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MACROECONOMIC NEWS, STOCK TURNOVER, AND VOLATILITY CLUSTERING IN DAILY STOCK RETURNS

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Abstract

We study volatility clustering in daily stock returns at both the index and firm levels from 1985 to 2000. We find that the relation between today's index return shock and the next period's volatility decreases when important macroeconomic news is released today and increases with the shock in today's stock market turnover. Collectively, our results suggest that volatility clustering tends to be stronger when there is more uncertainty and disperse beliefs about the market's information signal. Our findings also contribute to a better understanding of the joint dynamics of stock returns and trading volume.

JEL Classifications: G12, G14, D80

I. Introduction

We study variations in volatility clustering for the daily returns of both the aggregate U.S. equity market and individual firms.[1] Our primary goal is to provide new empirical evidence about marketwide effects in explaining volatility clustering in both index- and firm-level stock returns. Our secondary goal is to report new evidence that further characterizes price formation and bears on proposed explanations for volatility clustering. Finally, by studying volatility clustering with turnover shocks, our work also takes up the challenge from Lo and Wang (2000) for more research to better understand the time-series variation in volume and the relation among volume, prices, and other economic quantities.

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[1]By volatility clustering or volatility persistence, we mean the well-known positive serial correlation in volatility. More specifically, we are referring to the relation between the conditional volatility of stock returns and lagged return shocks in a time-series model of volatility.

Our innovation is to examine whether the relation between conditional volatility and the lagged index return shocks varies with other non-return-based market conditions. Specifically, we examine whether the relation between today's conditional volatility and last period's index return shock depends on macroeconomic news releases and stock market turnover from last period. In this sense, our work builds from Jones, Lamont, and Lumsdaine (1998), who find that serial correlation in bond return volatility is much lower on days following macroeconomic news releases. We use only lagged values of our explanatory and conditioning variables to avoid endogeneity problems and to permit direct application of our results to volatility forecasting problems.

We study firm-level stock returns in addition to the index-level returns for several reasons. First, Campbell et al. (2001) observe that there is relatively little empirical research on volatility at the industry or firm level. They argue that understanding firm-level volatility is important because: (1) individuals may not be adequately diversified, possibly because of restricted corporate compensation policies; (2) the number of individual stocks needed to form a diversified portfolio depends on time-varying idiosyncratic volatility; (3) arbitrageurs who trade to exploit mispricing in individual stocks may be exposed to idiosyncratic volatility; and (4) total firm-level volatility is what matters for both event studies and individual stock option pricing. Second, studying firm-level volatility enables us to comment on the cross-sectional pervasiveness of the conditional volatility patterns that appear in market-level returns. The volatility patterns in index returns may not be reliably evident in firm-level returns if aggregation is necessary to reveal the volatility patterns.

First, we evaluate whether the relation between conditional volatility and the lagged index return shock is different following major macroeconomic news releases. Here, one possibility is that macroeconomic news provides symmetric information to investors and helps resolve uncertainty, which leads to weaker volatility clustering following the news release. This possibility is suggested by the findings of Jones, Lamont, and Lumsdaine (1998) for the bond market and by the findings of Ederington and Lee (1996) for the bond and currency futures markets. On the other hand, it seems plausible that the price-formation process around major public information releases could generate stronger volatility clustering. For example, volatility clustering could result from an endogenous generation of news in response to the major macroeconomic news releases, or from subsequent price movements as the market reassesses the information over a few days. Thus, this aspect of our empirical investigation evaluates whether volatility clustering patterns in the stock market are similar to those in the bond and currency markets.

Second, we examine whether the relation between conditional volatility and the lagged index return shock is different following periods with abnormal turnover. We are the first to evaluate whether volatility clustering in daily stock returns varies with turnover shocks.[2] We examine turnover shocks that are formed from a simple model that controls for the autoregressive properties of turnover and the normal movement of turnover with the absolute return.[3] We evaluate turnover shocks both at the market and firm levels.

Intuition and the prior literature suggest several reasons the turnover shock might characterize the market signal and be informative about variations in volatility clustering. First, trading activity may reflect private information flows, and private information is more likely to be gradually incorporated into prices, which might generate stronger volatility clustering (e.g., Lamoureux and Lastrapes 1990; Bessembinder, Chan, and Seguin 1996). Second, the recent literature suggests that a greater dispersion in beliefs about the market signal is likely to be associated with both higher turnover and a stronger volatility clustering in returns (e.g., Harris and Raviv 1993; Brock and Lebaron 1996; Chen, Hong, and Stein 2001). Third, it seems likely that higher economic-state uncertainty would be associated both with stronger volatility clustering and more trading activity with more frequent portfolio reallocations (e.g., Veronesi 1999; Connolly, Stivers, and Sun 2005).

We study the daily returns of the aggregate U.S. stock market and of 29 large individual firms from 1985 to 2000 and document several new findings. First, we find that the relation between the conditional volatility of daily stock returns and the lagged index return shock is weaker following important macroeconomic news announcements. This pattern is reliably evident in index returns and in 20 of the 29 individual large firms. This finding is consistent with Jones, Lamont, and Lumsdaine's (1998) findings for bond returns and with Ederington and Lee's (1996) findings for bond and currency futures contracts. Next, we find that the relation between conditional volatility and the lagged index-return shock increases significantly with the market's aggregate turnover shock last period. This pattern is reliably evident in index returns and in 26 of the 29 individual large firms. Furthermore, these volatility patterns are reliably evident in our overall sample and in both first-half and second-half subsamples.

Thus, our study provides new evidence about the nature of intertemporal volatility clustering in daily stock returns. Our evidence indicates that all index return shocks are not equal in terms of their association with future stock volatility. The magnitude of the volatility patterns in firm-level returns suggests that the marketwide conditioning variables are associated with both marketwide

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[2]Other researchers study volatility and volume jointly but examine volume series that typically exhibit substantial positive autocorrelation at the daily frequency (e.g., see Lamoureux and Lastrapes 1990; Gallant, Rossi, and Tauchen 1992). We discuss this related literature in section II.

[3]The use of turnover (defined as shares traded divided by shares outstanding) is suggested by Lo and Wang (2000) as an appropriate measure of economic trading volume, in contrast to simple trading volume. Furthermore, because turnover adjusts for the number of shares outstanding, it tends to exhibit less of a time trend than simple trading volume.

and idiosyncratic volatility. Furthermore, our market-level turnover shocks appear more empirically relevant for understanding volatility clustering than do the firm-level turnover shocks, which suggests a marketwide interpretation of the volatility clustering information in turnover shocks. For example, the turnover shocks might be informative about the dispersion in beliefs about the market's common-factor signal or the degree of economic uncertainty.

II. Data Description and Variable Construction

Daily stock returns are obtained from the Center for Research in Security Prices (CRSP) return files from January 1985 to December 2000. For the index stock return, we use the CRSP value-weighted stock index of U.S. firms. For our firm-level analysis, we examine 29 of the 30 firms that make up the Dow Jones Industrial Average (DJIA) as of September 1, 1999.[4] These firms are chosen because they are large, economically important firms and because such firms should be minimally affected by frictions, such as nonsynchronous trading, that might affect return dynamics. Table 1 presents summary statistics for these daily stock returns.

Columns 5 and 6 of Table 1 report on the simple serial correlation in volatility, where the volatility measure is the absolute return. Column 5 reports the first-order autocorrelation for the absolute firm returns, and column 6 reports the first-order, cross-serial correlation between the current absolute firm return and the lagged absolute market return. These correlations indicate volatility clustering, with an average autocorrelation of 0.204 for the firms and an average serial correlation 0.188 for the market-to-firm relations.

We obtain economic news announcement data from Money Market Services International for January 1985 through December 2000. We focus on the Producer Price Index (PPI) and civilian unemployment.[5] This choice is based on the stock volatility behavior in our sample and it follows from Jones, Lamont, and Lumsdaine (1998) and Ederington and Lee (1996). In our sample we find that stock volatility also tends to be higher than normal on days when the PPI and unemployment are announced. We sort the daily return observations into news-release days and non-news-release days. For the CRSP stock index, the daily return standard

[4] We omit Citigroup because of its major reorganization over our sample period. Also, for Procter & Gamble, we exclude the last nine months of 2000 from our sample because including the –31.4% return on March 7, 2000, leads to unreliable and implausible parameter estimates in our conditional volatility models.

