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Modelling Price Movement in Trading Volume-Volatility Relations

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Abstract: This study investigated the association between volatility of stock returns and price movement-induced trading volume. In the trading volume and volatility relation, we modeled price movement using indicator variables and coupled them with trading volume. In a sample of Australian stocks, we found that upward price movement-induced trading volume was likely to affect conditional volatility more than downward price movement-induced trading volume. Evidence of this asymmetric effect was stronger in the case of price movement over the trading period than in price movement over the non-trading period. This association was observed even after controlling for asymmetry of news in the previous period.

Keywords: Conditional volatility, GARCH-type models, price movement, trading volume, volatility persistence
JEL classification: G10, G12, G14

1. Introduction

Information arrival (news) may trigger trading activity and therefore proxies for the information arrival rate become potential explanatory variables of stock return volatility. Empirical studies of the association between stock return volatility and trading activity generally adopt Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models as the basic methodological framework. What differs in such studies is the way in which the information arrival is conceptualised. The sequential information arrival hypothesis (SIAH) and the mixture of distribution hypothesis (MDH) are two hypotheses on how traders may receive and respond to new information in the market.[1] These hypotheses are tested by using trading volume as a proxy for the information arrival rate and testing

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[1] See section 2 for more on SIAH and MDH.

its impact on the persistence of GARCH effects. The idea is that as the information arrival rate increases, so does the trading volume and therefore trading volume may have the potential to explain volatility clustering. From a trader's view point, the news may be good or bad. Yet, irrespective of its type, news always influences the trading volume only in one way - which is to increase. In this paper, we investigated how the news type (good news and bad news) over the trading period and over the overnight non-trading period could affect the association between conditional volatility of stock returns and trading volume. A significant contribution of this paper is providing a modelling framework to construct a proxy for the information arrival rate using two variables of the information set. Previous studies on the association between stock return volatility and information arrival rate do not model additional information in the conditional volatility equation apart from using a proxy such as trading volume for the information arrival rate.

When investors differ in their beliefs about news, they may react to news differently. In other words, return volatility and differences in opinion of agents may be related (Chordia *et al.* 2011). Different type of news may also affect stock return volatility differently (Andersen 1996). The same argument may be extended to the case of informed and uninformed investors. For example, Easley *et al.* (1997) support the view that large-sized trades are more likely to be executed by better-informed investors. Therefore, when investigating the association between volatility and information arrival rate, the trading volume enhanced by additional information about the news type over the trading period may explain volatility persistence better than trading volume alone. A general idea of how the investors would have perceived news over a trading period may be captured through the overall movement in price (increase or decrease) over that trading period. We assessed the direction of the overall movement in price in the difference between the close price and the open price of that period. A positive (negative) difference was taken to indicate an overall upward (downward) movement in price suggesting that investors may have generally perceived the news over the trading period as good (bad).

We developed a model incorporating an interaction between direction of overall price movement and rate of information arrival in a GARCH framework.[2] Since there is no trading during the overnight non-trading period, the influence of noise traders on the next period open price may be high. Hence, it is plausible that the noise traders have a greater influence on the direction of price movement over the overnight non-trading period than on the direction of price movement over the trading period. Close price, on the other hand may be influenced more by activity during the trading period. Chordia *et al.* (2011) show evidence to link increased turnover to increased trading on private information. According to French and Roll (1986), private information is a dominant factor of price variation during the trading period. Turnover is sensitive to past returns as well (Chordia *et al.* 2011). Therefore, to investigate the association between volatility, trading volume and price movement, we considered the price movement over the overnight non-trading period and the price movement over the trading period separately.

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[2] When the errors in a regression equation do not have constant variance, the errors are said to be heteroscedastic. Volatility in the returns is usually modelled as a GARCH process due to the empirically observed stylised fact of volatility clustering. Bollerslev (1986) developed the GARCH model by extending the ARCH (autoregressive conditional heteroscedasticity) process proposed by Engle (1982).

This study aimed to investigate whether (i) price movement-induced trading volume decreases volatility persistence more than trading volume alone in GARCH-type models and (ii) the effect of price movement-induced trading volume on conditional volatility is asymmetric. These are important issues given the surge in trading activity in recent times. Trading activity at the Australian stock exchange (ASX) is no exception. ASX has an average daily turnover of A$4.685 billion and market capitalisation of approximately A$1.6 trillion. ASX is among the world's top fifteen listed exchange groups and is comparable to the Deutsche Boerse and the Korea Exchange. Given that Australia is one of the leading capital markets in the world, we investigated these issues in a sample of actively traded Australian stocks.[3]

We found that price movement-induced trading volume tended to reduce persistence in conditional volatility more than contemporaneous trading volume and lagged trading volume. Our empirical evidence suggests further that the effect of price movement induced trading volume on conditional volatility is asymmetric such that the effect of trading volume with an upward movement in price over the trading period is stronger on conditional volatility of stock returns than trading volume with a downward movement in price. This we observed with price movements over the trading period. According to behavioral finance literature, good news is thought to generate more trading than bad news (Ritter 2003). Our evidence in the case of Australian stocks extends the notion of asymmetry in the association between new type and trading activity to their effect on conditional volatility in the returns.

