# Evidence on the Economics of Equity Return Volatility Clustering

**by**

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**First Draft: November 12, 1999**

**This Version: December 30, 1999**

* Corresponding author. Thanks to Bill Lastrapes and Mark Lipson for helpful discussions.

## ABSTRACT

# Evidence on the Economics of Equity Return Volatility Clustering

The underlying economic sources of volatility clustering in asset returns remain a puzzle in financial economics. Using daily equity returns, we study variation in the volatility relation between the conditional variance of individual firm returns and yesterday's market return shock. We find a number of regularities in this market-to-firm volatility relation. (1) It decreases following macroeconomic news announcements; (2) it does not change systematically during the high-news months when firms announce quarterly earnings; and (3) it increases substantially with our measures of dispersion-in-beliefs across traders about the market's common-factor signal. Our evidence suggests that volatility-clustering is a natural result of a price formation process with heterogeneous beliefs across traders, and that volatility clustering is not attributable to an autocorrelated news-generation process around public information such as macroeconomic news releases or firms' earnings releases. We find consistent results in our sample of large-capitalization firms in Japan and the U.K., which suggests a generality of our results and bolsters our economic interpretation.

# Evidence on the Economics of Equity Return Volatility Clustering

## I. Introduction

Volatility clustering in short horizon asset returns is one of the most pervasive and widely studied empirical phenomena in finance. While there has been a huge empirical literature exploring statistical models of this volatility clustering, the underlying economic causality of this return dynamic remains very much a puzzle.[1]

One simple explanation for volatility clustering is that the underlying fundamental news flows are serially correlated. However, empirical studies that have tried to link equity return volatility with real news have had limited success (see e.g., Mitchell and Mulherin, 1994; and Haugen, Talmor, and Torous, 1991). Additionally, Jones, Lamont, and Lumsdaine (1998) find that volatility clustering in bond returns is much lower on days following macroeconomic news announcements. This suggests that the volatility clustering is not due to either an autocorrelated news-generation around public macroeconomic news releases or a systematic under- or over-reaction to the news announcement.

A second potential explanation is that volatility clustering may be a byproduct of a price formation process with dispersion-in-beliefs across risk-averse agents, even if the underlying fundamental information flows are not autocorrelated. For example, Harris and Raviv (1993) and Shalen (1993) present theoretical models where a dispersion-in-beliefs may generate volatility clustering. Similarly, Kurz and Motolese (1999) examine a model of rational beliefs with heterogeneous agents who have diverse, but correlated beliefs. In their framework, they argue that GARCH is generated by the structure of heterogeneous beliefs in the market. Brock and Lebaron (1996) propose a model of adaptive beliefs and conclude that volatility clustering may be generated from the trading and price formation process even when fundamental news is serially uncorrelated.[2]

1. See e.g., Bollerslev, Chou, and Kroner (1992) for a survey of the ARCH/GARCH literature. They state, “While serial correlation in conditional second moments is clearly a property of speculative prices, a systematic search for the causes of this serial correlation has only recently begun”.

2. Additionally, recent theory studies such as Wang (1993), Slezak (1994), and Jones and Slezak (1999) analyze return volatility in a noisy rational-expectations market with asymmetric information and risk-averse agents. They conclude that volatility in markets with imperfect information may be different than volatility in markets with perfect symmetric information.

In this study, we explore whether market information characteristics are systematically related to the strength of the volatility clustering phenomenon in daily equity returns. Our goal is to provide new empirical evidence that bears on the following questions. Is volatility clustering in daily equity returns generated by autocorrelated fundamental news? Or, is some of the volatility clustering attributable to the price formation process with risk-averse agents who have correlated but diverse beliefs? What information variables may be associated with stronger or weaker volatility clustering, and what can we learn from these conditional relations? Can conditioning variables related to market information characteristics substantially improve the modeling of the conditional variance of equity returns? Our study builds from, and is most closely related to, Jones, Lamont, and Lumsdaine (1998).

Specifically, we study how the conditional variance of individual firm returns is related to yesterday's market return shock. We examine whether the intertemporal market-to-firm volatility flow varies with either measures of identifiable information flows or measures of dispersion-in-beliefs across traders. We conduct our testing with a modified version of the widely used asymmetric GARCH(1,1) model. We insert yesterday's squared market return shock directly into the conditional variance equation for the individual firm returns and then allow the estimated coefficient on the lagged market shock to vary with our information variables.[3] We use only lagged values of the explanatory and conditioning variables to avoid endogeneity issues and to be consistent with the approach in the volatility forecasting literature.

We develop cross-sectional evidence on the economics of volatility clustering by focusing on individual firm returns. The great majority of existing studies have investigated the volatility dynamics of aggregate market returns. Our study contributes to the literature on volatility clustering by separating the contributions of common-factor and idiosyncratic effects on volatility clustering in firm-level returns.[4] We take advantage of the fact that aggregate market statistics such as the market return and cross-sectional return dispersion should be exogenous to any single firm return.

3. We use the asymmetric GARCH form proposed by Glosten, Jagannathan, and Runkle (1993).

4. Understanding how market volatility affects the total conditional variance of individual firm returns is also potentially important for option pricing.

We analyze the daily stock returns of the 30 large firms that comprise the Dow Jones Industrial Average as of September 1, 1999. We first examine whether the intertemporal market-to-firm volatility connection varies with public information flows. Specifically, we test for differences following important macroeconomics news announcements. While the timing of such macroeconomic news announcement is known and fixed (and thus not autocorrelated at the daily horizon), it may be possible that such news generates volatility clustering between firm returns and the lagged market return. Volatility clustering could result from an over- or under-response of firm-level prices to the macroeconomic news or from endogenous generation of additional news as policymakers respond to the news shock. However, we find that volatility clustering appears weaker following these macroeconomic news announcements, a result qualitatively similar to the findings from Jones, Lamont, and Lumsdaine (1998) for bond returns.

We also assess whether the intertemporal market-to-firm volatility connection may be altered by firm-level news flows. Specifically, we investigate whether there is a systematic monthly seasonal in volatility clustering during the 'high-news' months when firms typically announce their earnings. Cross-sectional correlation in earnings news would mean that this news might comprise a portion of the market's common-factor signal for a given period. Since firms typically report their quarterly earnings in the same month, it may be possible that the cycle of earnings announcements generates autocorrelated daily market volatility in these months (April, July, and October).[5] If so, this could produce a stronger market-to-firm volatility connection in these 'high-news' months. However, we find no systematic seasonal variation in the market-to-firm volatility relationship for these 'high-news' months. Both April and July appear to have weaker volatility clustering while October has stronger volatility clustering, as compared to the average month.

Next, we investigate the hypothesis that volatility clustering may be (at least partially) a byproduct of the price formation process when risk-averse investors have a difference of opinion (dispersion-in-beliefs) about the market's information signal. High dispersion-in-beliefs in particular market periods may be due to either relatively high differential information across investors and/or a

5. Mitchell and Mulherin (1994) find that the months of April, July, and October have the highest number of news announcements. U.S. firms typically report quarterly earnings in these three months. Annual earnings announcements are typically spread over January and February.

relatively high differential interpretation of public information.[6] This part of our work is motivated by the aforementioned theoretical papers that suggest that dispersion-in-beliefs may generate volatility clustering in asset returns, even when fundamental news is serially uncorrelated. Our previous results also suggest this may be a worthwhile exploration. If volatility clustering is weaker following identifiable macroeconomic news (presumably periods when there is less ambiguity about the sources and interpretation of market news), then volatility clustering may be stronger following periods with a relatively more ambiguous signal or a higher dispersion-in-beliefs.

Building from Amihud and Mendelson (1989), Bessembinder, Chan, and Seguin (1996), Stivers (1999), and Connolly and Stivers (1999), we use the market's relative cross-sectional return dispersion as a market information environment variable.[7] The intuition is as follows. A base level of return dispersion (RD) in a market should be generated from the cross-sectional dispersion in factor loadings and the common-factor shock. Presumably, variations from this base level of RD would be generated from firm-idiosyncratic information flows, noise, and differential firm-level interpretations of the market's common-factor signal.[8] Since idiosyncratic information flows and noise should be largely diversifiable, a relatively high market RD should reflect, on average, a relatively high variability in firm-level interpretations of the common-factor signal. Thus, after controlling for the market factor shock, a relatively high RD should reflect more ambiguity in the common-factor signal and a higher dispersion-in-beliefs across different firms' traders.

We find a much stronger intertemporal market-to-firm volatility relationship when the market's lagged RD is relatively high. For the 30 DJIA firms, 27 of them exhibit a significantly stronger market-to-firm volatility connection when the market's lagged RD is relatively high. The relation holds for

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6. Thus, we sidestep the debate about whether asymmetric information or asymmetric interpretation is the source of dispersion-in-beliefs, and concentrate on exploring whether there is a link between volatility clustering and signal quality/dispersion-in-beliefs. An asymmetric information interpretation would require a market of incomplete information in the sense of Merton (1987). See Kurz and Motolese (1999) for an excellent discussion that debates the "asymmetric information" versus "asymmetric interpretation" issue.

7. We use the cross-sectional standard deviation of individual firm returns about the market return for a period as our return dispersion metric.

8. A differential firm-level interpretation of the market's common-factor signal could result because traders for different firms have differential information in the sense of Merton (1987), or dispersion-in-beliefs in the sense of Harris and Raviv (1993), or Kurz and Motolese (1999).

different sample periods, different GARCH specifications, and different methods for forming the lagged market RD variable. The size and reliability of this conditional relation suggests that the phenomenon is economically as well as statistically significant.[9] As we show in later in the paper, we find comparable results for firm-level volatility clustering in Japan and the U.K.

Volume has also been proposed as a measure associated with dispersion-in-beliefs. In certain models, trading between speculative investors relies on a difference in beliefs. For 18 of the 30 DJIA firms, we find that the intertemporal market-to-firm volatility relation is stronger when there was a relatively high aggregate market volume yesterday. This finding is consistent with the above return dispersion findings. Further, both the volume and return dispersion conditioning remain largely evident in a volatility model that allows for both volume and RD conditioning jointly.

To summarize, our study provides new evidence that volatility clustering is not linked to identifiable periodic market or firm-level news. Instead our evidence suggest that the intertemporal market-to-firm volatility connection is stronger following periods of high signal ambiguity and high dispersion-in-beliefs. Our findings also suggest that including information environment variables in the volatility model may improve the modeling of the conditional volatility in daily equity returns.