[5] We focus on well-known regular periodic announcements rather than special and irregular announcements (such as Federal Reserve actions). In our view, the periodic monthly series provide good examples of important information that is homogeneous across investors and is widely anticipated at regular intervals. This news characterization seems to have a nice contrast with our unexpected turnover measure, which presumably is associated with irregular and unpredictable information that is likely to reflect a high dispersion in beliefs across investors. We also examine the Consumer Price Index and Industrial Production Index but do not find reliably higher stock volatility on the news release days for these two series.

TABLE 1. Descriptive Stock Return Statistics.

	Mean (%)	Std. Dev. (%)	Correlation $(\|R_{i,t}\|, \|R_{Mkt,t}\|)$	Correlation $(\|R_{i,t}\|, \|R_{i,t-1}\|)$	Correlation $(\|R_{i,t}\|, \|R_{Mkt,t-1}\|)$
CRSP index	0.062	0.95	N/A	0.177	N/A
Allied Signal	0.077	2.04	0.400	0.280	0.274
Alum. Co. America	0.078	1.97	0.381	0.199	0.189
American Express	0.089	2.14	0.544	0.226	0.195
AT&T	0.046	1.86	0.473	0.281	0.254
Boeing	0.076	1.86	0.344	0.190	0.154
Caterpillar	0.072	1.98	0.381	0.187	0.158
Chevron	0.071	1.56	0.342	0.112	0.158
Coca-Cola	0.102	1.77	0.502	0.274	0.257
DuPont	0.072	1.73	0.445	0.173	0.167
Eastman Kodak	0.043	1.89	0.361	0.231	0.179
Exxon	0.079	1.49	0.452	0.261	0.252
General Electric	0.097	1.58	0.632	0.197	0.208
General Motors	0.048	1.87	0.402	0.176	0.179
Goodyear	0.047	2.04	0.397	0.172	0.114
Hewlett Packard	0.089	2.46	0.405	0.139	0.151
IBM	0.053	1.89	0.417	0.183	0.197
Intern. Paper	0.057	1.91	0.471	0.179	0.153
JP Morgan	0.087	1.95	0.517	0.311	0.276
Johnson & Johnson	0.099	1.66	0.461	0.197	0.153
McDonalds	0.079	1.70	0.425	0.202	0.147
Merck	0.111	1.67	0.452	0.139	0.116
Minn. Mining & Mfg.	0.070	1.54	0.485	0.209	0.183
Philip Morris	0.098	1.88	0.365	0.175	0.111
Procter & Gamble	0.085	1.75	0.481	0.261	0.270
Sears	0.061	2.05	0.448	0.208	0.192
Union Carbide	0.110	2.21	0.284	0.209	0.193
United Technologies	0.079	1.70	0.405	0.157	0.194
Walmart	0.117	2.02	0.458	0.173	0.156
Walt Disney	0.100	1.96	0.491	0.228	0.212
Firm average	0.079	1.87	0.435	0.204	0.188

Note: The sample period is January 1985 to December 2000. $|R_{i,t}|$ is the absolute value of firm *i*'s daily stock return, $|R_{Mkt,t}|$ is the absolute daily return of the Center for Research in Security Prices (CRSP) value-weighted stock index of U.S. firms.

deviation is 1.13% for the news-release days and 0.88% for the non-news-release days (excluding the October 19, 1987, market crash; the volatility is 0.93% on the non-news-release days when including this market crash). Additionally, we estimate an augmented generalized autoregressive conditional heteroskedasticity (GARCH(1,1)) model on the CRSP stock index that includes a dummy explanatory variable in the conditional variance equation on days when there was a news release. The estimated coefficient on this news dummy is positive and statistically significant at the 1% level. We conclude that the volatility is appreciably higher on these news-release days, which fuels our interest in the relation between the return shock on the news-release day and the subsequent conditional volatility.

We collect daily share trading volume and shares outstanding for all New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) firms from 1985 to 2000 from the CRSP files. Using these data, we construct an aggregate daily turnover variable for each size-based decile portfolio of these stocks. The daily portfolio turnover is the average of the individual firm turnovers for the firms that make up each portfolio, where turnover is defined as shares traded divided by shares outstanding. We then use the turnover of the largest size-based decile as a market-level turnover variable. We use the largest decile because we desire an economic measure of turnover that represents the value-weighted market and is not subject to small firm concerns, such as nonsynchronous trading and high small firm idiosyncratic turnover.

Next, we construct a time series of market-level turnover shocks. Because it is well known that market volume is positively correlated with the absolute market return (Karpoff 1987), we desire a standardized turnover that reflects whether turnover is relatively high or low, after controlling for the absolute market return. Because trading volume tends to display substantial time trends, we also wish to control for the predictable turnover based on the autoregressive behavior of turnover. Accordingly, we construct a market-adjusted relative turnover (*MRTO*) variable that measures the turnover shock. *MRTO* is both market adjusted (orthogonal to the period's simple market return and absolute market return) and relative to recent turnover trends (orthogonal to lagged turnover). Our terminology and method follow from Connolly and Stivers (2003).[6]

$MRTO_t$ is constructed from the residual υ_t, obtained by estimating the following regression:

$$TO_{L,t} = \gamma_0 + \sum_{k=1}^{5} \gamma_k TO_{L,t-k} + \gamma_6 |R_{Mkt,t}| + \gamma_7 D_t^- |R_{Mkt,t}| + \upsilon_t \,, \tag{1}$$

where $TO_{L,t}$ is the log(turnover) of our largest size-based decile of stocks; $|R_{Mkt,t}|$ is the absolute index return; D_t^- equals 1 if the index return is negative, and 0 otherwise; and the γs are estimated coefficients. The log transformation of turnover is used to normalize the raw variable. To ensure non-negative values for our subsequent conditional volatility work, $MRTO_t$ is defined as the residual υ_t minus the minimum υ_t over the respective sample.

[6] Connolly and Stivers (2003) use a comparable turnover shock measure in their study of momentum and reversals in weekly equity index returns. They examine weekly marketwide turnover and find that: (1) unexpectedly high turnover in period t is associated with substantial momentum in consecutive weekly equity index returns from periods t and t–1, and (2) unexpectedly low turnover in period t is associated with substantial reversals in consecutive weekly equity index returns from periods t and t–1. They conjecture that a high turnover shock is more likely following periods when the trading motives were more attributable to a dispersion in beliefs with a more ambiguous stock market signal.

TABLE 2. Measuring Market-Level Turnover Shocks in U.S. Stocks.

Coefficient	1985–2000	1985–1992	1993–2000
γ_1	0.445***	0.412***	0.462***
γ_2	0.083***	0.078***	0.068***
γ_3	0.080***	0.062***	0.086***
γ_4	0.072***	0.056**	0.069***
γ_5	0.164***	0.142***	0.165***
γ_6	9.45***	13.43***	6.25***
γ_7	−2.16***	−6.04***	0.99
R^2 (%)	67.4%	50.2%	70.8%
MRTO mean	1.31	1.29	1.24
MRTO standard deviation	0.18	0.187	0.168
MRTO 10th/90th percentiles	1.12/1.50	1.09/1.51	1.08/1.41
MRTO range	0–2.79	0–2.73	0–1.91

Note: This table reports on the construction of our market-adjusted relative turnover (MRTO) measure, which is obtained from estimating the following regression:

$$TO_{L,t} = \gamma_0 + \sum_{k=1}^{5} \gamma_k TO_{L,t-k} + \gamma_6 |R_{Mkt,t}| + \gamma_7 D_t^- |R_{Mkt,t}| + \upsilon_t,$$

where $TO_{L,t}$ is the log(turnover) of our largest size-based decile of New York Stock Exchange and American Stock Exchange stocks; $|R_{Mkt,t}|$ is the absolute Center for Research in Security Prices (CRSP) index return; D_t^- equals 1 if the index return is negative, and 0 otherwise; and γs are estimated coefficients. The coefficients are estimated by ordinary least squares and reported in the table. $MRTO_t$ is defined as υ_t from this regression minus the minimum υ_t over the respective sample period (to ensure non-negative values for our subsequent conditional volatility work). The sample period is listed for each column. The last four rows report sample statistics for the constructed $MRTO_t$. The p-values are calculated with robust standard errors per the Newey-West method.

