prior hypotheses are unlikely to explain the daily asymmetric volatility. The presence of asymmetric volatility in high frequency data calls for a new explanation potentially based on trading activity.

This article finds that selling activity governs the asymmetric volatility phenomenon in individual stock returns. More specifically, the negative coefficient in the regression of volatility on lagged return is entirely captured by the interaction of lagged return and selling activity. We demonstrate that this empirical finding is consistent with economic theory. In particular, Hellwig (1980) and Wang (1993) have shown that non-informational liquidity-driven trading activity leads to enhanced volatility while informed trading leads to a decline in volatility. To identify informed versus uninformed trading activity, we turn to CGW (1993) who develop a model to show that non-informational trades are related to future price changes, whereas informed trades are unrelated to such changes. Informed (uninformed) trades result in zero (non-zero) serial correlation in returns. Thus, informed trading has no impact on the serial correlation in individual stock returns while the uninformed sell trades contribute to a reversal in individual stock returns. Therefore, price changes at the daily frequency due to uninformed trading reject the martingale behavior of stock prices over short horizons. At the daily frequency, this rejection of the martingale property of stock prices probably reflects a lack of liquidity rather than a rejection of market efficiency.

With perfectly elastic demand curves, non-informational order flow would have been absorbed without impacting the price.

Indeed, we find that proxies for informed trading (also identified as contrarian trading) lead to a reduction in volatility when the stock price rises while proxies for non-informational trading (also identified as herding trading) lead to an increase in volatility when the stock price falls. It is this impact of informed versus uninformed (or contrarian versus herding) trading on volatility that is consistent with the result that the asymmetric volatility varies with trading activity at the daily frequency.

Appendix A: Calculation of Standard Errors

Consider N stocks with T observations. The dependant variable is denoted by y and the set of K independent variables by x. For instance, y could denote volatility and x could include lags of volatility, day of week dummies, and trading-related variables. The regression equation is as follows:

$$y_{it} = x_{it}'\beta_i + \epsilon_{it}. \tag{A1}$$

We do not impose any distributional assumptions on the error term, ϵ_{it}. In particular, it could display heteroskedasticity, be autocorrelated, and/or cross-correlated (with leads and lags) with error terms of other stocks. The moment condition for identification is only that the error is orthogonal to the vector of independent variables, x_{it}.

Let us introduce some notation. Let $\beta = (\beta_1', \ldots, \beta_N')'$, let $x_t = (x_{1t}', \ldots, x_{Nt}')'$, $X_i = (x_{i1} \ldots x_{iT})'$, and let $Y_i = (y_{i1} \ldots y_{iT})'$. The GMM condition can be written as $E(f(x_t, \beta)) = 0$, where $f(x_t, \beta)$ is an NK valued function given by

$$f(x_t, \beta) = \begin{pmatrix} x_{1t}\epsilon_{1t} \\ \vdots \\ x_{Nt}\epsilon_{Nt} \end{pmatrix} \equiv \begin{pmatrix} x_{1t}(y_{1t} - x_{1t}'\beta_1) \\ \vdots \\ x_{Nt}(y_{Nt} - x_{Nt}'\beta_N) \end{pmatrix}. \tag{A2}$$

Here, the parameter vector β is itself of length NK. Since the number of moment conditions is exactly equal to the number of parameters, the system is exactly identified. Thus, we do not need the usual weighting matrix to carry out the optimization.[10] The solution is, of course, given by the usual OLS equations as

$$\hat{\beta}_i = (X_i{}'X_i)^{-1} X_i{}' Y_i. \tag{A3}$$

The variance of the estimator is given from the GMM formula as

$$T * \text{cov}(\hat{\beta}) = d^{-1} S d^{-1'}, \tag{A4}$$

where the score matrix d and the spectral density matrix S are given by

$$d = E\left(\frac{\partial f(x_t, \beta)}{\partial \beta'}\right) \tag{A5}$$

$$S = \sum_{s=-\infty}^{\infty} E[f(x_t,\beta) f(x_{t-s},\beta)']. \tag{A6}$$

[10] While the identity matrix leads to a consistent estimator, it is not the most efficient weighting matrix. The situation is analogous to the fact that we are running an OLS regression instead of a GLS regression. In our case, the number of stocks N exceeds the number of observations, thus rendering a feasible GLS impossible. We do, however, correct for the standard errors of the OLS estimates.