The paper is organized as follows. We describe our data and measurement methods in Section 2. We present the first round of empirical results involving U.S. data in Section 3. We extend the empirical work to Japanese and U.K. data in Section 4. Section 5 concludes the paper.

## II. Data Description

### A. Individual Stock Returns

For our empirical work, we gathered a sample of data from the U.S. and two foreign equity markets, Japan and the U.K. For the U.S., we obtain daily return data from the CRSP return files for the 30 firms that comprise the Dow-Jones Industrial Average (DJIA) as of September 1, 1999. We choose to examine these firms because we want to reduce as much as possible the possibility that frictions such as non-synchronous trading might affect return dynamics.

9. Relatedly, Stivers (1999) also finds that the market's lagged RD has a role in explaining volatility dynamics. He analyzes aggregate market return volatility at the weekly and monthly horizon and finds that the market's lagged RD is a sizeable and reliable explanatory variable for future market return volatility.

Table 1, Panel A presents summary statistics for the daily returns of these 30 large firms from January 1, 1985 through December 31, 1996. We focus on the 1985-1996 period as our primary sample period because this period coincides with our macroeconomic news announcement data.[10] The daily return standard deviation for each firm is presented in column two. The volatility for these 30 firms is comparable with a range of 1.38% to 2.23% for the daily return standard deviations.

Columns four and five of Table 1 examine volatility clustering by reporting simple first-order correlation coefficients. Column four reports the first-order autocorrelation for the absolute firm returns, and column five reports the first-order, cross-serial correlation between the current absolute firm return and the lagged absolute market return. The magnitudes for these two serial correlations are quite close with an average of 0.207 for the firm autocorrelation and 0.188 for the market-to-firm serial correlation. The magnitude and the cross-sectional pervasiveness of the volatility clustering is evident in these correlations. Both bits of evidence suggest that volatility clustering is an important economic phenomenon for both firm autocorrelation in volatility and for market-to-firm serial correlation in volatility.

For the Japanese and the U.K. markets, we collect the individual firm returns for the firms that comprise the Nikkei-225 for Japan and the FTSE-100 for U.K. We collect daily firm returns for all firms that are in each index as reported in Datastream International over the 1985 through 1996 time period. We study the conditional variances of 20 large-cap firms from each market. We select the 20 largest firms, based on the market capitalization on September 1996 from Datastream, that have the entire 12 years of daily firm returns. Banks are omitted. The cross-sectional return dispersion for each market (see section C below) is calculated from all individual firm returns that comprise each index, as reported in Datastream. For an aggregate market return in each country, we use the mean return of the available Nikkei-225 and FTSE-100 firm returns.

**B. Size-Based, Decile-Portfolios**

We also obtain daily firm return and market capitalization data for the July 1962 – December 1996 sample period from the CRSP return files for all NYSE and AMEX stocks. Size-based, decile-

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10. We also later analyze the pre-1985 firm returns for the tests that do not require macroeconomic news data.

portfolio returns are formed by sorting firms based on their market capitalization. All NYSE and AMEX firms with return and market capitalization data for the period are included. The decile-portfolio returns are an equal-weighted average of the component firm returns. The size-based portfolios are reformed every period based on the firms' market capitalization. Using this algorithm, we compute daily portfolio returns from July 1962 through December 1996. We also use the individual firm returns that make up each portfolio to construct a return dispersion (RD) metric for each portfolio every period.

**C. Cross-Sectional Return Dispersion (RD) and Relative RD (RRD) Metrics**

Our use and interpretation of the market's RD follows closely from Stivers (1999) and Connolly and Stivers (1999). We define the stock market's cross-sectional RD in period *t* as:

$$RD_t = \left[ \frac{1}{n-1} \sum_{i=1}^{n} (R_{i,t} - R_{Mkt,t})^2 \right]^{1/2} \qquad \textbf{(1)}$$

where *n* is the number of firms in the market-portfolio, and $R_{Mkt,t}$ is the return of the market portfolio. In the empirical testing of Section 3, we use the return dispersion from the largest size-based, decile-portfolio of NYSE/AMEX stock as a market RD statistic. Widely traded, large-cap firms are used to form a market RD statistic to ensure that small firm return characteristics do not dominate the measure. For example, a high degree of small-firm idiosyncratic volatility or non-synchronous trading could result in a high RD even when the RD of large firms was not abnormal.

The relative RD measure (RRD) is meant to indicate the level of the market's RD, after controlling for the RD attributed to the dispersion in factor loadings and the market factor shock. It is necessary to control for the relation between the market's RD and the market return because the cross-sectional variation in factor loadings generates return dispersion that is proportional to the absolute market return.[11]

The RRD metric is defined as the residual, $u_t$, obtained from estimating the following regression:

$$RD_t = \phi_0 + \gamma_1 \left| R^e_{Mkt,t} \right| + \gamma_2 Dum1_t \left| R^e_{Mkt,t} \right| + u_t \qquad \textbf{(2)}$$

11. See Stivers (1999) for a more detailed development of the relation between RD and the market return magnitude in a classic Sharpe-Lintner CAPM framework.

where RD is the cross-sectional return dispersion of the individual firm returns about the market-portfolio return for the period; $\left|R^{e}_{Mkt.t}\right|$ is the absolute value of the excess return of the market-portfolio return for period $t$ (the excess return is the nominal return less a risk-free rate from T-bills); $Dum1_t = 1$ if the portfolio excess return is negative, and is 0 otherwise; $u_t$ is the residual; and the $\phi$ and $\gamma$'s are estimated coefficients. The $\gamma_2$ coefficient allows for an asymmetric relation between negative and positive portfolio returns and RD as reported in Lamoureux and Pannikath (1994).

Panel B of Table 1 reports summary statistics for the portfolio return and the RD of the largest size-based, decile-portfolio return. As expected, the relation between RD and absolute market return is quite substantial with a simple correlation of 0.477 and an R-squared of 24.2% for the model given by (2).

Also, note the substantial autocorrelation of the RRD variable. Even after the RD is made orthogonal to the market return using (2), the first-order autocorrelation of the adjusted RRD series is still 0.368. The coefficients in an autoregressive model for RRD remain sizeable out to ten lags, with the sum of the ten AR coefficients equaling 0.737.[12] The R-squared for the AR(10) model is 22.1%. These time-series properties suggest that the information environment associated with a high market RRD is persistent. This seems reasonable if the RRD is informative about the signal ambiguity and dispersion-in-beliefs about the market's common-factor signal.

**D. Macroeconomic News Announcements**

To investigate the relation between public macroeconomic news and market volatility clustering and return dispersion, we obtain economic news announcement data from MMS International. Our economic news data spans the January 1985 - December 1996 period. We use the actual and expected value of the following economic news items: Consumer Price Index, Producer Price Index, Industrial Production Index, and civilian unemployment. We treat the median survey data of the expected news item, compiled by MMS International, as the market's expectations of the economic announcements. We form macroeconomic news shock variables by taking the actual monthly percentage change of the item minus the expected monthly percentage change.

12. The RRD is highly autocorrelated, but it is far from a unit root when tested using either Dickey and Fuller (1979) or Phillips and Perron (1988) tests.

We analyze whether these four news items affect contemporaneous market volatility and the market's RD as follows. First, we examine each news item individually in a GARCH model for market returns by adding a news announcement dummy variable in the conditional variance equation on days when there is an announcement. Only the PPI and unemployment are associated with an increase in market volatility. Based on this, we use a macroeconomic-news dummy variable that equals one on PPI and unemployment announcement days (and is zero otherwise) in our subsequent conditional volatility testing.

We also examine whether the market's RRD is systematically different on these news announcement days. The average RRD is 0.31 standard deviations lower for unemployment news announcement days (p-value of 0.1 per cent), and 0.20 standard deviations lower for PPI news announcement days (p-value of five per cent).[13] A lower market RRD on these major macroeconomic announcement days seems consistent with our use of RRD as a measure of signal ambiguity. Presumably, on days when market news is dominated by a large public macroeconomic news announcement we might expect to find a higher signal-to-noise ratio than in periods when there is no clearly identified source of market news.

We perform a similar exercise on macroeconomic news announcement for the Japan and U.K. markets.[14] We select the news announcements that have an effect on aggregate market volatility for use in the subsequent conditional variance testing of individual firm returns (Section IV). For Japan, our macroeconomic news dummy equals one on days with wholesale and consumer price index announcements and on money supply announcement days, and is zero otherwise. For the U.K., our macroeconomic news dummy equals one on industrial production, retail price index, and unemployment announcement days, and is zero otherwise.

13. The relation of the market's RRD to the CPI and industrial production announcement days is insignificant.

14. The announcement data is hand-collected for the Japanese and U.K. markets.

## III. Empirical Testing and Results

### A. Unconditional Volatility Clustering: Market to Firm

For the tests reported in this section, we need a market return shock to use as an explanatory variable in the conditional variance equation of each of the individual firms. We use the largest size-based, decile-portfolio of NYSE/AMEX stocks as a market proxy for several reasons. First, the returns of such large firms should be affected minimally by frictions such as non-synchronous trading. Second, large-firm portfolio returns have been shown to lead smaller-firm portfolio returns and thus may incorporate common-factor information more quickly.[15] Third, it is convenient to use this portfolio for creating the market RD statistic and relying on this portfolio ensures that small firm returns do not dominate the RD statistic (see Section II.C). Finally, the return on this portfolio is highly correlated with broader, value-weighted market indices. For example, over the July 1962 through December 1996 period, the contemporaneous correlation is 0.992 between the weekly returns of the CRSP value-weighted index and our equally-weighted portfolio of the largest size-based, decile-portfolio of NYSE/AMEX firms.

We estimate the following asymmetric GJR GARCH model to obtain the market return shock, $\varepsilon_{Mkt,t}$. We use the asymmetric GARCH(1, 1) model of Glosten, Jagannathan, and Runkle (1993) (GJR) because it has also been shown that conditional volatility is higher following negative return shocks, as compared to the conditional volatility following a positive return shock of the same magnitude.[16] All of the GARCH models in this paper are estimated simultaneously by maximum likelihood estimation using the conditional normal density.

