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GOOD NEWS, BAD NEWS AND GARCH EFFECTS IN STOCK RETURN DATA

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It is shown that the volume of trade can be decomposed into proportional proxies for stochastic flows of good news and bad news into the market. Positive (good) information flows are assumed to increase the price of a financial vehicle while negative (bad) information flows decrease the price. For the majority of a sample of ten split-stocks it is shown that the proposed decomposition explains more GARCH than volume itself. Using the proposed decomposition, the variance of returns for younger split stocks reacts asymmetrically to good news flowing into the market, while the variance for older split-stocks reacts symmetrically to good news and bad news.

JEL classification codes: C32, G14

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I. Introduction

The second moment analysis of Engle (1982) has introduced a wide literature investigating the persistence of variance in time series data, especially in financial contexts. The Autoregressive Conditional Heteroskedasticity (ARCH) model, and the extension by Bollerslev (1986) to the Generalized ARCH (GARCH) model, can be used to explain the serial correlation that is sometimes observed in daily returns to stock shares. The noticeable clustering of like-magnitude returns can be modeled using GARCH, and hypothesis testing is straightforward.

One possible interpretation of the observed like-magnitudes in variance is

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that information may be received and acted upon at different times by the agents in the market. Thus there is a difference between calendar time, which daily returns are based upon, and economic time that is actually generating the data.

Considering how to measure the information flows that can affect the variance of returns; Lamoureux and Lastrapes (1990) investigate the role that volume plays in explaining the persistence of volatility shocks by introducing it as a mixing variable. Their work attempts to justify the suggestions of Diebold (1986) and Stock (1987, 1988) that stochastic information flows can explain the persistence of volatility shocks. Using volume as a proportional proxy for information flows, Lamoureux and Lastrapes explain away the GARCH effects found in daily stock return data.

This paper offers an extension to this literature by replacing the proxy for information (daily trading volume) with a decomposition of volume which proxies as a proportional measure of good news and bad news entering into the market. Using ten split-stocks that are differentiated by age, I find that younger splits react asymmetrically to good news and bad news, with good news having a greater effect on the persistence of variance. On the other hand, older splits react symmetrically to good news and bad news, suggesting that the market has more complete information leading to more completely formulated expectations on the returns of older splits than younger.

The paper is developed as follows. Section II discusses the theoretical motivation of GARCH in stock return data and proposes a decomposed measure of volume into good news and bad news flowing into the market. Section III reports the empirical analysis. The final section contains concluding remarks.

II. GARCH in Stock Data

A. The Basic Model

The ARCH model introduced by Engle (1982) was enhanced by Bollerslev (1986) to include only the squares of the past residuals, leading to the

Generalized ARCH (GARCH) model. The model used here contains a GARCH formulation similar to that of Lamoureux and Lastrapes (1990), i.e.,

$$r_t = \mu_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, ...) \sim N(0, h_t^2)$$

$$h_t^2 = \alpha + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2$$

where r_t is the rate of return and μ is the conditional mean of r_t based upon all past information. The conditional variance is a deterministic function based upon the previous period's pointwise variance and the overall variance given the information at time *t-1*. Lamoureux and Lastrapes (1990) motivate their analysis by considering ε the innovation upon stock returns, as a linear combination of intraday price movements, i.e.,

$$\varepsilon_t = \sum_{i=1}^{n_t} \delta_{ti} \tag{1}$$

where δ_{ti} is the i^{th} intraday price increment in day *t* due to an information flow into the market, and n_t is the number of information flows within a given day. Thus, ε_t is an aggregation of price innovations from information flows into the market but does not differentiate on the type of information flows into the market. Different types of information flows would be expected to cause different innovations on price.

Introduced as a proportional proxy for information arrivals to the market, volume acts as a mixing variable. This is important because ε_t is assumed to be random draws upon alternative distributions, with variances depending upon information available at the time. This use of volume leads to a model of the conditional variance of

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 + \beta_1 V_t \tag{2}$$

where V_t is the volume of trade that occurs in time *t*. I use the same approach in attempting to explain the persistence of volatility in daily stock returns.[1] One method of measuring the persistence of volatility shocks is to consider $\gamma = (\alpha_1 + \alpha_2)$. As γ approaches 1, the persistence of volatility shocks increases; that is there is more evidence of GARCH.