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

Equation (1) explains a substantial proportion of the variation in turnover. Table 2 reports the results from estimating (1) for the full sample and one-half sample subperiods. The R^2s for model (1) are 67.4%, 50.2%, and 70.8% for the full sample, first-half subperiod, and second-half subperiod, respectively. We choose five lags because each of the lagged explanatory variables is individually significant. Our model estimation also depicts the positive relation between turnover and the absolute market return, with an estimated γ_6 that is positive and highly significant. For the overall sample and the first subperiod, negative market returns are associated with lower turnover as compared with positive market returns of the same magnitude.[7]

[7] We also added the contemporaneous squared return as an additional explanatory variable in (1) to allow for a nonlinear relation. The R^2 from this extended model is 67.5% versus the 67.4% from (1). Furthermore, the alternate $MRTO_t$ (with the squared return term) has a correlation of 0.998 with the standard $MRTO_t$ from (1).

The last four rows in Table 2 report summary statistics for the daily $MRTO_t$ series. Note that the means and standard deviations are similar across subperiods. Also, $MRTO_t$ is approximately homoskedastic over time and exhibits no apparent time trend. Thus, we interpret $MRTO_t$ as a series that reflects the unexpected shock in turnover, after controlling for the normal turnover variation with the market return and after controlling for the autoregressive properties of turnover.

In our subsequent empirical work, we examine whether the relation between conditional volatility and lagged return shocks vary with $MRTO_t$. We estimate two variations of the interactive term based on $MRTO_t$. First, we use $MRTO_t$ directly. Although this choice uses the full information of the *MRTO* distribution, this specification assumes that any variation in the conditional volatility relation is linearly related to $MRTO_t$. Furthermore, the estimated coefficients are not easily interpreted as far as depicting how much the volatility relation varies with $MRTO_t$.

The second *MRTO*-based variable is a simple dummy variable that equals 1 if $MRTO_t$ is above its median value, and 0 otherwise. This simple choice assumes no functional form for any variations in volatility clustering related to $MRTO_t$. Furthermore, the estimated coefficients with the $MRTO_t$ dummy clearly depict the change in the relation between the conditional volatility and lagged return shock (along the lines of the dummy variable used in the asymmetric Glosten, Jagannathan, and Runkle 1993 (GJR) GARCH model). In practice, we find that both *MRTO*-based variables perform similarly in terms of the estimated likelihood function value for the conditional volatility models and the statistical significance for the estimated coefficients.

Finally, we estimate an analogous turnover shock at the firm level. For each of the 29 firms in our sample, we estimate a firm-level version of (1) where firm returns and firm turnover replace the index variables. Then, we use the residual from the firm-level estimation to form an analogous firm-adjusted relative turnover (*FRTO*) measure. In our subsequent firm-level volatility testing, we compare the empirical relevance of *FRTO* versus the market-level *MRTO*. The time-series behavior of *FRTO* is similar to that of *MRTO* except that the series are more volatile. The time-series standard deviations of *FRTO* has an average value of 0.373 for the 29 firms with a range of 0.301 to 0.475. Thus, *FRTO* is about twice as volatile as *MRTO*. The pairwise correlations between each *FRTO* with *MRTO* has an average (median) value of 0.450 (0.456).

Related work that jointly examines volatility and volume include Lamoureux and Lastrapes (1990) and Gallant, Rossi, and Tauchen (1992). Lamoureux and Lastrapes use daily trading volume as a proxy for the mixing variable from a mixture of distributions perspective. Using return and volume data from the early 1980s, they study 20 firms with a sample length of one to two years (the sample length varies for different firms). They find that including contemporaneous volume as an explanatory variable in the conditional variance equation leads to a dramatic reduction in traditional ARCH relations. They use raw volume and do not adjust for volume trends because of the short length of their sample. Gallant, Rossi, and Tauchen examine daily market-level returns and volume from 1928 to 1987. Because of the length of their sample, they go through great efforts to detrend the volume to control for long-term trends. Although their method does a nice job of removing long-term trends, the detrended series still exhibits substantial positive autocorrelation. They then use a semi-nonparametric approach to estimate the joint density of return and detrended volume. They find a positive correlation between conditional volatility and volume. They also note that large price movements tend to be followed by high volume.

III. Conditional Volatility of Daily Equity Index Returns

Overview and Empirical Models for Index-Level Stock Volatility

In this section we investigate the relation between the conditional variance of index returns and the lagged index return shocks. We examine whether the volatility clustering is different following public information releases or following days with abnormal stock turnover. In section IV, we perform a similar investigation on the 29 large firms in our sample.

Our primary model for conditional variance is an augmented version of the asymmetric GJR GARCH(1,1) model. We make this choice for the following reasons. First, Engle and Ng (1993) compare several GARCH models and find that the asymmetric GJR model appears to be among the best parametric GARCH models. Second, this specification is parsimonious and it allows for the well-known leverage asymmetry, where conditional volatility is higher following negative return shocks. Third, the asymmetric GARCH(1,1) specification is straightforwardly modified to allow the relation between the return shocks and future volatility to depend on macroeconomic new releases and turnover shocks. Finally, the familiarity of this specification provides objectivity to our exploration and facilitates comparison of our results with prior studies.

We estimate seven variations of the following augmented GARCH model on the daily returns of the CRSP value-weighted stock index:

$$R_{Mkt,t} = \beta_0 + \beta_1 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,, \tag{2}$$

$$h_{Mkt,t} = \delta_0 + (\delta_1 + \delta_2 D^-_{t-1} + \delta_3 MN_{t-1} + \delta_4 TO_{t-1})\varepsilon^2_{Mkt,t-1} + \delta_5 h_{Mkt,t-1}\,, \tag{3}$$

where $R_{Mkt,t}$ is the daily return of the CRSP value-weighted stock index; $\varepsilon_{Mkt,t}$ is the index return residual; $h_{Mkt,t}$ is the conditional variance of the index return; D^-_t is a dummy variable that equals 1 if $\varepsilon_{Mkt,t-1}$ is negative, and 0 otherwise; MN_{t-1} is a dummy variable that equals 1 if there was a macroeconomic news announcement on day t–1 (PPI or unemployment), and 0 otherwise; TO_{t-1} equals either $MRTO_{t-1}$ (for model variations 3.5 and 3.7 in Table 3), or it is a dummy variable that equals 1 if $MRTO_{t-1}$ is above its median value, and 0 otherwise (for model variations 3.4 and 3.6 in Table 3). The βs and δs are coefficients to be estimated.

It is also an interesting question whether our turnover and macroeconomic news variables have explanatory power for volatility that is separate from their interactive role with the lagged return shocks. Accordingly, we estimate a conditional volatility model that includes lagged *MRTO* and news variables as separate, stand-alone explanatory variables. Additionally, we are interested in whether the estimated δ_3 and δ_4 change appreciably when including *MRTO* and news as separate explanatory variables in the conditional variance equation. Accordingly, we estimate extended versions of (3) that include the macroeconomic news and *MRTO* terms separately, with conditional variance equations as follows:

$$h_{Mkt,t} = \delta_0 + (\delta_1 + \delta_2 D^-_{t-1} + \delta_3 MN_{t-1} + \delta_4 TO_{t-1})\varepsilon^2_{Mkt,t-1} + \delta_5 h_{Mkt,t-1} + \delta_6 MN_{t-1}, \tag{4}$$

$$h_{Mkt,t} = \delta_0 + (\delta_1 + \delta_2 D^-_{t-1} + \delta_3 MN_{t-1} + \delta_4 TO_{t-1})\varepsilon^2_{Mkt,t-1} + \delta_5 h_{Mkt,t-1} + \delta_6 TO_{t-1}, \tag{5}$$

TABLE 3. Conditional Market-Level Volatility, Turnover Shocks, and Macroeconomic News.