Mean: $$R^e_{Mkt,t} = \alpha_0 + \beta_1 R^e_{Mkt,t-1} + \varepsilon_{Mkt,t} \qquad \textbf{(3)}$$

Variance: $$V_{Mkt,t} = \alpha_1 + \delta_1 \varepsilon^2_{Mkt,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{Mkt,t-1} + \delta_3 V_{Mkt,t-1} \qquad \textbf{(4)}$$

15. See Lo and MacKinlay (1990), Chan (1993), and Chordia and Swaminathan (1999).

16. Engle and Ng (1993) compare a number of GARCH models and find that the asymmetric GJR model appears to be the best parametric model.

where $R^e_{Mkt,t}$ is the daily excess return of the market proxy portfolio, $\varepsilon_{Mkt,t}$ is the market return residual, $V_{Mkt,t}$ is the conditional variance of the individual firm return, and $D^-_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{Mkt,t-1}$ is negative and is 0 otherwise. The $\alpha$, $\beta$, and $\delta$'s are coefficients to be estimated.

To analyze the unconditional volatility clustering between the firm returns and the lagged market returns, our model specification assumes that the market return residual is exogenous to any single individual firm return. Thus, the market return residual is consistently estimated from (3) and (4). Our model for the conditional mean and variance of firm-level returns is given by

Mean: $$R^e_{i,t} = \alpha_0 + \beta_1 R^e_{i,t-1} + \beta_2 R^e_{Mkt,t-1} + \varepsilon_{i,t} \qquad \textbf{(5)}$$

Variance: $$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} \qquad \textbf{(6)}$$

where $R^e_{i,t}$ = is the daily excess return of the individual firm, $R^e_{Mkt,t}$ is the daily excess return of the aggregate market return, $\varepsilon_{i,t}$ is the firm return residual, $V_{i,t}$ is the conditional variance of the individual firm return, $D^-_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{i,t-1}$ is negative and is 0 otherwise, and $\varepsilon_{Mkt,t}$ is the market return residual obtained from estimating the system given by (3) and (4). The $\alpha$, $\beta$, and $\delta$'s are coefficients to be estimated. Table 2 reports the results from estimating the above asymmetric GARCH model on the daily returns of the individual firms that make up the DJIA.

Our primary interest centers on the $\delta_4$ coefficient on the lagged market return shock in each firms' conditional variance equation. This coefficient is the focal point of the market-to-firm volatility connection. As reported in the last column of the table, this coefficient is positive and significant for 25 of the 30 firms, and is negative and significant for none of the firms. We also note that the coefficients for the own lagged firm return shocks are significant (through either the $\delta_1$ coefficient or the $\delta_2$ coefficient, or both). In this respect, our results are consistent with those of Engle and Lee (1993), who analyze a factor-GARCH model and conclude that the forecasts of individual stock volatilities depend upon both market shocks and the firm-specific shocks.[17]

On at least two other counts, the results in Table 2 seem quite reasonable. First, for 25 of the 30 firms we find a positive and significant estimated $\delta_2$ coefficient indicating bad news has larger volatility effects than good news. Second, our firms also exhibit substantial long-term volatility persistence as indicated by the $\delta_3$ coefficient on the lagged variance, with an average $\delta_3$ of 0.79 estimated for the 30 firms.

**B. Macroeconomic News Announcements and Market-to-Firm Volatility Clustering**

The next step in our study of the economics of volatility clustering is to assess whether it varies systematically when there is a major macroeconomic news announcement last period. In Table 3, we report the results from estimating a modified version of the conditional volatility model, (6), that permits the market-to-firm volatility relationship to vary when there is a macroeconomic news announcement during the previous trading day. Specifically, our new conditional volatility model is given by

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{news}_{t-1}\, \varepsilon^2_{Mkt,t-1} \tag{7}$$

where $D^{news}_{t-1}$ is a dummy variable that equals one if there was a Producer Price Index announcement or unemployment rate announcement in period t-1 and all other terms are as defined earlier. For our sample, the $D^{news}_{t-1}$ dummy variable = 1 for 7.0 % of the days. As before, the $\alpha$, $\beta$, and $\delta$'s are coefficients to be estimated.

Here, the primary coefficient of interest is the $\delta_5$ coefficient, which captures the differential market-to-firm volatility relationship conditional on a news announcement. As reported in the last column of the table, the $\delta_5$ coefficient is negative and significant for 19 of the 30 firms, and is positive and significant for none of the firms. Thus, the volatility clustering appears weaker following a major macroeconomic news announcement. In fact, the combined coefficient on $\varepsilon^2_{Mkt,t}$ ($\delta_4$ plus $\delta_5$) when

17. More specifically, they model the conditional variance of individual firm returns and include a market factor in the conditional variance equation.

there was a news announcement at *t-1* is essentially zero, with an average value of 0.013 over the 30 firms.

This finding suggests that market-to-firm volatility clustering is not due to either an over- or under-reaction to public macroeconomic news or to endogenous information generation following such major macroeconomic news announcements. In addition to being consistent with Jones, Lamont, and Lumsdaine (1998) results for bond returns, we believe these results are also consistent with the findings of Ederington and Lee (1996) and Donders and Vorst (1996). Both papers find that implied volatilities from option prices tend to drop following scheduled public news announcements.

**C. Market-to-Firm Volatility Clustering and Firm-Level News**

As noted earlier, volatility clustering at the firm level may simply reflect correlated firm-specific information flows. To assess whether this is the source of the market-to-firm volatility relationship, we check whether there are systematic differences in market-to-firm volatility clustering in the 'high news' months when firms typically announce their quarterly earnings. Mitchell and Mulherin (1994) report that the months of April, July, and October have the highest number of public news announcements on the Dow Jones News Retrieval service. Most firms report their quarterly earnings in these months. Firm news is likely to be cross-sectionally correlated, and thus may be aggregated to form a component of the market's common-factor signal. In turn, this pattern of earnings announcements may generate a relatively high autocorrelation in news, which in turn may generate stronger volatility clustering for these months.

Again, we modify the conditional volatility model (6) to accommodate controls for this potential effect on the market-to-firm volatility relationship. The new conditional volatility model is given by

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{April}_{t-1} \varepsilon^2_{Mkt,t-1} \qquad \textbf{(8)}$$

where $D^{April}_{t-1}$ is a dummy variable that equals one if the month is April, and is zero otherwise. The other variables and coefficients are as described for model (5) and (6). We then re-estimate the same model twice more, but now with a dummy variable for July ( $D^{July}_{t-1}$ ), and a dummy variable for October ( $D^{Octob}_{t-1}$ ).

The results are as follows. For April, volatility clustering appears to be slightly weaker with an average $\delta_5$ coefficient of –0.020 for the 30 firms, and a corresponding average t-statistic of –0.51. For six of the firms, the estimated $\delta_5$ coefficient is negative and significant. However, two of the estimated $\delta_5$ coefficients are positive and significant.

The volatility clustering appears to be even weaker for the month of July, as compared to the average month. The average $\delta_5$ coefficient is –0.076 for the 30 firms, with an average t-statistic of –1.27. For eight of the firms, the estimated $\delta_5$ coefficient is negative and significant, and only one of the 30 estimated $\delta_5$ coefficients is positive and significant.

However, the month of October is different. For October, the volatility clustering appears to be stronger, as compared to the average month. The average $\delta_5$ coefficient is 0.193 for the 30 firms, with an average t-statistic of 4.67. For 22 of the firms, the estimated $\delta_5$ coefficient is positive and significant. None of the estimated $\delta_5$ coefficients is negative and significant for October. However, this result for October disappears when we re-estimate (8) over the 1988 through 1996 period (post October 1987 crash). For this later period, the market-to-firm volatility connection does not appear reliably different for October as compared to the average month.

Thus, we do not find a consistent, systematic monthly seasonal in the strength of the volatility clustering for these three months. April and July both appear to have marginally weaker market-to-firm volatility clustering, while October is ambiguous.

**D. Market-to-Firm Volatility Clustering and Market RRD**

To this point, we have established that there is a statistically and economically significant market-to-firm volatility relationship, which appears to be weaker after public macroeconomic news shocks and is essentially unrelated to periodic firm-level news. This brings us to the question of whether the volatility clustering varies with the market's lagged relative return dispersion (RRD). The next test investigates the hypothesis that volatility clustering may be (at least partially) a byproduct of the price formation process when risk-averse investors have a dispersion-in-beliefs about the information signal, rather than autocorrelation in underlying real news.

We modify the conditional volatility model (6) to incorporate a market-to-firm volatility relationship that varies with lagged RRD:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{RRD}_{t-1} \varepsilon^2_{Mkt,t-1} \quad \textbf{(9)}$$

where $D^{RRD}_{t-1}$ is a dummy variable that equals one if the market $RRD_{t-1}$ is positive and is 0 otherwise. For our 1985-1996 sample, the daily RRD is positive for 44.0% of the days.[18]

We report conditional volatility model coefficient estimates in Table 4. The results are stand in stark contrast to our findings for macroeconomic news. For 27 of the 30 firms, the $\delta_5$ coefficient estimate is positive and statistically significant at the 5% level (or better). The average estimated $\delta_5$ coefficient is an economically substantial 0.360 with an average t-statistic of 5.4. Thus, for 90% of the firms we see a substantial and reliable increase in the volatility clustering when the market's $RRD_{t-1}$ is relatively high.

On the other hand, the average estimated $\delta_4$ coefficient (which measures volatility clustering for the low $RRD_{t-1}$ periods) is nearly zero with a value of 0.023. Fifteen of the 30 firms have a negative estimated $\delta_4$ coefficient. Thus, the $RRD_{t-1}$ conditioning appears to segregate the volatility clustering nicely into a 'strong volatility-clustering regime' and a 'nearly zero volatility-clustering regime.' The apparent strength and reliability of this conditional relation suggest the need for careful robustness checks, which we undertake before further discussion and interpretation of the results.

**E. Robustness of Volatility Clustering - RRD Relation**

We perform a series of robustness checks on this volatility clustering-$RRD_{t-1}$ relation. First, we report results from performing the same tests on returns from alternate sample periods. Second, we report on tests using alternate GARCH specifications. Third, we repeat our analysis from Section III.D using alternate measures of the market RRD. Finally, we test for the volatility clustering-$RRD_{t-1}$ relation using an RRD measure calculated from a different set of firm returns (firms from the second largest size-based decile-portfolio). This ensures idiosyncratic return effects from the DOW-30 firm returns are not somehow driving the RRD statistic and the volatility clustering-$RRD_{t-1}$ relation.[19]

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18. Since the RRD is defined as the residual from regression (2), it has a mean zero by construction. RRD is positive only 44.0% of the time due to its positive skewness.

19. To save space, we do not present the results cited in this subsection in the paper, but they are available upon request.