B. Good News and Bad News: Theoretical Foundations

In equation (1), ε_t is presented as an aggregation of intraday price changes caused by information flows into the market. However, ε_t can be decomposed into positive price changes summed over positive information flows (good news), and negative price changes summed over negative information flows (bad news). This leads to an alternative formulation of

$$\boldsymbol{e}_t = \sum_{i=1}^{n_t^+} \boldsymbol{d}_{ti}^+ - \sum_{j=1}^{n_t^-} \boldsymbol{d}_{tj}^- \tag{3}$$

where n_t^+ is the number of positive information flows into the market, and n_t^- is the number of negative information flows into the market on a given day. Further, let δ_{ti}^+ be the absolute values of the intraday price changes due to good news on day *t*, and δ_{tj}^- the absolute values of the intraday price changes due to bad news on day *t*.

This decomposition is motivated by the following intuition. If an item of bad news flows into the market three possibilities can lead to a decrease in the price: agents wishing to sell will do so only at a lower price; agents willing to buy will do so only at a lower price, or both may occur. This is because bad news, e.g., a change in management, destruction of capital, litigation or new government regulations, decreases the expected return of the firm and hence

[1] One problem with using volume as a proxy for information is investigated in Lamoureux and Lastrapes (1994) where they acknowledge possible problems associated with assuming the exogeneity of volume in the market and find that a single latent variable cannot explain both volume and GARCH. Here, I assume that volume is weakly exogenous.

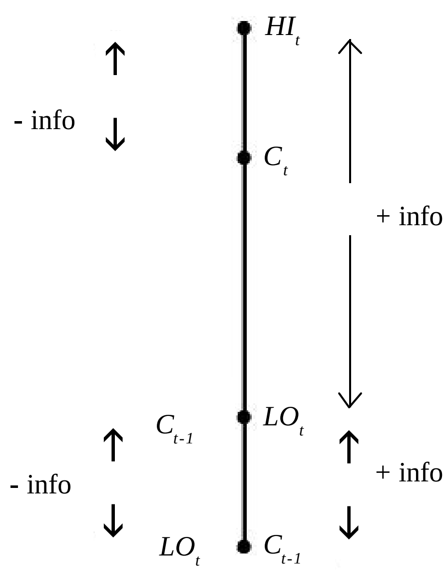
lowers the price of the stock. Likewise, good news, e.g., higher than expected profits, product innovation, increased market share, or deregulation, increases the expected future returns of the firm and causes an increase in the price of the stock.

Normalizing the absolute price changes associated with each type of information flow so that $\delta^{+}_{ti} = \delta^{-}_{tj} = \delta_t$, rewrite equation (3) as

$$\varepsilon_t = (n_t^{+} - n_t^{-})\delta_t$$

This normalization of the absolute price response to an information flow allows for up to three additional items of the information set at time t to be utilized in the explanation of GARCH. This follows because the price of a stock typically fluctuates over the course of a trading day and is frozen at the end of the trading day (see Figure 1). These intraday price changes can be used to develop proportional proxies for positive and negative information flows.

Figure 1. Price Changes from Stochastic Information Flows



The difference between the high price of the day (HI_t) and the low price of the day (LO_t) gives a total aggregation of positive increments in the price during the day. Further, if the close of the previous day (C_{t-1}) is lower than the low of the current day, then we have a further measure of positive information that is not captured by the difference between high and low price. This will occur if good news has accumulated while the market was closed. A proportional proxy for the number of positive information flows, n_t^+, can be derived by the total aggregation of positive price increments divided by the size of the positive increment d_{ti}^+.

An analogous proportional measure for the number of negative information flows, n_t^-, can be measured by the difference between the high price of the current day (HI_t) and the closing price of the current day (C_t). If the difference between the closing price of the previous day and the low price of the current day is positive then more negative information flows have accumulated in the market during non-trading hours. Therefore, a proportional proxy for total negative information flows is the aggregation of negative price increments divided by the size of the negative increment d_{ti}^-.