Our results provide evidence relevant to the ongoing debate about the structure of financial markets and provide valuable insights to market participants that may assist them in developing trading strategies. The next section reviews previous work. In Section 3 we present the models used while in Section 4 we describe the data. The results are discussed in Section 5. Section 6 investigates the robustness of the results and Section 7 concludes the paper.

2. Literature Review

Under SIAH, new information arrival is considered as a sequential random process (Copeland 1976). As a consequence, individuals react to new information at different points in time creating a sequential reaction. Once all traders receive the new information, a new equilibrium is reached. Reaction to news affects price and therefore the variation in price changes is potentially predictable with information on trading volume. An implication of this is that lagged trading volume should reduce volatility persistence. Evidence in support of SIAH is available in Darrat *et al.* (2003).

MDH implies that stock return volatility and trading volume are positively related. In this case, stock return variability is measured as the sum of the price changes within the trading period. In an econometric sense, this means that there exists a joint distribution between price and trading volume. Because of their joint dependence, the shift to a new equilibrium will be immediate. An implication of this assumption is that the changes in stock return volatility and trading volume will be contemporaneous. Clark (1973) suggests

[3] Australia is the second largest equity market in the Asia-Pacific region

that there is a positive association between trading volume and the number of within-day transactions. When the daily price change is measured as the sum of random number of within-day price changes, Clark (1973) argues that an increase or decrease in price levels is associated with an increase in the volume of transactions. Copeland (1976) established that the relation between absolute value of price changes and trading volume is positive and linear under SIAH and therefore an inverse correlation between absolute value of price changes and trading volume would imply simultaneous information arrival. More on MDH is available in Epps and Epps (1976) and Tauchen and Pitts (1983).

Diebold (1986), Stock (1987; 1988) and Gallant *et al.* (1997) show that daily trading volume causes time-series dependence of stock return volatility. Therefore, if MDH is correct, then daily trading volume should decrease persistence in volatility estimated in GARCH-type models substantially. In an analysis of 20 US stocks, Lamoureux and Lastrapes (1990) reveal that by incorporating contemporaneous trading volume in the conditional variance equation of the GARCH(1,1) model decreases volatility persistence dramatically and removes significance of the GARCH components. Brailsford (1996) investigated five individual stocks from the Australian stock market and reported that incorporation of daily trading volume in the conditional variance equation of the GARCH(1,1) model decreases volatility persistence substantially.In ten actively traded US stocks, Gallo and Pacini (2000) observed that volatility persistence decreases when contemporaneous trading volume is included in the conditional variance equation. However, when the lagged trading volume is used instead, they observed that volatility persistence does not decrease and the lagged trading volume is not significant in four out of the ten stocks analysed. Alsubaie and Najand (2009), in a sample of fifteen stocks in the Saudi stock market, found that lagged trading volume does not reduce persistence in volatility as much as contemporaneous trading volume does.

In a sample of seventy-nine stocks traded in the stock exchange in Egypt, Girard and Omran (2009) observed that lagged trading volume and contemporaneous trading volume do not eliminate persistence in the volatility of a GARCH-type model. However, they found that volatility persistence decreases when trading volume is decomposed into the expected and unexpected components. Girard and Omran (2009) reported a negative relation between the expected trading volume component and volatility.

Gallo and Pacini (2000) used overnight indicator (ONI) defined as the absolute difference between log open price of the trading day and log close price of the previous trading day as a substitute for contemporaneous trading volume. This is based on the premise that ONI is a good proxy for the number of trades during the day. In ten actively traded US stocks, Gallo and Pacini (2000) observed that ONI is always significant and reduces volatility persistence. They also used intra-day volatility (IDV) defined as the difference between the highest and lowest price in the trading day as a substitute for volatility and found that the lagged IDV (a proxy for previous trading day volatility) is consistently significant and reduce persistence. This finding is consistent with volatility spill over. When ONI is included as a lagged variable in the conditional variance equation, Alsubaie and Najand (2009) observed in fifteen stocks in the Saudi stock market that lagged ONI is consistently highly significant and reduces volatility persistence. When lagged IDV is included in the conditional variance equation, lagged IDV was also found to reduce persistence more than lagged trading volume.