Panel A. Full Sample, 1985 to 2000

Model	δ_1	δ_2	δ_3	δ_4	δ_5	$\delta_6 \times 10^6$
3.1: GARCH(1,1):	0.105***				0.876***	
	(0.004)				(0.006)	
3.2: GJR GARCH(1,1)	0.030***	0.150***			0.860***	
	(0.008)	(0.010)			(0.008)	
3.3: MN	0.042***	0.144***	−0.084***		0.862***	
	(0.009)	(0.010)	(0.015)		(0.008)	
3.4: MRTO dummy	−0.004	0.126***		0.065***	0.882***	
	(0.009)	(0.010)		(0.010)	(0.008)	
3.5: MRTO	−0.169***	0.134***		0.149***	0.879***	
	(0.030)	(0.010)		(0.023)	(0.008)	
3.6: MN and MRTO dummy	0.009	0.122***	−0.075***	0.062***	0.882***	
	(0.010)	(0.011)	(0.015)	(0.010)	(0.008)	
3.7: MN and MRTO	−0.141***	0.135***	−0.075***	0.135***	0.876***	
	(0.032)	(0.010)	(0.015)	(0.024)	(0.008)	
3.8: MN with δ_6	0.044***	0.146***	−0.101***		0.861***	8.02***
	(0.009)	(0.010)	(0.015)		(0.008)	(1.920)
3.9: MRTO dummy with δ_6	0.002	0.122***		0.046***	0.927***	2.80***
	(0.009)	(0.010)		(0.010)	(0.007)	(0.600)
3.10: MRTO with δ_6	−0.157***	0.132***		0.139***	0.881***	2.06
	(0.032)	(0.010)		(0.024)	(0.008)	(2.490)

(Continued)

TABLE 3. Continued.

Panel B. One-Half Subperiod Results

Model	δ_1	δ_2	δ_3	δ_4	δ_5
First-half subperiod: 1985–1992					
3.3: MN	0.030**	0.135***	−0.106***		0.841***
	(0.011)	(0.011)	(0.017)		(0.013)
3.4: MRTO dummy	0.008	0.111***		0.048***	0.839***
	(0.014)	(0.012)		(0.015)	(0.014)
3.5: MRTO	−0.127***	0.105***		0.122***	0.849***
	(0.037)	(0.012)		(0.028)	(0.014)
3.6: MN and MRTO dummy	0.008	0.113***	−0.094***	0.038***	0.868***
	(0.013)	(0.012)	(0.016)	(0.013)	(0.012)
Second-half subperiod: 1993–2000					
3.3: MN	0.029**	0.199***	−0.059***		0.866***
	(0.014)	(0.022)	(0.028)		(0.011)
3.4: MRTO dummy	−0.024	0.196***		0.059***	0.885***
	(0.016)	(0.019)		(0.015)	(0.011)
3.5: MRTO	−0.202**	0.208***		0.170***	0.873***
	(0.072)	(0.020)		(0.056)	(0.011)
3.6: MN and MRTO dummy	−0.009	0.188***	−0.046	0.055***	0.881***
	(0.019)	(0.021)	(0.028)	(0.017)	(0.011)

Note: This table reports on variations of the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model of daily index stock returns:

$$R_{Mkt,t} = \beta_0 + \beta_1 R_{Mkt,t-1} + \varepsilon_{Mkt,t},$$

$$h_{Mkt,t} = \delta_0 + (\delta_1 + \delta_2 D^-_{t-1} + \delta_3 MN_{t-1} + \delta_4 TO_{t-1})\varepsilon^2_{Mkt,t-1} + \delta_5 h_{Mkt,t-1} + \delta_6 TO(MN)_{t-1},$$

where $R_{Mkt,t}$ is the daily return of the Center for Research in Security Prices (CRSP) value-weighted stock index; $\varepsilon_{Mkt,t}$ is the index return residual; $h_{Mkt,t}$ is the conditional variance of the index return; D^-_t is a dummy variable that equals 1 if $\varepsilon_{Mkt,t-1}$ is negative, and 0 otherwise; MN_{t-1} is a dummy variable that equals 1 if there was a macroeconomic news announcement on day $t-1$ (Producer Price Index or unemployment), and 0 otherwise; for models 3.5, 3.7, and 3.10, TO_{t-1} equals lagged market-adjusted relative turnover ($MRTO_{t-1}$); for models 3.4, 3.6, and 3.9, TO_{t-1} is a dummy variable that equals 1 if $MRTO_{t-1}$ is above its median value, and 0 otherwise. For models 3.8 through 3.10, the $TO(MN)_{t-1}$ term (with δ_6) is equal to the TO or MN variable used with the corresponding δ_3 or δ_4 term for the respective model. The βs and δs are coefficients to be estimated. GARCH = generalized autoregressive conditional heteroskedasticity; GJR = Glosten, Jagannathan, and Runkle (1993). Standard errors are in parentheses below the coefficient estimates. The sample period is January 1985 to December 2000.

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

where MN_{t-1} and TO_{t-1} with the δ_6 coefficient are as defined for (3); all other terms are also as defined for equation (3). We retain (2) for the conditional mean equation. We estimate (5) with both the simple *MRTO* and the *MRTO* dummy variable.

All of the GARCH models in this study are estimated simultaneously by maximum likelihood estimation using conditional normal density. Our inferences rely on two methods. First, p-values for individual coefficients are based on conventional standard errors for each estimated coefficient. Second, we also report results from likelihood ratio tests to compare the unrestricted versus restricted variations of our specifications.

Empirical Results for Index-Level Stock Returns

Table 3 reports the results for the conditional volatility of the index returns. Panel A presents results for our full sample period (1985 to 2000), and Panel B reports results for the first-half and second-half subsamples (1985 to 1992 and 1993 to 2000, respectively).

First, we find that the typical GARCH and asymmetric GARCH behavior is exhibited (see models 3.1 and 3.2 in Table 3). The leverage asymmetry is particularly strong, with negative return shocks having a much stronger relation to future volatility as compared with positive return shocks of the same magnitude.

Next, model 3.3 in Table 3 evaluates whether the relation between conditional variance and the lagged return shock is different following macroeconomic news releases. We find that the estimated δ_3 coefficient is -0.084 and statistically significant, indicating weaker volatility clustering. Subperiod results are qualitatively similar.

In models 3.4 and 3.5 of Table 3, we evaluate whether the relation between the conditional variance and the lagged return shocks varies with turnover shocks. In model 3.4, we use a dummy variable with the δ_4 term, where the dummy equals 1 when $MRTO_{t-1}$ is above its median value, and 0 otherwise. Model 3.5 uses $MRTO_{t-1}$ directly. For both model variations, we find that the estimated δ_4 coefficient is reliably positive. This indicates that the volatility clustering increases with the turnover shock. For the conditional variance equation in model 3.4, the implied coefficient on the lagged index return shock is: (1) essentially 0 for positive-return shocks with a low $MRTO_{t-1}$, (2) 0.061 for positive-return shocks with a high $MRTO_{t-1}$, (3) 0.122 for negative-return shocks with a low $MRTO_{t-1}$, and (4) 0.187 for negative-return shocks with a high $MRTO_{t-1}$. Subperiod results in Panel B are qualitatively similar.

Next, models 3.6 and 3.7 allow the relation between the conditional index variance and the lagged return shock to vary with both macroeconomic news releases and *MRTO*. We find that the variations in the volatility clustering with the news and *MRTO* variables are essentially the same for the combined models as they were for the simpler models 3.3 through 3.5. Again, subperiod results are qualitatively similar, although for the second-half subperiod, the estimated δ_3 coefficients on the news terms are only significant at the 10% level.

In addition to the standard errors on the estimated coefficients reported in Table 3, we evaluate the statistical significance of the *MRTO* and macroeconomic news terms with likelihood ratio tests. For these tests, the restricted model is the base asymmetric GARCH model (model 3.2 in Table 3). We treat each *MRTO* and news model (models 3.3 through 3.7) as an unrestricted model for comparison with this restricted model. The null for this test is that the news and *MRTO* interactive terms do not provide reliable incremental information over the restricted model. When comparing the restricted model with the unrestricted model, the increase in the likelihood function value for the unrestricted model is distributed as a chi-square statistic with either 1 degree of freedom (for models 3.3 through 3.5) or 2 degrees of freedom (for models 3.6 and 3.7).