Restricting the normalization of incremental price changes to being discrete rather than continuous allows for closed-form solutions for n_t^+ and n_t^- in terms of observed data available at time t. Using the definitions developed above, define

$$
\begin{aligned}
&V_t = z\,(n_t^+ - n_t^-),\\
&n_t^+ = \frac{HI_t - LO_t + \max(0, LO_t - C_{t-1})}{d_t^+},\\
&n_t^- = \frac{HI_t - C_t + \max(0, C_{t-1} - LO_t)}{d_t^-},
\end{aligned}
\tag{4-6}
$$

where $\zeta > 0$ is a proportioning factor. Equations (4)-(6) comprise a system of three equations and three unknowns (δ_t, n_t^+, and n_t^-), which can be solved for the following closed-form solutions,

$$d_t = z\,(\frac{I_t + I_t^{'}}{V_t}),$$

$$zn_t^+ = \frac{V_t I_t}{I_t + I_t^{'}}, \qquad (7\text{-}9)$$

$$zn_t^- = \frac{V_t I_t^{'}}{I_t + I_t^{'}}$$

where

$$I_t = HI_t - LO_t + \max(0, LO_t - C_{t-1}),$$

$$I_t^{'} = HI_t - C_t + \max(0, C_{t-1} - LO_t).$$

Using these closed-form solutions for proportional proxies of positive and negative information flows on a given trading day offers a possible advantage over using only the volume of trade.

First, the decomposition allows for more information available at time t to be used in the explanation of GARCH effects: the current day's high and low prices and possibly the previous day's closing price. Further insight is available as to how GARCH is affected by qualitatively different information types; that is whether GARCH is driven by negative or positive information flows into the market.

This decomposition explicitly includes information flows that occur while the market is closed. Previous studies such as Baillie and Bollerslev (1989) and Bollerslev, Engle and Nelson (1993) have included qualitative variables to indicate times when markets are closed to control for asymmetric information flows between market and non-market hours. Laux and Ng (1993) further propose to remove volume completely, because it is an incomplete measure of information flows, and describe the flow as a linear combination of announcement-induced price changes and liquidity-preference-induced price changes. However, my purpose is to determine if volume used as a proportional proxy for information flows can be decomposed so as to better explain the persistence of variance evident in stock return data.

With the proportional proxies for the aggregated flows of good news and bad news into the market given in equations (7)-(9), substitution of ζn_t^+, and ζn_t^- for V_t yields a new specification of variance as

$$h_t^2 = a_0 + a_1 e_{t-1}^2 + a_2 h_{t-1}^2 + f_1(zn_t^+) + f_2(zn_t^-). \tag{10}$$

Inferences can be made on how good news and bad news explain the persistence in variance. In particular, the symmetry of good news and bad news in explaining the variance in stock returns can be investigated. If ϕ_1 and ϕ_2 are statistically equal to each other, the decomposition offers no advantage over the approach used by supports the results of Lamoureux and Lastrapes (1990) in that the effects of good news and bad news are symmetric.

III. Good News and Bad News: Empirical Results

To test the hypothesis that good news and bad news affects variance asymmetrically, a sample of 100 stocks was randomly selected. As GARCH is typically appropriate for time-series of 200 observations or more, of the one hundred selected stocks, all series shorter than 225 observations were discarded. Of the original hundred stocks, ten series were subsequently used. Five stocks in the sample are termed ‘old’ in that they have been split for at least six hundred trading days. The remaining five stocks in the sample are termed ‘young’ in that they have been split for less than 600 but more than 225 trading days. The series include the high price, low price, closing price, and volume of trade for each stock. Table 1 lists the stocks, their ticker symbols and time series lengths.