**E.1. Alternate sample period.** We repeat the analysis from Section III.D for two alternate sample periods. First, we estimate the system in (5) and (8) for the same 30 firms over the period of July 1962 through December 1984.[20] The results are qualitatively similar. For 27 of the 30 firms, the $\delta_5$ coefficient estimate is positive and significant with an average t-statistic of 3.68. The average $\delta_5$ estimate is substantially lower at 0.09 but the $\delta_3$ coefficient on the lagged variance is substantially larger at an average of 0.91, which indicates longer horizon volatility persistence and correspondingly smaller coefficients on the lagged shock measures. The average $\delta_4$ coefficient (which measures the volatility clustering for the low $RRD_{t-1}$ periods) is again much lower at only 0.03.

We also conducted the analysis from Section III.D for the January 1988 - December 1996 period to ensure our results are not due to the October 1987 crash. Again, the results are qualitatively similar. For 22 of the 30 firms, the $\delta_5$ coefficient estimate remains positive and significant with an average t-statistic of 3.19. The average $\delta_5$ estimate is sizeable at 0.27. The average $\delta_4$ coefficient is negative over this time-period with a value of –0.05. Based on these two sub-sample experiments, we conclude that the volatility clustering-$RRD_{t-1}$ relationship is robust across alternate sample periods.

**E.2. Alternate GARCH specifications.** Stivers (1999) analyzes aggregate market return volatility at the weekly and monthly horizon and finds that the market's lagged RD is a sizeable and reliable explanatory variable for future market volatility. He uses an asymmetric GARCH model and inserts the lagged RD directly into the conditional variance equation.

Our analysis differs in this paper in several ways. First, we analyze firm-level daily stock returns rather than weekly and monthly aggregate returns. Second, we study variations in market-to-firm volatility clustering rather than variations in the level of market return volatility. Nonetheless, his findings suggest that we should also check for variation in the volatility level as a function of the lagged RD by adding lagged RD directly into the conditional variance equation.

We modify (9) accordingly to see whether this variation affects our results:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{RRD}_{t-1} \varepsilon^2_{Mkt,t-1} + \delta_6 RD^2_{t-1} \qquad \textbf{(10)}$$

20. Not all of the 30 firms had the entire 22.5 years of daily returns. In this case, we analyzed the available daily firm returns from CRSP over this time period.

where the RD is the market's simple cross-sectional return dispersion, and $\delta_6$ is the additional coefficient to be estimated. All of the other variables and coefficients are as defined earlier.

We found the relation between volatility clustering and $RRD_{t-1}$ is still largely present, although it is somewhat weaker. This is not unexpected since the positive correlation between the $RRD_{t-1}$ dummy variable (with the $\delta_5$ coefficient) and the $RD^2_{t-1}$ variable (with the $\delta_6$ coefficient) might be expected to reduce the statistical significance of the estimated $\delta_5$ coefficient. For (10), the estimated $\delta_5$ coefficients remain positive and statistically significant (at the 5% level or better) for 20 of the 30 firms, but there are no negative and significant $\delta_5$ coefficient estimates among the 30 firms. The average estimated $\delta_5$ coefficient is 0.27 while the average estimated $\delta_4$ coefficient is only 0.018.

The $\delta_6$ coefficient is also reliably positive. For 22 of the 30 firms, the estimated $\delta_6$ coefficient is positive and statistically significant. This result is consistent with the Stivers' (1999) results for time-variation in market volatility at the weekly and monthly return horizon. Thus, we conclude that the lagged RD is important in jointly characterizing both time-variation in the strength of the market-to-firm volatility clustering (the $\delta_5$ coefficient) and time-variation in the base volatility level (the $\delta_6$ coefficient).

**E.3. Alternate Specifications of Market RRD Metric.** We also checked whether our results depended on the form of the model used to estimate the market RRD. We estimate an alternate market RRD by including non-linear transformations of the market return as additional explanatory variables in (2).[21] We then repeated the analysis from Section III.D with this alternate RRD measure. We find essentially identical results. Thus, we conclude that our results are not sensitive to variations in the RRD formation method.

Finally, we test for the volatility clustering-$RRD_{t-1}$ relation using an RRD measure calculated from another set of firm returns: firms from the second largest size-based decile-portfolio. This out-of-sample approach ensures that the market RD statistic comes from a different set of individual firm returns rather than the DJIA firm returns that we examine in the firm-level conditional variance modeling. If the RD is truly a market statistic, then this alternate RD should provide similar results. However, if RD is

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21. We re-estimate (2) with the addition of a squared market return explanatory variable and a log(absolute market return) explanatory variable.

driven by idiosyncratic firm return dynamics, then this alternate RD measure may provide different results. We find the same volatility clustering-$RRD_{t-1}$ relation (as in Section III.D above) using this alternate RRD. Twenty-two of the 30 DJIA stocks have a positive and statistically significant $\delta_5$ coefficient estimates using this alternate RRD measure. The average value for $\delta_5$ is 0.247, and the average t-statistic is 4.46.[22] Thus, we conclude that the volatility clustering-$RRD_{t-1}$ relationship is not due to idiosyncratic return movements of the individual firm returns that we model here.

**F. Market-to-Firm Volatility Clustering and the Lagged Aggregate Market Volume**

Volume has also been proposed as a metric that may be associated with a dispersion-in-beliefs. Certain models argue that trading between speculative investors relies on a difference in beliefs. Here we investigate lagged volume as an additional conditioning variable in the market-to-firm volatility relation.

If variation in aggregate volume is associated with variation in the signal ambiguity or dispersion-in-beliefs about the market's common-factor signal, then our results in Sections III.D and III.E seem to imply that the market-to-firm volatility connection will be stronger following periods of relatively high volume.[23] We construct an aggregate volume turnover measure from the daily turnover of the 30 DJIA stocks.[24] Then, we re-estimate the GARCH system as in model (9) but now use a conditioning dummy variable that equals one if the aggregate turnover is greater than its median value and equals zero otherwise (the dummy variable in the $\delta_5$ coefficient term). For 18 of the 30 DJIA firms, we find that the intertemporal market-to-firm volatility relation is stronger when there was a relatively high lagged aggregate market volume. The average estimated $\delta_5$ coefficient is 0.110 with an average t-statistic of 2.49. This finding is consistent with our interpretation of the conditional return dispersion findings. Further, both the volume and return dispersion conditioning remain largely evident in a volatility model that allows for joint volume and RD conditioning.

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22. This result is marginally weaker than the results from Table 4. This is consistent with our priors because we would expect the RRD from the smaller size-based portfolios to be a noisier market statistic as compared to the RRD from the largest size-based portfolio.

23. The relation between aggregate volume and return dispersion documented in Bessembinder, Chan, and Seguin (1996) also seem consistent with this conjecture.

24. Turnover is defined as shares traded divided by shares outstanding. This variable does not display a sizeable time trend over our 1985-1996 time period.

## IV. International Evidence and Interpretation of the Findings

In this section, we report results from applying the models and tests of the previous section to firm-level data from Japan and the U.K. Our aim is to establish whether the economic foundations of volatility clustering suggested by the tests on U.S. data in Section III are more general. We close this section with further discussion and some additional analysis of U.S. data.

### A. Results for Japan

We summarize the basic results for our analysis of Japanese firm-level data in Table 5. Panel A contains a summary of the simplest conditional volatility model (6). The average of estimated $\delta_1$, $\delta_2$, and $\delta_3$ coefficients are reasonable in size and sign, and they are broadly similar to what we observe for U.S. data. Somewhat differently than in U.S. data, we only find 11 of 20 firms have positive and significant estimates of the $\delta_4$ coefficient, and, somewhat disconcertingly, three of the 20 firms have negative and significant $\delta_4$ coefficient estimates.

In Panel B, we report a summary of our findings on the effects of macroeconomic news announcements in Japan on the market-to-firm conditional volatility relationship. Overall, we find little connection between public news announcements and the market-to-firm volatility relationship for Japanese data. The estimated $\delta_5$ coefficient is negative and significant for only 3 of the 20 firms. However, similar to the U.S. results, the average conditional coefficient ($\delta_5$) is negative and the sum of the $\delta_4$ and $\delta_5$ coefficients is essentially zero.

The most important issue is addressed in Table 5, Panel C. Here, we find that the market-to-firm volatility relationship is significantly positive and quite sizeable conditional on lagged RRD for all 20 firms. Interestingly, the unconditional effect switches from being positive and significant for 10 of 20 firms to being negative and significant for 13 of 20 firms. This effect is, on average, quite small, however. Our principal finding on the economics of the market-to-firm volatility relationship is confirmed in the Japanese firm-level data.

### B. Results for the U.K.

We report results for the 20 U.K. firms in Table 6. We note that bad news has statistically significant and larger volatility effects in only half of the 20 firms, unlike the earlier findings for the U.S.

and Japan. Panel A shows, however, that a statistically significant, positive market-to-firm volatility relationship exists for 15 of the 20 firms.

Our results suggest there is essentially no systematic impact of macroeconomic news announcements on the market-to-firm volatility relationship in the U.K. While the average $\delta_5$ is negative (consistent with the U.S. results), only five of the $\delta_5$ coefficient estimates are negative and significant, whereas four of the $\delta_5$ coefficient estimates are positive and significant. The other conditional volatility model coefficients are virtually unaffected (on average) by the inclusion of the macroeconomic news announcement variable.

When we estimate the impact of RDD on the market-to-firm volatility relationship, we find a positive and significant $\delta_5$ estimate for 65 per cent of U.K. firms. This compares with 90 per cent for U.S. firms and 100 per cent of Japanese firms. While present, the conditional impact of lagged RRD on the market-to-firm volatility relationship isn't quite as pervasive in the U.K. data as in the U.S. and Japanese data.

**C. Interpreting the Volatility Clustering - Lagged RRD Relation**

Our results indicate that there is a sizeable and reliable positive relationship between the market's lagged RRD and the volatility clustering exhibited between current firm-level returns and the lagged market return. Our investigation is motivated by assuming that the market RRD reflects the relative level of signal ambiguity or dispersion-in-beliefs across risk-averse investors. Under this assumption, our findings bear on understanding the relation between volatility clustering and the price formation process with risk-averse agents who have a dispersion-in-beliefs (either due to differential information or differential interpretation of information). In this sub-section, we conduct further testing to try and refine our interpretation of this relation.

One objection to our interpretation is that the volatility clustering-lagged RRD relation simply reflects autocorrelation in fundamental news flows. If a high RRD reflects a high level of fundamental news flows and these news flows are autocorrelated, then fundamental news flows could explain the volatility clustering-lagged RRD relation.[25] Since our conditioning variable is only lagged one day, this might be a plausible explanation.