Najand and Yung (1991) found that contemporaneous trading volume is not statistically significant and does not reduce volatility persistence in the conditional variance equation. However, when trading volume is included as a lagged variable they found lagged trading volume to be consistently significant suggesting that trading volume may be an endogenous variable. Lamoureux and Lastrapes (1990) argue that trading volume should not be assumed to be exogenous and therefore the lagged trading volume will be more appropriate. If contemporaneous trading volume is not exogenous, regressing return volatility on contemporaneous trading volume is subject to simultaneity bias (Karpoff 1987).

3. Methodology

Studies on trading volume and volatility in the returns usually include trading volume in the conditional variance equation in a GARCH-type process and investigate whether the introduction of trading volume reduces persistence in volatility (Lamoureux and Lastrapes 1990; Brailsford 1996; Gallo and Pacini 2000; Alsubaie and Najand 2009). However, trading volume does not account for the overall direction of price movement over the trading period explicitly. Therefore, we hypothesise that trading volume may have an asymmetric effect on conditional volatility depending on the overall trend (up or down) in price movement over the trading period. This is investigated by capturing the overall direction of price movement over the trading period through $P_t^{close} - P_t^{open}$ and integrating the sign of $P_t^{close} - P_t^{open}$ with trading volume where, P_t^{open} is the open price in trading day *t* and P_t^{close} is the close price in trading day *t*.

3.1 Incorporating Trading Period Price Movement with Trading Volume

We model the overall direction of price movement in the conditional volatility-volume relation using indicator variables. First, two indicator variables - one capturing the overall upward price movement and another capturing the overall downward price movement are defined. The two indicator variables are then multiplied by the trading volume (we refer to them as indicator-volume variables) and are included in the conditional volatility equation as two explanatory variables.[4]

The overall direction of price movement over the trading period is captured through two indicator variables (*TPIs*) defined as:

$$TPI_{1t} = \begin{cases} 1 \text{ if } P_t^{open} < P_t^{close} \\ 0 \quad \text{otherwise} \end{cases} \tag{1}$$

$$TPI_{2t} = \begin{cases} 1 \text{ if } P_t^{open} \geq P_t^{close} \\ 0 \quad \text{otherwise} \end{cases} \tag{2}$$

These two indicator variables are used to model price movement in the volatility equation through trading volume by constructing two variables $V_t^{TP+} = TPI_{2t}V_t$ and V_t^{TP-}

[4] When the trading volume is multiplied by the two indicator volume variables, two non-negative variables will be created. The sum of these two non-negative variables will be equal to the trading volume.

$= TPI_{2t}V_t$ where V_t is the trading volume in day t.[5,6] We refer to V_t^{TP+} and V_t^{TP-} as trading period indicator-volume (TPI-V) variables. The TPI-V variables capture the general type of information in the current period and the level of reaction of traders to such information. Under this framework, the level of reaction of traders to information in the current period is captured through contemporaneous trading volume.

We hypothesise that an upward price movement and a downward price movement modeled with trading volume together may affect conditional volatility differently. The rationale here is that even if all traders receive public information simultaneously, they may interpret news differently irrespective of its type due to divergence of opinion. Consequently traders may take positions at different points in time depending on the time taken to react to good news and bad news. Therefore, the overall movement in price during a period may reflect investor perception of news over that period that is masked in trading volume.[7]

3.1.1 Modelling trading period indicator-volume variables in conditional volatility

From an information variable perspective, TPI-V variables compete directly with contemporaneous trading volume. Therefore, the performance of TPI-V variables as explanatory variables of conditional volatility as opposed to contemporaneous trading volume is investigated first. The conditional volatility model adopted here is the GARCH(1,1) model. The conditional volatility equation of the GARCH(1,1) model with TPI-V variables is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_2 V_t^{TP+} + \delta_3 V_t^{TP-} \quad (3)$$

where σ_t^2 is conditional volatility in trading day t and ε_t is the error term in the mean equation given by

$$R_t = \mu + \alpha R_{t-1} + \varepsilon_t \quad (4)$$

where R_t is return in trading period t computed as $\ln(P_t^{close}) - \ln(P_t^{open})$ and $\varepsilon_t = \sigma_t z_t$ with $z_t \sim (0,1)$. We refer to (3) and (4) as the GARCH(1,1) TPI-V model. In this model, the degree of volatility persistence is measured in $(\alpha_1 + \beta_1)$ with high $(\alpha_1 + \beta_1)$ indicating a high level of persistence.[8] The main issues investigated here are:

(i) Do TPI-V variables reduce persistence in volatility in the GARCH(1,1) model more than contemporaneous trading volume? This is investigated by comparing volatility persistence in equation (3) with that in the GARCH(1,1) model with contemporaneous trading volume given by:

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[5] Effectively, the trading volume series is partitioned into two series V_t^{TP+} and V_t^{TP-} such that $V_t^{TP+} + V_t^{TP-} = V_t$

[6] Jones *et al.* (1994) decomposed trading volume into the two components: number of trades and average trade size. They found that stock price volatility is driven by the number of trades and average trade size offers no additional explanatory power. This is an example of decomposition of one information variable. We model the effect of two information variables together.

[7] Van den Bergh and Steenbeek (2002) argue that positive news may lead to a higher share price and the opposite occurs in the case of negative news and suggest a non-linear relationship between nature of news and stock return when financial leverage of the firm is high.

[8] When persistence is very high the sum of α_1 and β_1 is close to 1. R_{t-1} is included in equation (4) to account for autocorrelation that is usually present in return series.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_1 V_t \quad (5)$$

(ii) Is the effect of V_t^{TP+} on conditional volatility different from that of V_t^{TP-} We hypothesise that when news in the trading period is generally good, the investors may react swiftly (herd behaviour) as their decisions may not be subject to unwarranted risk. On the other hand, when the news in the trading period is generally bad, all investors may not react immediately as conservative investors may adopt a wait-and-see policy. Under this scenario, the rate of good news arrival is likely to affect conditional volatility more than the rate of bad news arrival. Accordingly, the hypothesis tested here is H_0: $\delta_2=\delta_3$ against the alternative of H_1: $\delta_2>\delta_3$.[9] δ_2 and δ_3 are the coefficients of V_t^{TP+} and V_t^{TP-} modelled in equation (3).

3.1.2 Modelling previous period information asymmetry and trading period indicator-volume variables in conditional volatility

Under the conditional volatility specifications of equations (3) and (5), positive and negative shocks in the previous trading period influence volatility to the same degree.[10] Therefore, even though the proposed TPI-V variables are intended to capture asymmetric information over the trading period only, it is plausible under specifications in equations (3) and (5) that any asymmetric effect of news from the previous trading period may also be channelled through V_t^{TP+} and V_t^{TP-}. To investigate potential asymmetric effect of TPI-V variables on conditional volatility, it is important to control for asymmetric information from the previous trading period. This may be done by adopting an asymmetric model such as the GJR-GARCH model proposed by Glosten *et al.* (1993) and the EGARCH model proposed by Nelson (1991). Asymmetric GARCH models do not enforce symmetric response of volatility to positive and negative shocks from the previous period. A question that arises here is whether an asymmetric GARCH model would render any asymmetric effect of TPI-V variables on conditional volatility insignificant? This we investigate in the EGARCH model since in the EGARCH model, it is not necessary to impose restrictions on the parameters whereas in the GJR-GARCH model, the parameters are restricted to non-negative. In this case, we replace the conditional volatility equation given in equation(3) with

$$log(\sigma_t^2) = \omega + \beta_2 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-} \quad (6)$$

In specification equation(6), volatility at time *t* depends on the size and the sign of the normalised errors and the asymmetry parameter γ is expected to be negative if the association between return and volatility is negative. In this EGARCH model, persistence is measured by β_2. The issues investigated here are:

(i) Do TPI-V variables reduce persistence in volatility in the EGARCH model more than contemporaneous trading volume? This is investigated by comparing volatility persistence in equation(6) with that in the following model where TPI-V variables in equation (6) are replaced with contemporaneous trading volume as

[9] This interpretation is based on the assumption that δ_2 and δ_3 are positive

[10] In the GARCH(1,1) model the impact of news from the previous period on conditional volatility is assumed to be symmetric

$$log(\sigma_t^2) = \omega + \beta_2 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_4 V_t \quad (7)$$

(ii) Do TPI-V variables in equation(6) affect conditional volatility differently? We investigate this by conducting a hypothesis test where H_0: $\delta_5 = \delta_6$ and H_1: $\delta_5 > \delta_6$