The special structure of f and β makes the computation of d especially straightforward. We have

$$\frac{\partial f(x_t,\beta)}{\partial \beta'} = \begin{bmatrix} -x_{1t}x'_{1t} & \dots & 0 \\ \vdots & & \vdots \\ 0 & \dots & -x_{Nt}x'_{Nt} \end{bmatrix}. \tag{A7}$$

This implies that

$$\hat{d} = \hat{E}\left(\frac{\partial f(x_t,\beta)}{\partial \beta'}\right) = \frac{1}{T}\begin{bmatrix} -X'_1X_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & -X'_NX_N \end{bmatrix}, \tag{A8}$$

where 0 is suitably defined $K * K$ matrices. Thus, the matrix d consists of K^2 blocks, with the $(ij)^{\text{th}}$ block equal to zero if $i \neq j$ and equal to $X_i'X_i$ when $i = j$. The diagonal nature of this matrix also makes the computation of the inverse of d trivial. The matrix S is also computed as consisting of K^2 blocks, where the (ij)th block is given by

$$S_{ij} = \sum_{s=-\infty}^{\infty} E[x_{it}x'_{jt-s}\epsilon_{it}\epsilon_{jt-s}] \tag{A9}$$

and is estimated using the Newey–West estimation technique with L lags as

$$\hat{S}_{ij} = \frac{1}{T}\left[\sum_{t=1}^{T}(x_{it}x'_{jt}e_{it}e_{jt}) + \sum_{s=1}^{L}\left(\frac{L-s}{L}\right)\sum_{t=s+1}^{T}(x_{it}x'_{jt-s}e_{it}e_{jt-s} + x_{jt}x'_{it-s}e_{jt}e_{it-s})\right]. \tag{A10}$$

Combining all the pieces together, we get

$$\widehat{\text{cov}}(\hat{\beta}_i, \hat{\beta}_j) = (X_i'X_i)^{-1}T\hat{S}_{ij}(X_j'X_j)^{-1}. \tag{A11}$$

Finally, we report the results for the average β coefficient across all stocks. This is estimated as

$$\hat{\hat{\beta}} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i, \tag{A12}$$

with the variance given by

$$\widehat{\text{cov}}(\hat{\hat{\beta}}) = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\widehat{\text{cov}}(\hat{\beta}_i, \hat{\beta}_j). \tag{A13}$$

References

Admati, A., and P. Pfleiderer, 1988, "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies*, 1, 3–40.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and H. Ebens, 2001, "The Distribution of Realized Stock Return Volatility," *Journal of Financial Economics*, 61, 43–76.

Avramov, D., T. Chordia, and A. Goyal, 2005, "Liquidity and Autocorrelation in Individual Stock Returns," working paper, The University of Maryland and Emory University, College Park and Atlanta, GA, forthcoming in *Journal of Finance*.

Bekaert, G., and G. Wu, 2000, "Asymmetric Volatility and Risk in Equity Markets," *Review of Financial Studies*, 13, 1–42.

Black, F., 1976, "Studies of Stock Price Volatility Changes," *Proceeding of the 1976 meetings of the American Statistical Association, Business and Economical Statistics Section*, 177–181.

Bollerslev, T., 1986, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, 31, 307–327.

Bollerslev, T., R. Y. Chou, and K. F. Kroner, 1992, "ARCH Modeling in Finance," *Journal of Econometrics*, 52, 5–59.

Breen, D., L. R. Glosten, and R. Jagannathan, 1989, "Economic Significance of Predictable Variations in Stock Index Returns," *Journal of Finance*, 44, 1177–1189.

Campbell, J. Y., S. J. Grossman, and J. Wang, 1993, "Trading Volume and Serial Correlation in Stock Returns," *The Quarterly Journal of Economics*, 108, 905–939.

Campbell, J. Y., and L. Hentschel, 1992, "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns," *Journal of Financial Economics*, 31, 281–318.

Chan, K., and W. M. Fong, 2000, "Trade Size, Order Imbalance, and the Volatility-Volume Relation," *Journal of Financial Economics*, 57, 247–273.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, "Commonality in Liquidity," *Journal of Financial Economics*, 56, 3–28.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market Liquidity and Trading Activity," *Journal of Finance*, 56, 501–530.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, "Order Imbalance, Liquidity, and Market Returns," *Journal of Financial Economics*, 65, 111–130.

Christie, A. A., 1982, "The Stochastic Behavior of Common Stock Variances - Value, Leverage and Interest Rate Effects," *Journal of Financial Economics*, 10, 407–432.

Conrad, J., A. Hameed and C. Niden, 1994, "Volume and Autocovariances in Short-Horizon Individual Security Returns," *Journal of Finance*, 49, 1305–1329.