We consider this possible explanation for our volatility clustering-lagged RRD relation. First, we believe that this explanation is inconsistent with our monthly seasonal results. If autocorrelation in fundamental news flows is generating the volatility clustering-lagged RRD relation, then it seems that volatility clustering would be higher during the months with the largest number of news releases (April, July, and October). To the contrary, we find that April and July appear to have a weaker level of volatility clustering.

**C.1. Alternate RRD Variable.** Next, we structure a new test to provide some contrast between the 'autocorrelation-in-fundamental news' explanation and the 'dispersion-in-beliefs' explanation for the volatility clustering–lagged RRD relation. While it may be plausible to expect sizeable autocorrelation in fundamental news flows between any two consecutive daily periods, such an explanation seems more unlikely as the lag length for the conditioning variable increases. We re-estimate the system given by (5) and (9) for the daily firm returns of the U.S., Japanese, and U.K. firms with an alternate RRD conditioning variable. The new RRD conditioning variable is a lagged average RRD, defined as the average daily RRD from periods *t-3* through *t-12*. We estimate the following model on the daily returns of the 30 DJIA firms:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 (D^{RRD\ Aver}_{t-3\ to\ t-12}) \varepsilon^2_{Mkt,t-1} \qquad \textbf{(11)}$$

where $D^{RRD\ Aver}_{t-3\ to\ t-12}$ is a dummy variable that equals one if the market's average daily RRD over the *t-3* to *t-12* period is positive and is zero otherwise. All other variables and coefficients are as defined earlier.

We choose this alternate RRD conditioning variable for the following reasons. First, since this measure is formed from an average of the daily $RRD_{t-3}$ through $RRD_{t-12}$, there is a much greater temporal lag between the current firm-level return volatility and the lagged RRD conditioning variable. This increase in temporal lag means that an 'autocorrelation-in-fundamental news' explanation should be much

25. Note that these information flows would almost certainly have to reflect a market-wide or common-factor signal since we are investigating for a volatility clustering effect across 30 different firms.

less likely as an explanation of volatility clustering. Second, using an average lagged RRD is in the spirit of a measure reflecting persistent variation in the signal quality/dispersion-in-beliefs.

We report the results in Table 7. For the U.S. data, the estimated $\delta_5$ coefficients remain positive and significant for 18 of the 30 firms, with an average value of 0.12. The estimated $\delta_4$ coefficients are relatively small with an average value of 0.09. For the Japanese data, the effect is also somewhat weaker. The average $\delta_5$ coefficient in the japanese data is about one-third of the value reported in Table 5, Panel C, and 15 of 20 firms have a statistically significant and positive value for $\delta_5$. The estimated $\delta_4$ coefficients remain very close to zero, however. For the U.K., we find 80 per cent of the estimated $\delta_5$ coefficients are positive and statistically significant. The average value is about 30 per cent smaller than the comparable estimates reported in Table 6, Panel C. Overall, we believe these findings are consistent with the main results in Section III.D and support our economic interpretation of this phenomenon.

**C.2. The Volatility Clustering-RRD$_{t-1}$ Relation with 3 Relative Sub-Divisions of RRD.** Our economic interpretation of the volatility clustering-RRD$_{t-1}$ relation also suggests that a larger relative RRD should be associated with a stronger market-to-firm volatility connection. Here, we investigate this conjecture. Additionally, this investigation allows us to check whether only a small set of extreme RRD periods drive the volatility clustering-RRD$_{t-1}$ relation.

We create two dummy relative RRD dummy variables so that each period is divided into one of three relative RRD categories. The first dummy takes a value of one when the market RRD value lies in the 50$^{th}$ – 75$^{th}$ percentile range (and zero otherwise), and the second takes a value of one when the market RRD value lies in the 75$^{th}$ – 100$^{th}$ percentile range (and zero otherwise).

For all three countries, we estimate the following modification of the conditional volatility model (6) that incorporates these two dummy variables:

$$\begin{aligned} V_{i,t} &= \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} \\ &+ \delta_5 (D^{RRD50-75}_{t-1}) \varepsilon^2_{Mkt,t-1} + \delta_6 (D^{RRD75-100}_{t-1}) \varepsilon^2_{Mkt,t-1} \end{aligned} \qquad \textbf{(12)}$$

where the $\delta_5$ and $\delta_6$ coefficients measure the differential market-to-firm volatility when market RRD lies in the 50$^{th}$ – 75$^{th}$ percentile range and in the 75$^{th}$ – 100$^{th}$ percentile range, respectively, and all other variables are as defined earlier.

We report results for these alternative conditional volatility models in Table 8. For the U.S. and Japan, there are very large, positive, and statistically significant interaction effects involving RRD in the 75th – 100th percentile range (the $\delta_6$ coefficient) for all but one U.S. firm (that is, 49 of 50 total firms). The same holds true for Japan for the 50th – 75th percentile range variable for 75 per cent of the firms, but only about one-third of U.S. firms still show this interaction (the $\delta_5$ coefficient). For both countries, the estimated $\delta_4$ coefficients are quite small, implying the market-to-firm volatility relationship exists primarily in conjunction with our RRD variables. Thus, the results for the U.S. and Japan seem to support our economic interpretation. The market-to-firm volatility connection is substantially stronger for higher values of the RRD (the $\delta_6$ coefficients) and the connection is still somewhat stronger for more modest positive value of the RRD (the $\delta_5$ coefficients).

For the U.K., the picture is a bit less dramatic. The strongest interaction effects are found for the 50th – 75th percentile range variable, and then, only 11 of 20 firms show a positive, statistically significant effect. The strongest results for the U.K. still appear to be found using the RRD average value, as in Table 7.

To sum up the results presented in this section, there are several broad findings. For the U.S. and Japan, these alternate RRD mesures perform much the same as the $RRD_{t-1}$ conditioning variable, but the effects appear to be a bit weaker. In general terms, the estimates appear to divide the sample into a 'strong volatility clustering regime' and a 'near zero volatility clustering regime'. We believe these results suggest that the market RRD measure reflects more than simply the daily information draws of firm news. Rather, the time-series characteristics of the RRD measure, the volatility clustering-lagged RRD relation, and the negative relation between RRD and the macroeconomic news announcements taken together all suggest that a high RRD value reflects an ambiguous market information environment with relatively higher dispersion-in-beliefs across agents.

## V. Summary and Conclusions

We investigate volatility clustering between individual firm stock returns and the lagged market return. The goal of our empirical exploration is to provide new evidence that bears on the following questions. Is the volatility clustering in daily equity returns generated from a straightforward autocorrelation in fundamental news? Or, is some of the volatility clustering a byproduct of the dynamic price formation process with risk-averse agents who have correlated but diverse beliefs? What information variables may be associated with stronger or weaker volatility clustering and what can we learn from these conditional relations? Are conditional market-to-firm volatility relations important in modeling the total conditional variance of individual firm returns?

Our tests examine whether volatility clustering between individual firm returns and the lagged market return varies with measures of identifiable information flows, or our proxies for dispersion-in-beliefs. Empirically, we use a modified version of the widely-used asymmetric GARCH(1,1) model. We modify the specification to allow the volatility clustering between firm returns and the lagged market return to vary with our information variables.

We examine the daily stock returns of the 30 firms that make up the Dow Jones Industrial Average and 20 large-cap firms each for the U.K. and Japan. We have three main findings. First, for the U.S., we find that the volatility clustering is weaker following macroeconomic news announcements. Results for the Japan and U.K. are consistent but much weaker. Overall, this evidence is consistent with the findings of Jones, Lamont, and Lumsdaine (1998) for bond returns. This result suggests that volatility clustering is not due to either an over- or under-response of firm-level prices to macroeconomic news or due to an endogenous generation of additional news as policymakers respond to the news shock.

Second, we find no evidence of a systematic seasonal variation in volatility clustering for 'high-news' months when firms typically announce their quarterly earnings (April, July, and October). Compared to the average month, April and July appear to have marginally weaker volatility clustering while October is inconclusive. This suggests that volatility clustering is not primarily due to periodic firm-level news that may be cross-sectionally correlated (and thus aggregated to form a common-factor signal).

Third, we find a large increase in the 'market-to-firm' volatility connection when our proxies for dispersion-in-beliefs are relatively large. This portion of our work is motivated by Harris and Raviv (1993), Shalen (1993), Brock and LeBaron (1996) and Kurz and Motolese (1999). These papers propose theoretical models where diverse beliefs may result in volatility clustering as a byproduct of the price formation process. This literature suggests that volatility clustering may occur even when the underlying real news flow is serially uncorrelated. We use the market's relative cross-sectional return dispersion

(RD) as an information environment variable to proxy for dispersion-in-beliefs. We also investigate aggregate volume as an alternate measure of dispersion-in-beliefs.

For our sample, 90% of the 30 DJIA firms exhibit a significantly stronger volatility clustering between the firm return and the lagged market return when the market's lagged RD is relatively high. This relation is robust to alternate sample periods, alternate specifications for the GARCH model, and alternate methods in forming and smoothing the RRD variable. In fact, the RRD variable does a good job of segregating sample periods into two regimes, a 'strong volatility clustering' regime and a 'nearly zero volatility clustering' regime. Thus, this finding suggests a positive association between volatility clustering and dispersion-in-beliefs. Broadly, we find this result generalizes to Japan and the U.K., although the results are somewhat stronger for Japan than the U.K. Consistently, we find that the market-to-firm volatility connection is stronger following periods of relatively high volume in the U.S. market.

To conclude, this paper provides new evidence that volatility clustering is not linked to identifiable information flows, for either periodic macroeconomic news or periodic firm-level news. Rather, 'market-to-firm' volatility clustering appears to be associated with periods of high signal ambiguity and high dispersion-in-beliefs. Our findings also suggest that the conditional variance of daily firm returns may be better modeled by using interactive information-environment variables (such as the market's lagged RRD) with the lagged market return shocks.