3.2 Incorporating the Non-trading Period Price Movement with Trading Volume

In this section, we focus on information from the overnight non-trading period. As far as the current period is concerned, the information in the overnight non-trading period will be past information that may not have been accounted for until trading begins in the next period. Therefore, we expect the effect of overnight non-trading period price movement induced trading volume on conditional volatility to be different from that of the current period price movement-induced trading volume. To investigate the effect of the interaction between the trend in price movement over the overnight non-trading period and trading volume in the subsequent trading period on conditional volatility of stock returns, we define the overnight non-trading period price movement indicator variables (*NTPIs*) in day *t* as:

$$NTPI_{1t} = \begin{cases} 1 \text{ if } P_t^{open} > P_{t-1}^{close} \\ 0 \quad \text{otherwise} \end{cases} \quad (8)$$

$$NTPI_{2t} = \begin{cases} 1 \text{ if } P_t^{open} \leq P_{t-1}^{close} \\ 0 \quad \text{otherwise} \end{cases} \quad (9)$$

NTPI may reflect the reaction of investors to news from the markets that are active during the overnight non-trading period. As in the previous case, we create two variables $V_t^{NTP+} = NTPI_{1t}V_t$ and $V_t^{NTP-} = NTPI_{2t}V_t$. Effectively, the trading volume series is partitioned into two series, V_t^{NTP+} and V_t^{NTP-}, such that $V_t^{NTP+} + V_t^{NTP-} = V_t$. We refer to V_t^{NTP+} and V_t^{NTP-} as overnight non-trading period indicator-volume (NTPI-V) variables. These two variables are then included in the GARCH(1,1) model and in the EGARCH(1,1) model as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_7 V_t^{NTP+} + \delta_8 V_t^{NTP-} \quad (10)$$

$$log(\sigma_t^2) = \omega + \beta_1 log(\sigma_{t-1}^2) + \alpha\alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_9 V_t^{NTP+} + \delta_{10} V_t^{NTP-} \quad (11)$$

and the same issues outlined in Section 3.1 are investigated.

4. Data

The sample consisted of twenty actively traded stocks in Australia. The investigation period was 4 January 2000 to 19 April 2011. We obtained daily open price, close price, highest price, lowest price and trading volume of these stocks from the Datastream database. Initially we collected data on the 200 stocks included in the ASX200 index. When we removed all stocks with missing data and with infrequent trading (for more than 5 days), the sample was reduced to forty-five stocks and twenty of them were chosen randomly for the analysis. Summary statistics of daily returns of the sampled stocks are given in Table 1. Augmented Dickey-Fuller test reveal that the return series is stationary, the

Table 1. Summary statistics of daily returns

Stock No.	Stock Name	Industry	Mean	Standard deviation	Skew	Kurtosis
1	Telstra	TS	-0.048	1.110	-0.003	1.775
2	News Corp. CDI. 'B' (ASX)	ME	0.037	1.218	0.230	4.305
3	BHP Billiton	M	-0.010	1.231	0.223	3.559
4	David Jones	R	-0.030	1.728	0.074	2.983
5	Cochlear	HCES	-0.045	1.755	-0.832	20.223
6	Ansell	HCES	-0.015	1.756	-0.016	2.886
7	Toll Holdings	T	-0.047	1.776	-0.371	10.291
8	Brambles	CPS	0.025	1.854	6.269	175.330
9	GWA Group	CG	-0.016	1.943	0.254	3.134
10	Iluka Resources	M	0.033	1.967	0.324	5.533
11	Computershare	SS	0.010	1.991	0.490	4.156
12	Flight Centre	CS	0.008	2.021	-0.246	11.247
13	Ardent Leisure Group	RE	-0.047	2.058	-0.097	4.432
14	Caltex Australia	E	-0.051	2.135	-0.317	4.511
15	Oil Search	E	-0.114	2.196	0.150	6.783
16	Aristocrat Leisure	CS	-0.029	2.281	0.164	4.796
17	Adelaide Brighton	M	-0.044	2.307	0.882	11.639
18	ROC Oil Company	E	-0.208	2.542	0.047	4.657
19	SMS Man. & Tech.	SS	-0.107	3.217	2.115	36.701
20	Austar United Comms.	ME	-0.263	3.534	0.455	18.988

Notes: CPS=Commercial and Professional Services, HCES=Health Care Equipment and Services, SS=Software and Services, R=Retailing, ME=Media, TS=Telecommunication Services, RE=Real Estate, CS=Consumer Services, CG=Capital Goods, M=Materials, T=Transportation, E=Energy, Sample period is 3 January 1996 to 19 April 2011. Stocks are sorted in ascending order on standard deviation in the returns.

Jarque-Bera test rejects normality in the returns and the Lagrange Multiplier test justifies using a GARCH(p,q)-type model for all stocks. We tried several combinations of (p,q) and all sampled stocks reveal that the GARCH(1,1) model generally offers a good fit.