These stocks are first modeled using the GARCH(1,1) specification in equation (2), constraining the coefficient on the volume of trading, β_1, to zero. The results are listed in Table 2. For all stocks other than stocks 6 and 7

Table 1. The 10 Companies in the Sample

Company	Name	Ticker	Series Length (observations)	Type
1	CNVX	CNVX	01-19-87 to 11-14-89 (716)	Old
2	General Motors	GM	09-04-87 to 11-14-89 (556)	Old
3	Hewlett-Packard	HWP	08-27-87 to 11-17-89 (564)	Old
4	IBM	IBM	04-24-86 to 11-14-89 (902)	Old
5	Intergraph Corp.	INGR	11-12-86 to 11-14-89 (761)	Old
6	QMS, Inc.	AQM	11-22-88 to 11-14-89 (248)	Young
7	CDNC	CDNC	01-20-89 to 11-14-89 (208)	Young
8	Carolina Power	CPL	01-20-89 to 11-14-89 (208)	Young
9	Texaco	TX	01-20-89 to 11-14-89 (208)	Young
10	Florida Power Corp.	FPC	10-20-88 to 11-14-89 (271)	Young

the γ measurement of volatility persistence is above 0.7, indicating that these time series have persistence in variance.

I then model the variance of the ten stocks in the sample using the specification offered in (2), that is restricting $\phi_1 = \phi_2$ in equation (10), and results are reported in Table 3. Volume is statistically significant at the 0.05 level for all the ten stocks in the sample. For every stock in the sample the measure of GARCH is driven towards zero, suggesting that the specification given in Lamoureux and Lastrapes (1990) is successful in explaining much of the persistence in variance.

However, the specification in equation (2) is a special case of equation (10). Therefore, I relax the restriction of $\phi_1 = \phi_2$ and re-estimate the model using the specification of variance in equation (10). Upon estimation, the null hypothesis that $\phi_1 = \phi_2$ is tested. If the null cannot be rejected then the specification of variance is identical to that proposed by Lamoureux and Lastrapes (1990) and there is no advantage in using the decomposed information flows. The results of the estimation and asymptotic t-statistics for the null hypothesis are reported in Table 4.

Table 2. GARCH(1,1) Results

Company	α_0	α_1	α_2	γ
1	196.620	0.184	0.659	0.843
	(9.05)*	(6.97)*	(21.60)*	
2	29.556	0.096	0.793	0.889
	(4.02)*	(5.23)*	(18.93)*	
3	116.693	0.244	0.554	0.798
	(6.15)*	(11.45)*	(11.14)*	
4	35.684	0.300	0.609	0.909
	(7.59)*	(12.47)*	(18.16)*	
5	227.210	0.120	0.632	0.752
	(5.73)*	(4.33)*	(11.57)*	
6	283.253	0.053	0.524	0.577
	(1.53)	(1.29)	(1.85)*	
7	201.048	0.170	0.505	0.675
	(2.47)*	(3.18)*	(3.23)*	
8	12.104	0.026	0.747	0.773
	(0.91)	(0.83)	(2.78)*	
9	115.215	0.084	0.644	0.728
	(32.20)*	(2.29)*	(6.75)*	
10	3.658	0.020	0.888	0.908
	(1.76)*	(0.79)	(13.70)*	

Notes: Asymptotic *t*-statistics in parentheses. * denotes significance at the 5% level.

The results obtained in this sample are encouraging. For seven of the ten stocks, the decomposition of aggregated information flows captures more of the observed persistence of variance than using volume alone, that is γ is driven closer to zero. Further, the good news proxy is significant at the 0.05 level for nine of the ten stocks, and significant at the 0.10 level for Company

Table 3. GARCH(1,1) with Daily Volume of Trade

Company	α_0	α_1	α_2	β_1	γ
1	18.407	0.100	0.018	8.421	0.118
	(0.76)	(2.84)*	(0.75)	(15.92)*	
2	0.000	0.071	0.005	0.236	0.076
	(0.00)	(2.46)*	(0.33)	(20.44)*	
3	-0.011	0.078	0.012	0.824	0.090
	(-10.95)*	(3.14)*	(0.69)	(16.73)*	
4	-0.005	0.054	0.038	0.135	0.093
	(-10.14)*	(2.18)*	(1.11)	(23.47)*	
5	0.007	0.044	0.000	2.005	0.044
	(0.00)	(2.47)*	(-1.59)	(18.69)*	
6	0.033	0.000	0.179	12.607	0.179
	(0.00)	(-0.14)	(1.77)	(8.30)*	
7	0.181	0.000	0.104	3.435	0.104
	(0.00)	(0.20)	(1.15)	(9.27)*	
8	23.441	0.070	0.000	0.160	0.070
	(2.49)*	(1.17)	(0.00)	(3.84)*	
9	29.334	0.033	0.00	0.396	0.033
	(0.91)	(0.91)	(0.00)	(8.15)*	
10	19.388	0.022	0.056	0.189	0.078
	(2.73)*	(0.32)	(0.30)	(2.68)*	

Notes: Asymptotic t-statistics reported in parentheses. * denotes significance at the 5% level.