The results from the likelihood ratio tests also indicate that the addition of the *MRTO* and macroeconomic news terms provides reliable additional information for the conditional volatility model. The increases in the likelihood function value for models 3.3 through 3.7, as compared with the base model 3.2, are all statistically significant at the 1% level or better. We also note that there is little to distinguish between the *MRTO* models 3.5 and 3.7 and the MRTO dummy models 3.4 and 3.6, based on the likelihood function values.

Overall, our findings indicate that all market return shocks are not equal in terms of their association with future stock volatility. Consistent with Jones, Lamont, and Lumsdaine's (1998) results in the bond market, the relation between the conditional variance and the lagged market return shock is weaker following macroeconomic news releases. Furthermore, the relation between conditional variance and the lagged market return shock is stronger following periods of unexpectedly high stock turnover.

Next, we estimate the extended versions of the conditional volatility model, equations (4) and (5). These model variations examine whether the *MRTO* and news variables, by themselves, provide incremental information about future volatility (in addition to their interactive role with the lagged return shocks through the δ_3 and δ_4 coefficients). The results are reported in models 3.8 through 3.10 in Table 3.

For the principal issues in this study, the important result is that the estimated δ_3 coefficients remain negative and significant, and the estimated δ_4 coefficients remain positive and significant. Thus, our principal volatility results remain qualitatively similar for these extended models. For the overall sample, the estimated δ_6 is positive and significant for both the macroeconomic news term and the *MRTO* dummy variable (models 3.8 and 3.9), which suggests that the stand-alone *MRTO* and macroeconomic news variables may also provide incremental information about future volatility.

IV. Conditional Volatility of Daily Firm-Level Stock Returns

Overview and Empirical Models for Firm-Level Stock Volatility

In this section we extend our analysis by investigating firm-level stock volatility. Our firm-level investigation characterizes the relation between firm volatility and index return shocks and explores the cross-sectional pervasiveness of the index-level volatility patterns documented in Table 3.

First, we document the simple relation between a firm's conditional variance and the lagged index return shock, while controlling for the lagged firm return shocks from the respective firm. This specification also serves as a baseline model for comparison with our subsequent models that allow the relation between a firm's conditional volatility and the lagged index return shocks to vary with other market variables. We estimate the following augmented asymmetric GARCH model:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,, \tag{6}$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + \phi_4 \varepsilon^2_{Mkt,t-1}, \tag{7}$$

where $R_{i,t}$ is the daily return of individual firm *i;* $R_{Mkt,t}$ is the daily return of the CRSP stock index; $\varepsilon_{i,t}$ is firm *i*'s return residual; $h_{i,t}$ is the conditional return variance of firm *i;* $D^{-}_{i,t-1}$ is a dummy variable that equals 1 if $\varepsilon_{i,t-1}$ is negative, and 0 otherwise; and $\varepsilon_{Mkt,t}$ is the market return residual. The $\varepsilon_{Mkt,t}$ residual is retained after estimating the asymmetric GJR GARCH model on the CRSP stock index (model 3.2 in Table 3). The βs and ϕs are coefficients to be estimated, and the primary coefficient of interest is ϕ_4.

With this specification (and the subsequent models in this section), we assume that the market return residual is weakly exogenous to any single individual firm return (in the statistical sense of Engle, Hendry, and Richard 1983). We follow Engle and Lee (1993) in this approach.

Next, we investigate whether the relation between conditional firm volatility and the lagged index return shock varies following a macroeconomic news release. For each firm, we estimate the following conditional variance equation with (6) as the conditional mean equation:

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + (\phi_4 + \phi_5 MN_{t-1})\varepsilon^2_{Mkt,t-1}, \tag{8}$$

where MN_{t-1} is a dummy variable that equals 1 if there was a PPI or unemployment new release in period t–1, and 0 otherwise, and the other terms are as defined for (6) and (7). The primary coefficient of interest is ϕ_5.

We also investigate whether the relation between a firm's conditional volatility and the lagged index return shock varies with the market's turnover shock. For each firm, we estimate the following conditional variance equation with (6) as the conditional mean equation:

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + (\phi_4 + \phi_6 TO_{t-1})\varepsilon^2_{Mkt,t-1}, \tag{9}$$

where TO_{t-1} equals the *MRTO* dummy variable, which equals 1 if $MRTO_{t-1}$ is above its median value, and 0 otherwise.[8] The primary coefficient of interest is ϕ_6. All other terms are as defined for equations (6) and (7).

After establishing the results when evaluating our macroeconomic news and turnover shock variables individually, we estimate a combined model that allows the relation between a firm's conditional volatility in period *t* and the index return shock in period *t*–1 to vary: (1) with the sign of the index return (to check for the sign asymmetry of Glosten, Jagannathan, and Runkle 1993), (2) with the release of macroeconomic news in period *t*–1, and (3) with *MRTO* in period *t*–1. For each firm, we estimate the following conditional variance equation with (6) as the conditional mean equation:

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + (\phi_4 + \phi_5 MN_{t-1} + \phi_6 TO_{t-1} + \phi_7 D^{-}_{Mkt,t-1})\varepsilon^2_{Mkt,t-1}, \tag{10}$$

where $D^{-}_{Mkt,t-1}$ is a dummy variable that equals 1 if the market return residual is negative, and 0 otherwise, and all other terms are as defined for equations (6) through (9). The primary coefficients of interest are ϕ_5 and ϕ_6.

Finally, to explore linkages between volatility clustering and turnover shocks, we investigate firm-level turnover shocks. For each firm, we estimate the following conditional variance equation with (6) as the conditional mean equation:

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1} + \phi_8 TO_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1}\,, \tag{11}$$

where $TO_{i,t-1}$ is a dummy variable that equals 1 if firm *i*'s $FRTO_{i,t-1}$ is above its median value, and 0 otherwise, and all other terms are as defined for equations (6) and (7). Here we are interested in whether the relation between a firm's conditional volatility and its own lagged return shock varies with the turnover shock of the respective firm; therefore, ϕ_8 is the primary coefficient of interest. Because *FRTO* is appreciably positively correlated with *MRTO,* a finding that the estimated ϕ_8 coefficients are positive and large (relative to the comparable index-level volatility results) would suggest that our prior *MRTO*-based results could be interpreted as an aggregated firm-level or bottom-up phenomenon.

Firm-Level Empirical Results

The results for estimating the baseline firm-level conditional volatility model, (6) and (7), are reported in Table 4. Here, the primary coefficient of interest

[8] We also estimated a variation of the model where TO_{t-1} equals the raw *MRTO* variable and find similar importance for the ϕ_6 term. In Tables 7 and 8, we report results with the *MRTO* dummy variable for ease of interpretation in illustrating the magnitude of the turnover-related variation.

TABLE 4. Firm-Level Conditional Volatility and Lagged Index Return Shocks.