5. Results

5.1 Measures of Trading Activity as Explanatory Variables of Conditional Volatility

Table 2 gives the parameters estimated in the GARCH(1,1) model without and with contemporaneous trading volume as an explanatory variable of conditional volatility. The results in the GARCH(1,1) model reveal that conditional volatility in all stocks is highly persistent with the sum of the persistent parameters ($\alpha_1+\beta_1$) varying from 0.8090 to 1.0298.[11] In sixteen stocks the association between contemporaneous trading volume and conditional volatility is positive and significant at the 5 per cent level. Contemporaneous trading volume does not explain conditional volatility in three stocks. The association between contemporaneous trading volume and conditional volatility is negative and

[11] ($\alpha_1+\beta_1$) >1 only in one of the 20 stocks.

Table 2. GARCH(1,1) parameters estimated without and with contemporaneous trading volume

Variance equations of the estimated models: (M1) $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$ and (M2) $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \delta_1 V_t$

Stock	(M1)			(M2)			
No.	α_1	β_1	$\alpha_1+\beta_1$	α_1	β_1	$\alpha_1+\beta_1$	δ_1
1	0.0384*	0.9561*	0.9945	0.0585*	0.9236*	0.9821	$4.78\text{x}10^{-7*}$
2	0.0609*	0.9366*	0.9975	0.0652*	0.9295*	0.9948	$2.16\text{x}10^{-6*}$
3	0.0663*	0.9171*	0.9834	0.0728*	0.9079*	0.9807	$1.60\text{x}10^{-6*}$
4	0.0377*	0.9503*	0.9880	0.1313*	0.0384	0.1696	$1.17\text{x}10^{-3*}$
5	0.0571*	0.7519*	0.8090	0.0924*	-0.0130	0.0794	$5.98\text{x}10^{-3*}$
6	0.0312*	0.9658*	0.9970	0.0309*	0.9664*	0.9973	$-1.00\text{x}10^{-5}$
7	0.1467*	0.8222*	0.9689	0.2771*	0.4979*	0.7750	$1.38\text{x}10^{-4*}$
8	0.3368*	0.6527*	0.9895	0.4253*	0.0324*	0.4577	$2.40\text{x}10^{-4*}$
9	0.0422*	0.9526*	0.9948	0.0546*	0.9341*	0.9887	$8.69\text{x}10^{-5*}$
10	0.0798*	0.8873*	0.9672	0.1863*	0.5924*	0.7788	$3.37\text{x}10^{-4*}$
11	0.0370*	0.9533*	0.9903	0.1698*	0.1149*	0.2847	$9.47\text{x}10^{-4*}$
12	0.2927*	0.7371*	1.0298	0.3511*	0.2824*	0.6335	$6.64\text{x}10^{-3*}$
13	0.0530*	0.9376*	0.9906	0.1002*	0.8540*	0.9542	$2.80\text{x}10^{-4*}$
14	0.0580*	0.9222*	0.9802	0.0576*	0.9229*	0.9805	$-2.73\text{x}10^{-6}$
15	0.0287*	0.9695*	0.9982	0.2085*	0.0073	0.2158	$3.06\text{x}10^{-4*}$
16	0.0310*	0.9634*	0.9944	0.2395*	0.0064	0.2459	$9.61\text{x}10^{-4*}$
17	0.1095*	0.8864*	0.9959	0.0976*	0.8925*	0.9901	$-1.35\text{x}10^{-5*}$
18	0.0781*	0.8835*	0.9616	0.1464*	-0.0495	0.0969	$1.91\text{x}10^{-3*}$
19	0.0220*	0.9767*	0.9986	0.2279*	0.0289*	0.2569	$2.57\text{x}10^{-2*}$
20	0.0664*	0.9300*	0.9964	0.0678*	0.9285*	0.9963	$-5.48\text{x}10^{-7}$

Notes: V_t is trading volume in day *t*. * indicates significance at the 5% level

significant in one stock.[12] In the stocks where a substantial decrease in persistence is observed, contemporaneous trading volume renders previous period volatility insignificant.

Lamoureux and Lastrapes (1990) argue that if contemporaneous trading volume is not strictly exogenous then the lagged trading volume is a better option. When we repeat the analysis with lagged trading volume in the conditional volatility equation, we observe that persistence in volatility does not decrease as much as when contemporaneous trading volume is included.[13] Following Gallo and Pacini (2000), we consider two other proxies for trading activity: overnight indicator defined as $ONI_t = \left|log\frac{P_t^{open}}{P_{t-1}^{close}}\right|$ and intraday volatility defined as $IDV_{t-1} = P_{t-1}^H - P_{t-1}^L$ where P^H_{t-1} is the highest price in trading

[12] The negative coefficient observed here is not unusual. Gallo and Pacini (2000) report that in four of the ten stocks that they investigated, the coefficient of the lagged trading volume in the GARCH(1,1) model is negative. Alsubaie and Najand (2009) also report negative coefficient with lagged trading volume in three of the five industry indices of the Saudi market.