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## Table 1

# Summary Statistics for Daily Returns of the DJIA Individual Firms[1]

**Panel A**

| DJIA Firm | Daily Mean Return, % | Daily Return Standard Deviation, % | Correlation,[2] $\lvert R_{i,t}\rvert, \lvert R_{Mkt,t}\rvert$ | Correlation, $\lvert R_{i,t}\rvert, \lvert R_{i,t-1}\rvert$ | Correlation, $\lvert R_{i,t}\rvert, \lvert R_{Mkt,t-1}\rvert$ |
|---|---|---|---|---|---|
| **Allied Signal** | 0.080 | 1.82 | 0.474 | 0.287 | 0.300 |
| **Alum. Co. America** | 0.071 | 1.76 | 0.448 | 0.200 | 0.205 |
| **American Express** | 0.073 | 2.01 | 0.565 | 0.234 | 0.214 |
| **ATT** | 0.063 | 1.56 | 0.541 | 0.261 | 0.244 |
| **Boeing** | 0.084 | 1.64 | 0.378 | 0.180 | 0.107 |
| **Caterpillar** | 0.076 | 1.81 | 0.446 | 0.181 | 0.180 |
| **Chevron** | 0.077 | 1.48 | 0.431 | 0.144 | 0.177 |
| **Citigroup** | 0.034 | 1.87 | 0.383 | 0.234 | 0.098 |
| **Coca-Cola** | 0.122 | 1.63 | 0.633 | 0.314 | 0.274 |
| **DuPont** | 0.084 | 1.49 | 0.546 | 0.142 | 0.145 |
| **Eastman Kodak** | 0.070 | 1.79 | 0.487 | 0.275 | 0.248 |
| **Exxon** | 0.079 | 1.38 | 0.566 | 0.308 | 0.278 |
| **General Electric** | 0.088 | 1.45 | 0.677 | 0.216 | 0.221 |
| **General Motors** | 0.048 | 1.77 | 0.433 | 0.180 | 0.190 |
| **Goodyear** | 0.079 | 1.92 | 0.466 | 0.142 | 0.117 |
| **Hewlett Packard** | 0.089 | 2.23 | 0.402 | 0.123 | 0.123 |
| **IBM** | 0.037 | 1.63 | 0.415 | 0.180 | 0.127 |
| **Intern. Paper** | 0.063 | 1.66 | 0.575 | 0.109 | 0.140 |
| **J P Morgan** | 0.085 | 1.76 | 0.566 | 0.366 | 0.336 |
| **Johnson & Johnson** | 0.098 | 1.59 | 0.532 | 0.198 | 0.168 |
| **McDonalds** | 0.085 | 1.57 | 0.504 | 0.194 | 0.166 |
| **Merck** | 0.110 | 1.52 | 0.473 | 0.122 | 0.074 |
| **Minn. Mining &Mfg.** | 0.072 | 1.39 | 0.603 | 0.222 | 0.230 |
| **Philip Morris** | 0.110 | 1.63 | 0.455 | 0.128 | 0.098 |
| **Procter & Gamble** | 0.091 | 1.51 | 0.591 | 0.301 | 0.296 |
| **Sears** | 0.082 | 1.82 | 0.526 | 0.229 | 0.189 |
| **Union Carbide** | 0.125 | 2.06 | 0.340 | 0.195 | 0.211 |
| **United Technologies** | 0.070 | 1.54 | 0.411 | 0.103 | 0.146 |
| **Walmart** | 0.097 | 1.83 | 0.497 | 0.179 | 0.130 |
| **Walt Disney** | 0.119 | 1.81 | 0.576 | 0.252 | 0.203 |
| **Average:** | **0.082** | **1.70** | **0.498** | **0.207** | **0.188** |

1. We analyze the 30 Dow Jones Industrial Average firms as of 1 September 1999.
2. $\lvert R_{i,t}\rvert$ is the absolute value of firm i's excess return (nominal return less a risk-free rate), $\lvert R_{Mkt,t}\rvert$ is the absolute value of the aggregate market's excess return. We use the largest size-based, decile-portfolio of NYSE/AMEX stocks for the market proxy.

## Table 1

# Summary Statistics for the Portfolio Return and the Cross-Sectional Return Dispersion of the Largest Size-based, Decile-Portfolio of NYSE/AMEX Stocks

This panel reports descriptive statistics for the returns from the largest size-based, decile-portfolio of NYSE/AMEX stocks. The sample is from 1985-1996, n=3033.

For a given period, a portfolio's RD is the cross-sectional standard deviation of the individual firm returns that comprise the portfolio about the aggregate portfolio return for that period. The RRD is the relative return dispersion, defined as the residual $u_t$ obtained from estimating the following regression model:

$$RD_t = \phi_0 + \gamma_1 \left| R^e_{Mkt,t} \right| + \gamma_2 D1_t \left| R^e_{Mkt,t} \right| + u_t$$

where $RD_t$ is the return dispersion; $\left| R^e_{Mkt,t} \right|$ is the absolute value of the excess portfolio return; $D1_t$= 1 if the portfolio excess return is negative, and is 0 otherwise; $u_t$ is the residual; and $\phi$ and the $\gamma$'s are estimated coefficients. The $u_t$ residual is termed the relative return dispersion (*$RRD_t$*) because it indicates the relative dispersion after controlling for the dispersion attributed to the magnitude of the portfolio return. The R-squared for the above RRD model is 24.2 %; the estimated coefficients are: $\gamma_1$ = 0.330 (T-statistic = 6.37) and $\gamma_2$ = -0.106 (T-statistic = -4.62); we calculated heteroskedastic and autocorrelation consistent standard errors.

**Panel B**

| Variable | Daily Mean, % | Daily Standard Deviation, % | Auto-Correlation | Correlation, with $\left| R^e_{Mkt,t} \right|$ |
|---|---|---|---|---|
| $R^e_{Mkt,t}$ | 0.0745 | 0.891 | 0.104 | - |
| $\left| R^e_{Mkt,t} \right|$ | 0.582 | 0.679 | 0.209 | 1.0 |
| **RD** | 1.45 | 0.379 | 0.566 | 0.477 |
| **RRD** | 0.00[1] | 0.330 | 0.368 | 0[1] |

1. The RRD's mean and correlation with $\left| R^e_{Mkt,t} \right|$ are zero by construction.

**Table 2**

## Unconditional volatility clustering between firm-level returns and the lagged market return

This table reports the results from estimating the following asymmetric GARCH model on the daily individual firm returns of the 30 firms that comprise the Dow Jones Industrial Average. The equations are estimated simultaneously by maximum likelihood estimation using the conditional normal density.

Mean: $$R^e_{i,t} = \alpha_0 + \beta_1 R^e_{i,t-1} + \beta_2 R^e_{Mkt,t-1} + \varepsilon_{i,t}$$

Variance: $$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1}$$

where $R^e_{i,t}$ = is the daily excess return of the individual firm, $R^e_{Mkt,t}$ is the daily excess return of the aggregate market return; $\varepsilon_{i,t}$ is the firm return residual; $V_{i,t}$ is the conditional variance of the individual firm return; $D^-_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{i,t-1}$ is negative and is 0 otherwise; $\varepsilon_{Mkt,t}$ is the market return residual obtained from estimating a separate GJR-asymmetric GARCH model on the market return. The $\alpha$, $\beta$, and $\delta$'s are estimated coefficients. Here the return of the largest size-based, decile-portfolio of NYSE/AMEX stocks is used as a proxy for the market return.

We analyze the 30 firms comprising the DJIA as of September 1, 1999. The sample runs from January 1985 through December 1996 to coincide with the macroeconomics news data.

The estimated coefficients for the conditional variance equation are shown below, the coefficients for the mean equation are not reported for brevity. ***, **, * indicates significance at the 0.1%, 1%, and 5% respectively, based on asymptotic standard errors.

## Table 2 (cont.)

# Unconditional Volatility Clustering Between Firm-Level Returns and the Lagged Market Return

| Firm Ticker | $\delta_1$ ($\varepsilon^2_{i,t-1}$) | $\delta_2$ ($D^-_{i,t-1}\varepsilon^2_{i,t-1}$) | $\delta_3$ ($V_{i,t-1}$) | $\delta_4$ ($\varepsilon^2_{Mkt,t-1}$) |
|---|---|---|---|---|
| ALD | 0.105*** | 0.179*** | 0.617*** | 0.188*** |
| AA | 0.052*** | 0.029 | 0.817*** | 0.187*** |
| AXP | 0.046*** | 0.056*** | 0.869*** | 0.065* |
| T | 0.057*** | 0.071** | 0.649*** | 0.123*** |
| BA | 0.131*** | 0.119*** | 0.333*** | 0.144** |
| CAT | 0.031** | 0.092*** | 0.693*** | 0.240*** |
| CHV | 0.059*** | -0.006 | 0.876*** | 0.106*** |
| C | 0.119*** | 0.084*** | 0.795*** | 0.092*** |
| KO | 0.042*** | 0.068*** | 0.850*** | 0.067** |
| DD | 0.026* | 0.079*** | 0.789*** | 0.125*** |
| EK | 0.076*** | 0.069*** | 0.659*** | 0.267*** |
| XON | 0.051*** | 0.039** | 0.831*** | 0.097*** |
| GE | 0.025*** | 0.028*** | 0.944*** | 0.017 |
| GM | 0.044*** | 0.070*** | 0.881*** | -0.014 |
| GT | 0.041*** | 0.046*** | 0.888*** | 0.099*** |
| HWP | 0.022 | 0.088*** | 0.687*** | 0.422*** |
| IBM | 0.035*** | 0.117*** | 0.877*** | -0.013 |
| IP | 0.059*** | -0.006 | 0.797*** | 0.261*** |
| JPM | 0.078*** | 0.061* | 0.689*** | 0.357*** |
| JNJ | 0.026* | 0.088*** | 0.874*** | -0.001 |
| MCD | 0.038*** | 0.031** | 0.884*** | 0.068*** |
| MRK | 0.036*** | 0.046*** | 0.909*** | 0.012 |
| MMM | 0.063*** | -0.043** | 0.812*** | 0.192*** |
| MO | 0.109*** | -0.044* | 0.782*** | 0.076*** |
| PG | 0.036** | 0.078*** | 0.804*** | 0.085*** |
| S | 0.078*** | 0.076*** | 0.827*** | 0.037 |
| UK | 0.044*** | 0.097*** | 0.695*** | 0.396*** |
| UTX | 0.011 | 0.056*** | 0.888*** | 0.082*** |
| WMT | 0.028*** | 0.033** | 0.916*** | 0.060* |
| DIS | 0.071*** | 0.064*** | 0.765*** | 0.122*** |
| **Average:** | **0.055** | **0.059** | **0.790** | **0.132** |

**Table 3**

## Volatility clustering between firm-level returns and the lagged market return when there is a macroeconomic news announcement last period

This table reports the results from estimating the following asymmetric GARCH model on the daily individual firm returns of the 30 firms that comprise the Dow Jones Industrial Average. The equations are estimated simultaneously by maximum likelihood estimation using the conditional normal density.