Firm	ϕ_1	ϕ_2	ϕ_3	ϕ_4
Allied Signal	0.103***	0.125***	0.667***	0.402***
Alum. Co. America	0.047***	0.032***	0.887***	0.134***
American Express	0.037***	0.056***	0.886***	0.099***
AT&T	0.077***	−0.006	0.838***	0.190***
Boeing	0.050***	0.071***	0.697***	0.315***
Caterpillar	0.049***	0.037***	0.784***	0.294***
Chevron	0.045***	0.018	0.908***	0.051***
Coca-Cola	0.033***	0.069***	0.873***	0.096***
DuPont	0.029***	0.032***	0.943***	0.009
Eastman Kodak	0.073***	0.009	0.697***	0.296***
Exxon	0.050***	0.043***	0.859***	0.087***
General Electric	0.018**	0.047***	0.936***	0.036**
General Motors	0.053***	0.041***	0.877***	0.053***
Goodyear	0.039***	0.049***	0.903***	0.079***
Hewlett Packard	0.030***	0.007	0.888***	0.263***
IBM	0.032***	0.087***	0.907***	0.044***
Intern. Paper	0.068***	0.012	0.837***	0.259***
JP Morgan	0.052***	0.039**	0.869***	0.189***
Johnson & Johnson	0.024***	0.091***	0.879***	0.012
McDonalds	0.029***	0.039***	0.883***	0.110***
Merck	0.025***	0.061***	0.916***	0.021**
Minn. Mining & Mfg.	0.063***	−0.013	0.845***	0.158***
Philip Morris	0.046***	0.013	0.916***	0.057***
Procter & Gamble	0.022**	0.073***	0.863***	0.180***
Sears	0.056***	0.060***	0.859***	0.135***
Union Carbide	0.050***	0.052***	0.775***	0.416***
United Technologies	0.017***	0.067***	0.905***	0.062***
Walmart	0.028***	0.044***	0.913***	0.087***
Walt Disney	0.057***	0.031**	0.805***	0.258***
Firm average	0.045	0.044	0.856	0.151
Panel results	0.045***	0.048***	0.864***	0.125***
	(0.002)	(0.002)	(0.002)	(0.004)

Note: This table reports on the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model for daily firm stock returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,,$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^-_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + \phi_4 \varepsilon^2_{Mkt,t-1},$$

where the βs and δs are estimated coefficients, and other terms are as defined in Table 3, with subscript i denoting returns, conditional variances, and return residuals for each respective firm i listed in the table. The sample period is January 1985 to December 2000. The final row reports results for a panel estimation of all 29 firms simultaneously where only the intercept coefficients, β_0 and ϕ_0, are allowed to vary for each firm. Standard errors are in parentheses.

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

is ϕ_4, which captures the relation between the firm's conditional volatility and the lagged index return shocks. We find that the estimated ϕ_4 coefficients are positive and significant for 27 of the 29 firms, with an average value of 0.151. Thus, the lagged index return shocks appear to contain reliable incremental information for firm-level conditional volatility, beyond the information contained in the respective firm's lagged return shocks.

Next, the results for estimating the firm-level volatility model with macroeconomic news, equations (6) and (8), are reported in Table 5. Here, the primary coefficient of interest is the ϕ_5 coefficient, which allows the relation between conditional firm volatility and the lagged index return shock to be different following a macroeconomic news announcement at *t*–1. We find that the estimated ϕ_5 coefficient is negative and significant for 20 of the 29 firms, with an average value of –0.139. Thus, the relation between firm-level volatility and lagged index returns appears weaker following the macroeconomic news announcements.

We compare the restricted model in Table 4 with the unrestricted macroeconomic news model in Table 5 by using a likelihood ratio test. The null for this test is that the MN_{t-1} conditioning does not provide reliable incremental information for the unrestricted model, given by (6) and (8), as compared with the restricted model, given by (6) and (7). We find that a likelihood ratio test rejects this null for 11 of the 29 firms at the 10% level or better. Thus, the results for the likelihood ratio test reinforce the results in Table 5.

The volatility patterns depicted in Tables 3 and 5 are consistent with Jones, Lamont, and Lumsdaine's (1998) results for bond returns Additionally, we believe these results are consistent with Ederington and Lee (1996), who find that implied volatilities from option prices tend to drop following scheduled public news announcements. Our results also imply that the macroeconomic news releases may resolve uncertainty, which leads to lower subsequent volatility clustering.

Next, the results for estimating the firm-level volatility models with the market turnover shocks, equations (6) and (9), are reported in Table 6. Here, the primary coefficient of interest is the ϕ_6 coefficient, which allows the relation between the conditional firm volatility and the lagged index return shock to vary with $MRTO_{t-1}$. We find that the estimated ϕ_6 coefficient is positive and significant for 26 of the 29 firms. The average ϕ_6 coefficient is substantial at 0.197. Thus, the relation between firm-level conditional volatility and lagged index return shocks is stronger following periods with a relatively high market-level turnover.

By comparison, the comparable *MRTO*-related coefficient, ϕ_4, with the index returns is 0.065. This difference suggests that the *MRTO*-related increase in the relation between conditional volatility and the lagged index return shock is associated with both market-level and idiosyncratic volatility. The coefficient on

TABLE 5. Firm-Level Conditional Volatility, Lagged Index Returns, and Macroeconomic News.

Firm	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5
Allied Signal	0.104***	0.126***	0.663***	0.416***	−0.100
Alum. Co. America	0.044***	0.031***	0.890***	0.148***	−0.133***
American Express	0.037***	0.055***	0.885***	0.128***	−0.195***
AT&T	0.078***	−0.006	0.836***	0.195***	−0.017
Boeing	0.050***	0.069***	0.691***	0.381***	−0.306***
Caterpillar	0.045***	0.031***	0.806***	0.305***	−0.255***
Chevron	0.044***	0.017	0.910***	0.058***	−0.075**
Coca-Cola	0.034***	0.067***	0.871***	0.110***	−0.092
DuPont	0.030***	0.033***	0.941***	0.022**	−0.084***
Eastman Kodak	0.070***	0.011	0.715***	0.312***	−0.275***
Exxon	0.049***	0.042***	0.867***	0.100***	−0.155***
General Electric	0.018**	0.047***	0.934***	0.042***	−0.029
General Motors	0.055***	0.040***	0.873***	0.073***	−0.114**
Goodyear	0.040***	0.052***	0.897***	0.116***	−0.233***
Hewlett Packard	0.031***	0.008	0.888***	0.282***	−0.212**
IBM	0.032***	0.079***	0.915***	0.056***	−0.144***
Intern. Paper	0.064***	0.009	0.860***	0.238***	−0.217***
JP Morgan	0.052***	0.039**	0.872***	0.207***	−0.217***
Johnson & Johnson	0.024***	0.090***	0.880***	0.017	−0.037
McDonalds	0.029***	0.039***	0.883***	0.112***	−0.011
Merck	0.026***	0.062***	0.912***	0.036***	−0.065**
Minn. Mining & Mfg.	0.056***	−0.008	0.863***	0.157***	−0.159***
Philip Morris	0.046***	0.010	0.912***	0.042***	0.199***
Procter & Gamble	0.032**	0.076***	0.809***	0.199***	−0.220***
Sears	0.058***	0.060***	0.853***	0.174***	−0.195***
Union Carbide	0.050***	0.050***	0.761***	0.533***	−0.460***
United Technologies	0.018***	0.066***	0.902***	0.073***	−0.043
Walmart	0.029***	0.044***	0.911***	0.105***	−0.109**
Walt Disney	0.057***	0.029	0.805***	0.271***	−0.077
Firm average	0.045	0.044	0.855	0.169	−0.139
Panel results	0.045***	0.047***	0.867***	0.138***	−0.118***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.007)

Note: This table reports on the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model for daily firm stock returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,,$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^-_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + (\phi_4 + \phi_5 MN_{t-1})\varepsilon^2_{Mkt,t-1},$$

where the βs and ϕs are estimated coefficients, and other terms are as defined in Table 3, with subscript i denoting returns, conditional variances, and return residuals for each respective firm i listed in the table above. The sample period is January 1985 to December 2000. The final row reports results for a panel estimation of all 29 firms simultaneously, as explained in Table 4.

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

TABLE 6. Firm-Level Conditional Volatility, Lagged Index Returns, and Market Turnover Shocks.