[13] The exception is in stock 9 where the persistence with lagged trading volume is 0.6419 compared to 0.9887 with contemporaneous trading volume.

day *t-1* and P^L_{t-1} is the lowest price in trading day *t-1*.[14] Gallo and Pacini (2000) propose *ONI* and *IDV* as good candidates to explain persistence in volatility. The results reveal that contemporaneous trading volume in the GARCH(1,1) model reduces persistence in volatility the most compared to the reduction with lagged trading volume, the *ONI* and *IDV*. Therefore, in the rest of the analysis we consider contemporaneous trading volume as a proxy for news arrival implying that our modelling framework aligns with the mixture of distribution hypothesis.

5.2 Trading Period Indicator-Volume Variables

5.2.1 Performance under the GARCH specification

Here we discuss the parameters estimated in the GARCH(1,1) model with TPI-V variables. The results are reported in Table 3. In terms of reduction in volatility persistence, this model performs better than the GARCH(1,1) model with contemporaneous trading volume in the variance equation. Evidence of this is found in sixteen of the twenty stocks. Persistence in the conditional volatility with TPI-V variables is below 0.1 in six stocks and below 0.5 in a further five stocks. In the case with contemporaneous trading volume in the volatility equation, persistence is below 0.1 only in two stocks and below 0.5 in six stocks. We provide the following as an explanation for this finding.

In the GARCH-type models, we expect the two non-negative indicator variables that capture information asymmetry (good news and bad news) and trading volume (which is non-negative) to have more explanatory power of conditional volatility than trading volume alone. For example, when the two non-negative explanatory variables have positive influence on conditional volatility in the GARCH(1,1) model, we expect the combined effect of the lagged conditional volatility and previous period shock to reduce as a tradeoff. Hence, a higher reduction in volatility persistence is expected with information on price movement and trading volume than with trading volume alone.

Further, the coefficient of V_t^{TP+}, δ_2 in sixteen stocks and the coefficient of V_t^{TP-}, δ_3 in thirteen stocks are positive and statistically significant at the 5 per cent level. According to the Wald test, δ_2 in sixteen stocks is greater than δ_3 at the 5 per cent level. These results suggest that when volatility in the stock returns is positively associated with trading volume, the effect of an interaction between upward price movement (good news) and trading volume is more likely to be greater on conditional volatility than an interaction between downward price movement (bad news) and trading volume.

5.2.2 Performance under the EGARCH specification

Now we investigate the performance of TPI-V variables in an asymmetric GARCH model. The interest is in the performance of TPI-V variables after controlling for asymmetric

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[14] Gallo and Pacini (2000) argue that innovation at the opening of the markets is bound to have an important impact on the market during the day. During market's closure, information accumulates and that will have an impact at the opening of the markets. Therefore, ONI is thought to be a good candidate as a proxy for information arrival. Alsubaie and Najand (2009) use lagged ONI and IDV divided by the closing price. Gallo and Pacini (2000) suggest the use of lagged IDV as a substitute for the lagged volume. They argue that lagged IDV captures the volatility due to the trade that occurs in the previous day and possible spillover effects onto the next day.

Table 3. GARCH(1,1) parameters estimated with trading period indicator-volume variables
Variance equation of the estimated model: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_2 V_t^{TP+} + \delta_3 V_t^{TP-}$