Mean:

$$R^{e}_{i,t} = \alpha_0 + \beta_1 R^{e}_{i,t-1} + \beta_2 R^{e}_{Mkt,t-1} + \varepsilon_{i,t}$$

Variance:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^{-}_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{news}_{t-1}\ \varepsilon^2_{Mkt,t-1}$$

where $R^{e}_{i,t}$ = is the daily excess return of the individual firm, $R^{e}_{Mkt,t}$ is the daily excess return of the aggregate market return; $\varepsilon_{i,t}$ is the firm return residual; $V_{i,t}$ is the conditional variance of the individual firm return; $D^{-}_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{i,t-1}$ is negative and is 0 otherwise; $\varepsilon_{Mkt,t}$ is the market return residual obtained from estimating a separate GJR-asymmetric GARCH model on the market return; and $D^{news}_{t-1}$ is a dummy variable that equals one if there was a Producer Price Index announcement or unemployment rate announcement in period t-1. For our sample, the $D^{news}_{t-1}$ dummy variable = 1 for 7.0 % of the days. The $\alpha$, $\beta$, and $\delta$'s are estimated coefficients. Here the return of the largest size-based, decile-portfolio of NYSE/AMEX stocks is used as a proxy for the market return.

We analyze the 30 firms comprising the Dow Jones Industrial Average as of September 1, 1999. The sample runs from January 1985 through December 1996 to coincide with the macroeconomic news data.

The estimated coefficients for the conditional variance equation are shown below, the coefficients for the mean equation are not reported for brevity. ***, **, * indicates significance at the 0.1%, 1%, and 5% respectively, based on asymptotic standard errors.

**Table 3 (cont.)**

## Volatility clustering between firm-level returns and the lagged market return when there is a macroeconomic news announcement last period

| Firm Ticker | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{news}_{t-1}\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| ALD | 0.109*** | 0.172*** | 0.615** | 0.192*** | -0.103 |
| AA | 0.050*** | 0.026 | 0.830*** | 0.185*** | -0.088 |
| AXP | 0.047*** | 0.059*** | 0.866*** | 0.084** | -0.135* |
| T | 0.062*** | 0.072** | 0.645*** | 0.115*** | 0.038 |
| BA | 0.133*** | 0.120*** | 0.334*** | 0.016** | -0.099 |
| CAT | 0.029* | 0.084*** | 0.705*** | 0.267*** | -0.261*** |
| CHV | 0.062*** | -0.004 | 0.868*** | 0.123*** | -0.124** |
| C | 0.112*** | 0.080*** | 0.803*** | 0.127*** | -0.176*** |
| KO | 0.044*** | 0.070*** | 0.840*** | 0.101*** | -0.211*** |
| DD | 0.022* | 0.075*** | 0.813*** | 0.134*** | -0.147** |
| EK | 0.072*** | 0.076*** | 0.677*** | 0.289*** | -0.435*** |
| XON | 0.054*** | 0.038** | 0.823*** | 0.129*** | -0.192*** |
| GE | 0.024*** | 0.029*** | 0.944*** | 0.023 | -0.032 |
| GM | 0.046*** | 0.069*** | 0.873*** | 0.001 | -0.096* |
| GT | 0.040*** | 0.047*** | 0.886*** | 0.136*** | -0.238*** |
| HWP | 0.020 | 0.101*** | 0.659*** | 0.423*** | 0.449 |
| IBM | 0.031*** | 0.100*** | 0.896*** | 0.006 | -0.141*** |
| IP | 0.054*** | -0.006 | 0.830*** | 0.251*** | -0.273*** |
| JPM | 0.074*** | 0.059* | 0.709*** | 0.395*** | -0.419*** |
| JNJ | 0.024* | 0.096*** | 0.866*** | 0.014 | -0.096** |
| MCD | 0.038*** | 0.031** | 0.885*** | 0.065*** | 0.015 |
| MRK | 0.036*** | 0.049*** | 0.907*** | 0.022* | -0.062** |
| MMM | 0.062*** | -0.033* | 0.816*** | 0.197*** | -0.166*** |
| MO | 0.110*** | -0.043* | 0.782*** | 0.078*** | -0.028 |
| PG | 0.036** | 0.075*** | 0.807*** | 0.116*** | -0.218*** |
| S | 0.081*** | 0.063*** | 0.831*** | 0.053 | -0.085 |
| UK | 0.042*** | 0.088*** | 0.699*** | 0.456*** | -0.269* |
| UTX | 0.014* | 0.049*** | 0.874*** | 0.120*** | -0.117** |
| WMT | 0.033*** | 0.031** | 0.911*** | 0.067* | -0.066 |
| DIS | 0.074*** | 0.061*** | 0.769*** | 0.136*** | -0.155 |
| **Average:** | **0.054** | **0.058** | **0.792** | **0.144** | **-0.131** |

## Table 4

# Market-to-Firm Volatility Clustering and the Market's Lagged Cross-Sectional Return Dispersion

This table reports the results from estimating the following asymmetric GARCH model on the daily individual firm returns of the 30 firms that comprise the Dow Jones Industrial Average. The equations are estimated simultaneously by maximum likelihood estimation using the conditional normal density.

Mean:
$$R^{e}_{i,t} = \alpha_0 + \beta_1 R^{e}_{i,t-1} + \beta_2 R^{e}_{Mkt,t-1} + \varepsilon_{i,t}$$

Variance:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^{-}_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 D^{RRD}_{t-1} \varepsilon^2_{Mkt,t-1}$$

where $R^{e}_{i,t}$ = is the daily excess return of the individual firm, $R^{e}_{Mkt,t}$ is the daily excess return of the aggregate market return; $\varepsilon_{i,t}$ is the firm return residual; $V_{i,t}$ is the conditional variance of the individual firm return; $D^{-}_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{i,t-1}$ is negative and is 0 otherwise; $\varepsilon_{Mkt,t}$ is the market return residual obtained from estimating a separate GJR-asymmetric GARCH model on the market return; and $D^{RRD}_{t-1}$ is a dummy variable that equals one if the market's relative return dispersion ($RRD_{t-1}$) is positive and is 0 otherwise. For our sample, the $D^{RRD}_{t-1}$ dummy variable = 1 for 44.0 % of the days. The $\alpha$, $\beta$, and $\delta$'s are estimated coefficients. Here the return of the largest size-based, decile-portfolio of NYSE/AMEX stocks is used as a proxy for the market return.

We analyze the 30 firms comprising the Dow Jones Industrial Average as of September 1, 1999. The sample runs from January 1985 through December 1996 to coincide with the macroeconomics news data.

The following table reports the estimated coefficients for the conditional variance equation only, the coefficients for the mean equation are not reported for brevity. ***, **, * indicates significance at the 0.1%, 1%, and 5% respectively, based on asymptotic standard errors.

**Table 4 (cont.)**

## Market-to-Firm Volatility Clustering and the Market's Lagged Cross-Sectional Return Dispersion

| Firm Ticker | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{RRD}_{t-1}\,\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| **ALD** | 0.111*** | 0.192*** | 0.525*** | -0.157** | **0.792*** ** |
| **AA** | .053*** | 0.028 | 0.813*** | 0.178*** | **0.029** |
| **AXP** | 0.047*** | 0.048*** | 0.857*** | -0.011 | **0.251*** ** |
| **T** | 0.067*** | 0.065* | 0.513*** | -0.036 | **0.435*** ** |
| **BA** | 0.131*** | 0.117*** | 0.306*** | 0.081 | **0.224* ** |
| **CAT** | 0.035** | 0.084*** | 0.666*** | 0.044 | **0.495*** ** |
| **CHV** | 0.062*** | -0.007 | 0.870*** | 0.072** | **0.076* ** |
| **C** | 0.091*** | 0.076*** | 0.804*** | -0.065** | **0.490*** ** |
| **KO** | 0.052*** | 0.064*** | 0.822*** | 0.028 | **0.150** ** |
| **DD** | 0.026* | 0.084*** | 0.744*** | 0.108** | **0.133* ** |
| **EK** | 0.082*** | 0.020 | 0.602*** | -0.055 | **0.948*** ** |
| **XON** | 0.062*** | 0.033 | 0.810*** | 0.053* | **0.117*** ** |
| **GE** | 0.024*** | 0.291*** | 0.946*** | 0.021 | **-0.015** |
| **GM** | 0.042*** | 0.062*** | 0.861*** | -0.084*** | **0.265*** ** |
| **GT** | 0.057*** | 0.048*** | 0.825*** | -0.013 | **0.409*** ** |
| **HWP** | 0.012 | 0.133*** | 0.520*** | -0.026 | **1.588*** ** |
| **IBM** | 0.042*** | 0.133*** | 0.821*** | -0.120*** | **0.311*** ** |
| **IP** | 0.066*** | -0.011 | 0.768*** | 0.197*** | **0.245*** ** |
| **JPM** | 0.087*** | 0.053* | 0.662*** | 0.243*** | **0.310*** ** |
| **JNJ** | 0.027* | 0.090*** | 0.864*** | -0.037 | **0.077* ** |
| **MCD** | 0.035*** | 0.033** | 0.874*** | 0.019 | **0.145*** ** |
| **MRK** | 0.037*** | 0.046*** | 0.906*** | -0.007 | **0.036** |
| **MMM** | 0.072*** | -0.504** | 0.776*** | 0.081*** | **0.321*** ** |
| **MO** | 0.122*** | -0.040* | 0.728*** | -0.052 | **0.264*** ** |
| **PG** | 0.048** | 0.036 | 0.520*** | -0.037 | **0.802*** ** |
| **S** | 0.080*** | 0.047* | 0.783*** | -0.092** | **0.679*** ** |
| **UK** | 0.050*** | 0.114*** | 0.644*** | 0.309*** | **0.346** ** |
| **UTX** | 0.010 | 0.056*** | 0.876*** | 0.063** | **0.084* ** |
| **WMT** | 0.033*** | 0.030* | 0.882*** | 0.024 | **0.224*** ** |
| **DIS** | 0.083*** | 0.037 | 0.723*** | -0.042 | **0.574*** ** |
| **Average:** | **0.058** | **0.049** | **0.744** | **0.023** | **0.360** |

## Table 5

# Volatility Clustering Between Firm-Level Returns and the Lagged Market Return for Japanese Firms

This table reports the results from estimating the asymmetric GARCH models from Tables 2, 3, and 4 on the daily individual firm returns of 20 large Japanese firms. The data spans 1/1985 – 12/96. See Section 2.x and Appendix A for the selection criteria and list of Japanese firms. For brevity, we report only summary statistics on the estimated coefficients for the conditional variance equations, rather than point estimates for each coefficient. Row 2 (3) in each panel reports the number of coefficients, out of 20, that were positive (negative) and significant at the 10% level or greater.