Firm	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_6
Allied Signal	0.104***	0.125***	0.666***	0.366***	0.071
Alum. Co. America	0.041***	0.037***	0.895***	−0.036	0.337***
American Express	0.035***	0.052***	0.895***	0.041	0.102
AT&T	0.071***	−0.008	0.850***	0.081***	0.205***
Boeing	0.050***	0.063***	0.688***	0.097**	0.547***
Caterpillar	0.048***	0.037***	0.797***	0.117***	0.337***
Chevron	0.042***	0.012	0.910***	−0.006	0.145***
Coca−Cola	0.026***	0.064***	0.880***	0.037	0.148***
DuPont	0.028***	0.028***	0.945***	−0.034***	0.118***
Eastman Kodak	0.067***	−0.004	0.722***	0.086***	0.413***
Exxon	0.044***	0.035**	0.869***	0.016	0.161***
General Electric	0.012	0.048***	0.939***	−0.005	0.107***
General Motors	0.047***	0.035***	0.898***	−0.006	0.107***
Goodyear	0.027***	0.032***	0.939***	−0.051***	0.207***
Hewlett Packard	0.026***	0.007	0.911***	0.096***	0.233***
IBM	0.031***	0.082***	0.912***	0.005	0.074***
Intern. Paper	0.058***	0.016	0.872***	0.024	0.322***
JP Morgan	0.038***	0.031**	0.904***	0.005	0.284***
Johnson & Johnson	0.022***	0.083***	0.887***	−0.007	0.053
McDonalds	0.027***	0.033***	0.898***	0.034	0.136***
Merck	0.024***	0.058***	0.918***	−0.017	0.109***
Minn. Mining & Mfg.	0.061***	−0.019	0.862***	0.050***	0.176***
Philip Morris	0.048***	0.014	0.912***	0.080***	−0.043
Procter & Gamble	0.023**	0.065***	0.884***	0.052**	0.187***
Sears	0.051***	0.051***	0.874***	−0.010	0.297***
Union Carbide	0.045***	0.057***	0.795***	0.196***	0.420***
United Technologies	0.008	0.062***	0.917***	−0.014	0.191***
Walmart	0.026***	0.045***	0.907***	0.041	0.159***
Walt Disney	0.053***	0.029**	0.818***	0.193***	0.097**
Firm average	0.041	0.040	0.868	0.049	0.197
Panel results	0.040***	0.042***	0.882***	0.023***	0.183***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)

Note: This table reports on the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model of firm stock returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,,$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^-_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} + (\phi_4 + \phi_6 TO_{t-1})\varepsilon^2_{Mkt,t-1},$$

where the βs and ϕs are estimated coefficients; TO_{t-1} equals 1 if lagged market-adjusted turnover ($MRTO_{t-1}$) is above its median value, and 0 otherwise; and other terms are as defined in Table 3, with subscript i denoting returns, conditional variances, and return residuals for each respective firm i listed in the table. The sample period is January 1985 to December 2000. The final row reports results for a panel estimation of all 29 firms simultaneously, as explained in Table 4.

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

$\varepsilon^2_{Mkt,t-1}$ when the $MRTO_{t-1}$ is above its median value (which equals ϕ_4 plus ϕ_6) is substantial, with an average value of 0.246 over the 29 firms.[9]

We also compare the restricted model in Table 4 with the unrestricted *MRTO* model in Table 6 by using a likelihood ratio test. The null for this test is that the $MRTO_{t-1}$ conditioning does not provide reliable incremental information for the unrestricted model, given by (6) and (9), as compared with the restricted model, given by (6) and (7). We find that a likelihood ratio test rejects this null for 22 of the 29 firms at the 10% level or better. Thus, this test reinforces our previous inference about the importance of the *MRTO* conditioning.

We also estimate the system with the continuous version of the *MRTO* variable rather than the *MRTO* dummy variable. The results are similar and are not reported in tabular form. For the continuous variation, the estimated ϕ_6 coefficient is positive and significant for 28 of the 29 firms.

Next, Table 7 reports the results for our combined model, equations (6) and (10), which allows the relation between a firm's conditional volatility in period *t* and the index return shock in period *t*–1 to vary: (1) with the sign of the index return shock (to check for the sign asymmetry of Glosten, Jagannathan, and Runkle 1993), (2) with the release of macroeconomic news in period *t*–1, and (3) with *MRTO* in period *t*–1. Here, the primary coefficient of interest is ϕ_5 (with the macroeconomic news term) and ϕ_6 (with the *MRTO* term). We find that the estimated ϕ_5 coefficients are negative and significant for 17 of the 29 firms, with an average value of –0.099. The estimated ϕ_6 coefficients are positive and significant for 27 of the 29 firms, with an average value of 0.182. Thus, the volatility patterns from Tables 5 and 6 largely survive intact in our combined model estimation.

We also note that the estimated ϕ_7 coefficient (which incorporates the sign asymmetry) is positive and significant for only 12 of the 29 firms, with an average value of 0.073. By comparison, the coefficient for the sign asymmetry with index-level returns is 0.122 (model 3.6 in Table 3). Thus, the sign asymmetry appears less important for the firm-level conditional volatilities as compared with the index conditional volatility.

We also estimate this combined model for the one-half subperiods. For the MN_{t-1} term, we find that the estimated ϕ_5 coefficient is negative and significant for 25 of the 29 firms for the 1985 to 1992 period, and for 5 of the 29 firms for the 1993 to 2000 period. For the $MRTO_{t-1}$ term, we find that the estimated ϕ_6 coefficient is positive and significant for 23 of the 29 firms for the 1985 to 1992 period, and for 22 of the 29 firms for the 1993 to 2000 period. Finally, for the sign asymmetry term, we find that the estimated ϕ_7 coefficient is positive and significant for 11 of the 29 firms for the 1985 to 1992 period, and for 14 of the 29 firms for the 1993 to

[9]This is an interesting contrast to the results of Lamoureux and Lastrapes (1990). They find that lagged firm volume has little relation to a firm's conditional volatility (see their footnote 4).

TABLE 7. The Market to Firm Volatility Relation, Turnover Shocks, and Macroeconomic News.

Firm	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_6	ϕ_4	ϕ_6
Allied Signal	0.112***	0.102***	0.669***	0.245***	0.048	0.010	0.290***
Alum. Co. America	0.037***	0.036**	0.900***	−0.025	−0.218***	0.356***	0.003
American Express	0.035***	0.050***	0.894***	0.059	−0.187***	0.099**	0.020
AT&T	0.075***	−0.018	0.857***	0.005	0.052	0.192***	0.113**
Boeing	0.050***	0.053***	0.689***	0.097	−0.117	0.510***	0.098
Caterpillar	0.046***	0.032**	0.812***	0.115**	−0.148**	0.295***	0.036
Chevron	0.042***	0.005	0.915***	−0.034	−0.023	0.142***	0.051**
Coca-Cola	0.030***	0.059***	0.878***	0.027	−0.044	0.147***	0.034
DuPont	0.022***	0.035***	0.950***	0.006	−0.110***	0.120***	−0.056
Eastman Kodak	0.062***	−0.013	0.744***	0.047	−0.089	0.361***	0.113**
Exxon	0.046***	0.027**	0.878***	0.004	−0.093**	0.133***	0.050
General Electric	0.015	0.043***	0.939***	−0.013	−0.036	0.110***	0.021
General Motors	0.051***	0.028**	0.893***	−0.018	−0.100**	0.109**	0.052
Goodyear	0.030***	0.024***	0.939***	−0.079***	−0.149***	0.181***	0.110***
Hewlett Packard	0.023***	0.012	0.916***	0.153**	−0.184**	0.231***	−0.079
IBM	0.032***	0.071***	0.918***	−0.001	−0.114***	0.052***	0.050
Intern. Paper	0.051***	0.014	0.897***	0.031	−0.157***	0.274***	−0.021
JP Morgan	0.040***	0.014	0.917***	−0.053	−0.099	0.267***	0.109**
Johnson & Johnson	0.026**	0.076***	0.886***	−0.021	−0.045	0.056	0.036
McDonalds	0.030***	0.026**	0.900***	0.009	−0.025	0.139***	0.045
Merck	0.024***	0.055***	0.919***	−0.011	−0.063**	0.116***	0.001
Minn. Mining & Mfg.	0.043***	−0.027**	0.938***	−0.018	−0.116***	0.083***	0.090***
Philip Morris	0.050***	0.009	0.905***	0.057**	0.215***	−0.054	0.025
Procter & Gamble	0.040***	0.036	0.835***	0.012	−0.144**	0.187***	0.119**
Sears	0.055***	0.041***	0.874***	−0.031	−0.238***	0.300***	0.098
Union Carbide	0.049***	0.043***	0.786***	0.117**	−0.507***	0.404***	0.337***
United Technologies	0.008	0.058***	0.921***	−0.020	−0.035	0.191***	0.017
Walmart	0.030***	0.036***	0.907***	0.004	−0.152**	0.183***	0.085
Walt Disney	0.068***	0.003	0.806***	0.070	−0.003	0.075	0.276***
Firm average	0.042	0.032	0.872	0.025	−0.099	0.182	0.073
Panel results	0.041***	0.036***	0.888***	0.006	−0.085***	0.174***	0.048***
	(0.002)	(0.003)	(0.002)	(0.007)	(0.008)	(0.005)	(0.008)

Note: This table reports on the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model of firm-level stock returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,,$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^-_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1} \; + (\phi_4 + \phi_5 MN_{t-1} + \phi_6 TO_{t-1} + \phi_7 D^-_{Mkt,t-1})\varepsilon^2_{Mkt,t-1},$$

where the βs and ϕs are estimated coefficients; $D^-_{Mkt,t-1}$ is a dummy variable that equals 1 if the index return residual is negative, and 0 otherwise; TO_{t-1} is as defined for Table 6; and all other terms are as defined in Table 3, with subscript i denoting returns, conditional variances, and return residuals for each respective firm i listed in the table. The sample period is January 1985 to December 2000. The final row reports results for a panel estimation of all 29 firms simultaneously, as explained in Table 4.