4. The bad news proxy is significant at the 0.05 level for eight of the ten stocks and is insignificant for Company 7 and Company 10.

Older splits in the sample fail to reject the null hypothesis that $\phi_1 = \phi_2$ three of five times. Companies 1, 3 and 4 therefore support the specification

Table 4. GARCH(1,1) with Decomposed Volume and $H_0: \phi_1 = \phi_2$

Company	γ	ϕ_1	ϕ_2	H_0:$\phi_1 = \phi_2$
1	0.173	11.253	8.922	0.99
	(4.77)*	(6.03)*		
2	0.072	0.384	0.158	5.09*
	(8.68)*	(4.41)*		
3	0.042	0.810	0.719	0.82
	(7.36)*	(11.02)*		
4	0.000	0.052	0.053	0.05
	(1.75)	(2.03)*		
5	0.036	2.622	1.006	5.51*
	(8.94)*	(3.80)*		
6	0.215	14.363	8.665	1.72
	(4.34)*	(2.94)*		
7	0.148	4.854	0.753	6.28*
	(7.43)*	(1.03)		
8	0.074	0.154	0.223	-0.99
	(2.22)*	(2.41)*		
9	0.000	0.566	0.202	3.77*
	(5.87)*	(2.63)*		
10	0.045	0.602	0.000	3.38*
	(3.38)*	(-0.34)		

Notes: Asymptotic *t*-statistics reported in parentheses. * denotes significance at the 5% level.

of variance offered in Lamoureux and Lastrapes (1990). However, Companies 2 and 5 reject the null hypothesis with positive information holding more strength in explaining the variance of returns. For Company 2 positive information has a coefficient approximately three times as large as the coefficient on bad news, while for Company 5 good news has a coefficient approximately twice as large as bad news.

On the other hand, four of the five younger splits in the sample reject the null hypothesis; Company 8 is the only young split that fails to reject the null hypothesis. The asymmetric effect of positive information on the volatility of returns is pronounced for young splits. Company 7 exhibits the most asymmetric effect in that the coefficient on good news is approximately seven times as large as the coefficient on bad news. The fact that more young splits reject the null hypothesis may indicate that the market has incompletely formulated expectations on the future returns of the firm. As the market has more completely formed expectations of the future returns of the firm, the less an individual stochastic information flow will have on the variance of price.

The older splits of the sample support the Lamoureux and Lastrapes (1990) formulation for explaining away the persistence of variance evident in the data. In modeling the variance of the older splits, the aggregated information flows into the market holds as much power as the decomposed levels of good news and bad news. Therefore, the decomposition offers no advantage in explaining the variance of price. On the other hand, younger splits are more vulnerable to the level of positive and negative information flows as reflected in the proxies developed here. These findings may indicate that the market has incompletely formulated expectations on the firm's ability to provide positive returns in the future.

IV. Conclusions

This paper utilizes a sample of ten firms that have split their stock in trade. The results of Lamoureux and Lastrapes (1990) are replicated, and the gross level of information flows, as proxied by the volume of trade, does explain much of the persistence in variance apparent in the data.

A decomposition of aggregated information flows into the market is developed. It is possible to derive closed-form solutions for proportional proxies of good news and bad news entering into the market, the former raising the price of financial instrument and the latter decreasing the price. These proxies are based upon the volume of trade, the closing price of the previous day and the high and low-price of the current trading day. Thus up to three additional items of information are available for explaining the persistence of variance.

I model the variance in stock market returns by substituting the proportional proxies for positive and negative information flows for the aggregated proxy for information flows. For nine of the ten stocks in the sample, the amount of persistence in variance explained by decomposed information flows is greater than using the aggregated measure. I find that the variance of younger stocks reacts asymmetrically to good news perhaps reflecting incompletely formulated expectations on the part of the market, while older stocks in the market respond symmetrically to the type of information flows into the market.

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