**Panel A: Basic volatility clustering (Model as in Table 2 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|
| **Average coefficient** | 0.083 | 0.074 | 0.845 | 0.024* |
| # $d_i$ **> 0 & significant** | 20 | 19 | 20 | 11 |
| # $d_i$ **< 0 & significant** | 0 | 0 | 0 | 3 |

* The average t-statistic on the 20 $\delta_4$ coefficients is 1.97.

**Panel B: Volatility clustering following news announcements (Model as in Table 3 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{news}_{t-1}\,\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| **Average coefficient** | 0.083 | 0.085 | 0.839 | 0.026* | -0.027* |
| # $d_i$ **> 0 & significant** | 20 | 20 | 20 | 10 | 2 |
| # $d_i$ **< 0 & significant** | 0 | 0 | 0 | 3 | 3 |

* The average t-statistic on the 20 $\delta_4$'s is 1.87, and on the 20 $\delta_5$'s is -0.63.

**Panel C: Volatility clustering conditional on market $RRD_{t-1}$ (Model as in Table 4 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{RRD}_{t-1}\,\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| **Average coefficient** | 0.089 | 0.069 | 0.788 | -0.020* | 0.243* |
| # $d_i$ **> 0 & significant** | 20 | 17 | 20 | 3 | 20 |
| # $d_i$ **< 0 & significant** | 0 | 0 | 0 | 13 | 0 |

* The average t-statistic on the 20 $\delta_4$'s is -4.12 , and on the 20 $\delta_5$'s is 7.60.

## Table 6

# Volatility Clustering Between Firm-Level Returns and the Lagged Market Return for U.K. Firms

This table reports the results from estimating the asymmetric GARCH models from Tables 2, 3, and 4 on the daily individual firm returns of 20 large U.K. firms. The data spans 1/1985 – 12/96. See Section 2.x and Appendix A for the selection criteria and list of U.K. firms. For brevity, we report only summary statistics on the estimated coefficients for the conditional variance equations, rather than point estimates for each coefficient. Row 2 (3) in each panel reports the number of coefficients, out of 20, that were positive (negative) and significant at the 10% level or greater.

**Panel A: Basic volatility clustering (Model as in Table 2 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|
| **Average coefficient** | 0.063 | 0.017 | 0.863 | 0.075 |
| # $d_i$ **> 0 & significant** | 20 | 10 | 20 | 15 |
| # $d_i$ **< 0 & significant** | 0 | 1 | 0 | 0 |

* The average t-statistic on the 20 $\delta_4$ coefficients is 3.74.

**Panel B: Volatility clustering following news announcements (Model as in Table 3 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{news}_{t-1}\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| **Average coefficient** | 0.062 | 0.016 | 0.827 | 0.078 | -0.015 |
| # $d_i$ **> 0 & significant** | 20 | 9 | 20 | 16 | 4 |
| # $d_i$ **< 0 & significant** | 0 | 0 | 0 | 0 | 5 |

* The average t-statistic on the 20 $\delta_4$'s is 3.61, and on the 20 $\delta_5$'s is 0.009. The $D^{news}_{t-1}$ dummy variable = 1 for 6.5% of the observations.

**Panel C: Volatility clustering conditional on market $RRD_{t-1}$ (Model as in Table 4 for U.S. firms)**

| **Coefficient data** | $\delta_1$ $(\varepsilon^2_{i,t-1})$ | $\delta_2$ $(D^-_{i,t-1}\varepsilon^2_{i,t-1})$ | $\delta_3$ $(V_{i,t-1})$ | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{RRD}_{t-1}\varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|---|---|
| **Average coefficient** | 0.096 | 0.051 | 0.827 | 0.047* | 0.144* |
| # $d_i$ **> 0 & significant** | 20 | 9 | 20 | 13 | 13 |
| # $d_i$ **< 0 & significant** | 0 | 3 | 0 | 1 | 1 |

* The average t-statistic on the 20 $\delta_4$'s is 1.80, and on the 20 $\delta_5$'s is 2.63. The $D^{RRD}_{t-1}$ dummy variable = 1 for 40.7 % of the observations.

**Table 7**

# Volatility Clustering Conditional on a Lagged, 10-day Moving Average RRD

This table reports the results from estimating the following model on the daily returns of the 30 U.S. DJIA firms, the 20 large-cap Japanese firms, and the 20 large-cap U.K. firms:

Mean: $$R^{e}_{i,t} = \alpha_0 + \beta_1 R^{e}_{i,t-1} + \beta_2 R^{e}_{Mkt,t-1} + \varepsilon_{i,t}$$

Variance:

$$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^{-}_{i,t-1} \varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 (D^{RRD\ Aver}_{t-3\ to\ t-12}) \varepsilon^2_{Mkt,t-1}$$

where $D^{RRD\ Aver}_{t-3\ to\ t-12}$ is a dummy variable that equals one if the respective market's average daily RRD over the 10 days of the *t-3* to *t-12* period is positive, and is zero otherwise. All other variables are as defined in the model of Table 4. The $\alpha$, $\beta$, and $\delta$'s are estimated coefficients where $\delta_4$ and $\delta_5$ in the conditional variance equations are the coefficients of interest. The table below reports summary statistics on these estimated coefficients for the firms in each country's market.

| **Coefficient:** / **Data Sample:** | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{RRDav}_{t-3\ to\ t-12} \varepsilon^2_{Mkt,t-1})$ |
|---|---|---|
| **Panel A: U.S. Dow 30** | | |
| **Average coefficient** | 0.089 | 0.118 |
| **Average t-statistic** | 3.50 | 1.72 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 20/ (2) | 18/ (1) |
| **Panel B: Japan 20** | | |
| **Average coefficient** | 0.019 | 0.085 |
| **Average t-statistic** | 0.68 | 3.46 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 7/ (5) | 15/ (0) |
| **Panel C: U.K. 20** | | |
| **Average coefficient** | 0.058 | 0.100 |
| **Average t-statistic** | 2.42 | 2.74 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 10/ (0) | 16/ (1) |

**Table 8**

## Volatility Clustering Conditional on Interval Stratifications of $RRD_{t-1}$

This table reports the results from estimating the following model on the daily returns of the 30 U.S. DJIA firms, the 20 large-cap Japanese firms, and the 20 large-cap U.K. firms:

Mean: $$R^e_{i,t} = \alpha_0 + \beta_1 R^e_{i,t-1} + \beta_2 R^e_{Mkt,t-1} + \varepsilon_{i,t}$$

Variance: $$V_{i,t} = \alpha_1 + \delta_1 \varepsilon^2_{i,t-1} + \delta_2 D^-_{i,t-1}\varepsilon^2_{i,t-1} + \delta_3 V_{i,t-1} + \delta_4 \varepsilon^2_{Mkt,t-1} + \delta_5 (D^{RRD50-75}_{t-1})\varepsilon^2_{Mkt,t-1} + \delta_6 (D^{RRD75-100}_{t-1})\varepsilon^2_{Mkt,t-1}$$

where $D^{RRD50-75}_{t-1}$ is a dummy variable that equals one if the respective market's $RRD_{t-1}$ is in the $50^{th}$ to $75^{th}$ percentile range and is zero otherwise, and $D^{RRD75-100}_{t-1}$ is a dummy variable that equals one if the respective market's $RRD_{t-1}$ is in the $75^{th}$ to $100^{th}$ percentile range and is zero otherwise. All other variables are as defined in the model of Table 4. The $\alpha$, $\beta$, and $\delta$'s are estimated coefficients where $\delta_4$, $\delta_5$, and $\delta_6$ in the conditional variance equations are the coefficients of interest. The table below reports summary statistics on the coefficients of interest for the firms in each country's market.

| **Coefficient:** / **Data Sample** | $\delta_4$ $(\varepsilon^2_{Mkt,t-1})$ | $\delta_5$ $(D^{RRD\,50-75}_{t-1}\ \varepsilon^2_{Mkt,t-1})$ | $\delta_6$ $(D^{RRD\,75-100}_{t-1}\ \varepsilon^2_{Mkt,t-1})$ |
|---|---|---|---|
| **Panel A: U.S. Dow 30** | | | |
| **Average coefficient** | 0.010 | 0.119 | 0.507 |
| **Average t-statistic** | -0.14 | 0.92 | 5.78 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 9/ (8) | 11/ (3) | 29/ (0) |
| **Panel B: Japan 20** | | | |
| **Average coefficient** | -0.016 | 0.139 | 0.315 |
| **Average t-statistic** | -3.27 | 3.71 | 6.04 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 2/ (12) | 15/ (0) | 20/ (0) |
| **Panel C: U.K. 20** | | | |
| **Average coefficient** | 0.035 | 0.174 | 0.052 |
| **Average t-statistic** | 1.32 | 3.14 | 0.80 |
| **# $d_i$ > 0 & significant/ (# $d_i$ < 0 & significant)** | 9/ (2) | 11/ (0) | 5/ (0) |

## Appendix A

# Sample of Individual Japanese and U.K. Firms

This appendix lists the individual Japanese and U.K. firms whose returns were tested and reported on in Tables 5, 6, 7, and 8. These are the 20 largest Japanese and U.K. firms that have daily firm return data in Datastream from 1985 through 1996. The size is from Datastream's equity market value data from December 1996. Banks are omitted.

| Japanese Firms | United Kingdom Firms |
|---|---|
| BRIDGESTONE | BARCLAYS |
| CANON | BASS |
| DENSO | BP AMOCO |
| FUJI PHOTO FILM | BRITISH AMERICAN TOBACCO |
| FUJITSU | BRITISH TELECOM. |
| HITACHI | CABLE & WIRELESS |
| HONDA MOTOR | DIAGEO |
| KANSAI ELECTRIC POWER | GENERAL ELEC. |
| MATSUSHITA ELECTRIC INDUSTRIES | GLAXO WELLCOME |
| MITSUBISHI | GRANADA GROUP |
| MITSUBISHI HEAVY INDUSTRIES | HSBC HOLDINGS |
| NEC | MARKS & SPENCER |
| NIPPON STEEL | PRUDENTIAL CORP. |
| NOMURA SECURITIES | REUTERS GP. |
| SHARP | RIO TINTO |
| SONY | SHELL TRANSPORT & TRADING |
| TAKEDA CHEMICAL INDUSTRIES | SMITHKLINE-BEECHAM |
| TOKYO ELECTRIC POWER | STANDARD CHARTERED |
| TOSHIBA | TESCO |
| TOYOTA MOTOR | UNILEVER |