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

2000 period. Thus, the results for the one-half subperiods are largely similar to the results in Table 7 for the overall sample, although the macroeconomic news effect is marginal in the second-half period.

Finally, Table 8 reports the results for estimating firm-level conditional volatility with the turnover shocks from the respective firm (rather than the market-level turnover shocks), equations (6) and (11). Here, the primary coefficient of interest is ϕ_8, which allows the relation between conditional firm volatility and the lagged own-firm-return shocks to vary with the respective firm's $FRTO_{t-1}$. We find that the estimated ϕ_8 coefficient is positive and significant for only 12 of the 29 firms, with a modest average value of 0.015. This suggests that the turnover results seem to be more of a marketwide rather than firm-level phenomenon.

The final row in Tables 4 through 8 reports the results for a panel model estimation across all 29 firm returns, where only the intercept coefficients (β_0 and ϕ_0) are allowed to vary across firms. The panel estimation reinforces our findings from the individual firm estimations. We find estimated panel coefficients that are close to the simple average of the comparable coefficients for the stand-alone firm estimations. The statistical significance for the panel coefficients is stronger, which is not surprising as the panel estimation has nearly 120,000 return observations.

V. Summary and Conclusions

We provide new empirical evidence about marketwide effects in explaining volatility clustering in both index- and firm-level stock returns. Our findings suggest that incorporating non-return-based market information, such as aggregate stock turnover shocks and macroeconomic news releases, may lead to a better conditional volatility model for both index- and firm-level returns. Our findings also contribute to a better understanding of the nature of volatility clustering and the joint dynamics of stock returns and turnover.

Specifically, we study volatility clustering in daily returns for the aggregate U.S. equity market and 29 large firms from 1985 to 2000. Similar to Jones, Lamont, and Lumsdaine's (1998) work in the bond market, we evaluate whether all index return shocks are equal in terms of their explanatory power for future volatility. We study how the relation between today's index return shock and future stock volatility varies, conditional on today's turnover shock and conditional on whether there was an important macroeconomic news release today.

First, we find that the relation between today's index return shock and future volatility is weaker when there was a PPI or an unemployment news release today. Second, we find that the relation between today's index return shock and future volatility varies positively with today's market-level turnover shock. Our findings are reliably present both for index- and firm-level stock returns. Furthermore, subperiod analysis over 1985 to 1992 and 1993 to 2000 yields similar results.

TABLE 8. Autocorrelation in Firm-Level Volatility and Own-Firm Turnover Shocks.

Firm	ϕ_1	ϕ_2	ϕ_8	ϕ_4
Allied Signal	0.111***	0.170***	0.061***	0.702***
Alum. Co. America	0.050***	0.043***	−0.022***	0.927***
American Express	0.033***	0.065***	0.012	0.904***
AT&T	0.083***	0.026***	0.000	0.875***
Boeing	0.016***	0.035***	−0.010**	0.962***
Caterpillar	0.059***	0.094***	−0.001	0.821***
Chevron	0.029***	0.033***	0.025***	0.927***
Coca-Cola	0.006	0.069***	0.043***	0.917***
DuPont	0.031***	0.032***	−0.006	0.947***
Eastman Kodak	0.050***	0.092***	0.130***	0.704***
Exxon	0.020**	0.043***	0.040***	0.920***
General Electric	0.015**	0.052***	0.011**	0.947***
General Motors	0.037***	0.049***	0.017	0.905***
Goodyear	0.024***	0.062***	0.026***	0.916***
Hewlett Packard	0.024***	0.014***	−0.016**	0.967***
IBM	0.014***	0.091***	0.033***	0.917***
Intern. Paper	0.029***	0.014**	0.026***	0.949***
JP Morgan	0.051***	0.093***	0.016	0.882***
Johnson & Johnson	0.014	0.092***	0.021**	0.884***
McDonalds	0.025***	0.045***	0.011	0.931***
Merck	0.020***	0.058***	0.010	0.930***
Minn. Mining & Mfg.	0.055***	0.006	−0.015**	0.938***
Philip Morris	0.035***	0.015**	0.017**	0.935***
Procter & Gamble	0.022***	0.070***	0.014**	0.928***
Sears	0.043***	0.075***	0.028**	0.887***
Union Carbide	0.044***	0.062***	−0.018**	0.904***
United Technologies	0.023**	0.073***	−0.012	0.925***
Walmart	0.031***	0.043***	0.002	0.935***
Walt Disney	0.061***	0.068***	−0.002	0.877***
Firm average	0.036	0.058	0.015	0.902
Panel results	0.011***	0.076***	0.063***	0.885***
	(0.003)	(0.002)	(0.003)	(0.002)

Note: This table reports on the following augmented asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) model of firm stock returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{Mkt,t}\,,$$

$$h_{i,t} = \phi_0 + (\phi_1 + \phi_2 D^{-}_{i,t-1} + \phi_8 TO_{i,t-1})\varepsilon^2_{i,t-1} + \phi_3 h_{i,t-1},$$

where the βs and ϕs are estimated coefficients; $TO_{i,t-1}$ is a dummy variable that equals 1 if the respective firm's firm-adjusted turnover ($FRTO_{i,t-1}$) is above its median value; and all other terms are as defined in Table 3, with subscript i denoting returns, conditional variances, and return residuals for each respective firm i listed in the table. The sample period is January 1985 to December 2000. The final row reports results for a panel estimation of all 29 firms simultaneously, as explained in Table 4.

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

Because the average magnitude of the conditional relations is larger for the firm returns as compared with the index returns, our results suggest that our news and turnover conditioning factors are informative about both future market-level and idiosyncratic volatility.

Finally, with regard to variations in volatility clustering, our results suggest that aggregate turnover shocks are more empirically relevant than firm-level turnover shocks. Thus, the volatility clustering information in turnover shocks seems to have more of a marketwide interpretation (rather than an interpretation attributed to the aggregation of firm-level volatility patterns). For example, the market-level turnover shocks might be informative about the dispersion in beliefs about the market signal (in the sense of Harris and Raviv 1993) or about the degree of economic uncertainty (in the sense of Veronesi 1999).

Our evidence directly supports Jones, Lamont, and Lumsdaine's (1998) conclusions for the bond market in that return shocks seem to vary in their persistence depending on their sources. Under the assumptions that scheduled macroeconomic news releases tend to resolve uncertainty and that abnormally high turnover is more likely during periods with higher dispersion in beliefs and economic uncertainty, our findings suggest that volatility clustering is: (1) weaker following periods when the market's information signal is relatively clear and symmetric across investors and (2) stronger following periods when the market's information signal reflects higher dispersion in beliefs and uncertainty.

Our study suggests several avenues for future research. First, our findings may have direct applications to risk management, option pricing, event studies, or other applications that rely on conditional volatility estimates. A formal evaluation of these potential applications would be interesting. Second, subsequent theoretical and empirical work may refine the interpretation of our evidence and further explore the empirical relevance of turnover shocks in explaining return behavior. Finally, our findings may generalize to other asset markets and settings. We look forward to further developments in this literature.

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