Cutler, D., J. M. Poterba, and L. H. Summers, 1989, "What moves stock prices?," *Journal of Portfolio Management*, 15, 4–12.

Cutler, D. M., J. M. Poterba, and L. H. Summers, 1990, "Speculative Dynamics and the Role of Feedback Traders," *American Economic Review*, 80, 63–68.

De Long, B. J., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance*, 45, 379–395.

Duffee, G., 2002, "Balance Sheet Explanations for Asymmetric Volatility," working paper, University of California, Berkeley.

Easley, D., and M. O'Hara, 1987, "Price, Trade Size and Information in Securities Markets," *Journal of Financial Economics*, 19, 69–90.

Engle, R., 1982, "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica*, 50, 987–1008.

French, K. R., and R. Roll, 1986, "Stock Return Variances: The Arrival of Information and the Reaction of Traders," *Journal of Financial Economics*, 17, 5–26.

French, K. R., G. W. Schwert, and R. Stambaugh, 1987, "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, 3–29.

Friedman, M., 1953, "The Case for Flexible Exchange Rates," in Milton Friedman (ed.), *Essays in Positive Economics*, University of Chicago Press, Chicago, IL.

Froot, K. A., D. S. Scharfstein, and J. C. Stein, 1992, "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation," *Journal of Finance*, 47, 1461–1484.

Ghysels, E., P. Santa-Clara, and R. Valkanov, 2005, "There is a Risk-Return Tradeoff After All," *Journal of Financial Economics*, 76, 509–548.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, 1993, "On the Relation Between the Expected Value and the Volatility of the Nominal Excess Returns of Stocks," *Journal of Finance*, 48, 1779–1801.

Graham, J. R., and C. R. Harvey, 2005, "Expectations of Equity Risk Premia, Volatility and Asymmetry from a Corporate Finance Perspective," working paper, Duke University, Durham, NC.

Hellwig, M.F., 1980, "On the Aggregation of Information in Competitive Markets," *Journal of Economic Theory*, 22, 477–498.

Jegadeesh, N., 1990, "Evidence of Predictable Behavior of Security Returns," *Journal of Finance*, 45, 881–898.

Jones, C., G. Kaul, and M. Lipson, 1994, "Transactions, Volume, and Volatility," *Review of Financial Studies*, 7, 631–651.

Lamoureux, C. G., and W. D. Lastrapes, 1990, "Heteroskedasticity in Stock Return Data: Volume Versus Garch Effects," *Journal of Finance*, 45, 221–229.

Lee, C., and M. Ready, 1991, "Inferring Trade Direction from Intraday Data," *Journal of Finance*, 46, 733–747.

Lehmann, B., 1990, "Fads, Martingales, and Market Efficiency," *Quarterly Journal of Economics*, 105, 1–28.

LeRoy, S. and R. Porter, 1981, "The Present-Value Relation: Tests Based on Implied Variance Bounds," *Econometrica*, 49, 555–574.

Li, C., 2003, "The Skewness Premium and the Asymmetric Volatility Puzzle," working paper, University of California Riverside.

Merton, R. C., 1980, "On Estimating the Expected Return on the Market: An Exploratory Investigation," *Journal of Financial Economics*, 8, 323–361.

Pindyck, R. S., 1984, "Risk, Inflation and the Stock Market," *American Economic Review*, 74, 334–351.

Roll, R., 1984, "Orange Juice and Weather," *American Economic Review*, 74, 861–880.

Roll, R., 1988, "R^2," *Journal of Finance*, 43, 541–566.

Schwert, G. W., 1989, "Why Does Stock Market Volatility Change Over Time?" *Journal of Finance*, 44, 1115–1153.

Schwert, G. W., 1990, "Stock Volatility and the Crash of '87," *Review of Financial Studies*, 3, 77–102.

Shiller, R., 1981, "Do Stock Prices Move Too Much to Be Justified By Subsequent Changes in Dividends?," *American Economic Review*, 71, 421–436.

Shleifer, A., 1986, "Do Demand Curves for Stocks Slope Down?" *Journal of Finance*, 41, 579–590.

Sims, C. A., 1984, "Martingale-like Behavior of Prices and Interest Rates," Discussion Paper No. 205, Center for Economic Research, University of Minnesota, Minneapolis.

Wang, J., 1993, "A Model of intertemporal asset prices under assymetric information," *Review of Economic Studies*, 60, 249–282.

Wang, J., 1994, "A Model of Competitive Stock Trading Volume," *Journal of Political Economy*, 102, 127–168.

Wu, G., 2001, "The Determinants of Asymmetric Volatility," *Review of Financial Studies*, 14, 837–859.