Stock No.	α_1	β_1	$\alpha_1+\beta_1$	δ_2	δ_3	$H_1: \delta_2>\delta_3$
1	0.0741*	-0.0104	0.0636	$7.52 \times 10^{-5*}$	$1.02 \times 10^{-5*}$	Y
2	0.0650*	0.9299*	0.9949	1.51×10^{-6}	$2.52 \times 10^{-6*}$	N
3	0.0727*	0.9080*	0.9807	1.52×10^{-6}	1.67×10^{-6}	N
4	0.0830*	-0.0708*	0.0122	$3.25 \times 10^{-3*}$	$7.88 \times 10^{-4*}$	Y
5	0.0578*	-0.0174*	0.0404	$2.05 \times 10^{-2*}$	$3.28 \times 10^{-3*}$	Y
6	0.0303*	0.9666*	0.9969	-1.77×10^{-5}	-8.06×10^{-8}	N
7	0.2971*	0.4326*	0.7297	$2.60 \times 10^{-4*}$	$1.20 \times 10^{-4*}$	Y
8	0.3819*	-0.0022	0.3892	$4.26 \times 10^{-4*}$	$1.90 \times 10^{-4*}$	Y
9	0.0592*	0.9261*	0.9854	$1.81 \times 10^{-4*}$	2.23×10^{-5}	Y
10	0.2014*	0.1396*	0.3410	$2.09 \times 10^{-3*}$	$4.31 \times 10^{-4*}$	Y
11	0.0998*	-0.0056	0.0942	$3.35 \times 10^{-3*}$	$4.14 \times 10^{-4*}$	Y
12	0.3566*	0.3084*	0.6650	$7.64 \times 10^{-3*}$	$4.97 \times 10^{-3*}$	Y
13	0.1150*	0.8288*	0.9438	$6.71 \times 10^{-4*}$	9.42×10^{-5}	Y
14	0.0453*	0.9404*	0.9857	$-7.50 \times 10^{-5*}$	3.55×10^{-5}	N
15	0.0759*	-0.0688*	0.0071	$1.53 \times 10^{-3*}$	$1.36 \times 10^{-4*}$	Y
16	0.2053*	-0.0712*	0.1341	$2.42 \times 10^{-3*}$	$4.64 \times 10^{-4*}$	Y
17	0.2589*	0.1749*	0.4338	$2.01 \times 10^{-3*}$	-2.34×10^{-5}	Y
18	0.1394*	-0.0476*	0.0918	$4.83 \times 10^{-3*}$	$1.03 \times 10^{-3*}$	Y
19	0.1953*	0.0260*	0.2213	$6.14 \times 10^{-2*}$	$4.62 \times 10^{-3*}$	Y
20	0.0745*	0.9216*	0.9961	$3.01 \times 10^{-5*}$	$-1.34 \times 10^{-6*}$	Y

Notes: Trading period indicator-volume variables are defined as $V_t^{TP+} = TPI_{1t} V_t$ and $V_t^{TP-} = TPI_{2t} V_t$ where V_t is the trading volume in day t, $TPI_{1t} = \begin{cases} 1 \text{ if } P_t^{open} < P_t^{close} \\ 0 \quad \text{otherwise} \end{cases}$, $TPI_{2t} = \begin{cases} 1 \text{ if } P_t^{open} \geq P_t^{close} \\ 0 \quad \text{otherwise} \end{cases}$, P_t^{open} is the opening price on day t and P_t^{close} is the closing price on day t. Columns 5 and 10 report Wald test results of H_0: $\delta_2=\delta_3$ against H_1: $\delta_2>\delta_3$ with Y indicating rejection of the null hypothesis in favour of the alternative at the 5% level. * indicates significance at the 5% level.

information in the previous trading period. The asymmetric GARCH model used here is the EGARCH model. First, we discuss the performance of contemporaneous trading volume as an explanatory variable of conditional volatility estimated under the EGARCH(1,1) specification. Table 4 reports the parameters estimated in the EGARCH(1,1) model and in the EGARCH(1,1) model with contemporaneous trading volume.

The results reveal that in sixteen out of the twenty stocks, introduction of contemporaneous trading volume in the EGARCH(1,1) model does not affect a substantial reduction in persistence. In the GARCH(1,1) model, the corresponding number is four. In thirteen stocks, the persistence parameter, $\beta_1$is above 0.95. Further, in ten stocks, the asymmetry parameter γ is not statistically significant at the 5 per cent level suggesting that in these stocks the type of news (good and bad) in the previous trading period may not have an effect on the volatility in the current period. Twelve stocks reveal that the association between contemporaneous trading volume and conditional volatility is positive and significant at the 5 per cent level.

Table 4. EGARCH(1,1) parameters estimated without and with contemporaneous trading volume

Variance equations of the estimated models:

(M3): $log(\sigma_t^2) = \omega + \beta_1 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ and|

(M4): $log(\sigma_t^2) = \omega + \beta_1 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta V_t$

Stock	(M3)			(M4)			
No.	β_1	α_2	γ	β_1	α_2	γ	δ
1	0.993*	0.082*	-0.023*	0.9913*	0.0886	-0.0218*	5.99×10^{-8}
2	0.995*	0.132*	-0.009	0.9951*	0.1331	-0.0086	2.33×10^{-7}
3	0.984*	0.139*	-0.017*	0.9829*	0.1437*	-0.016	$9.19 \times 10^{-7*}$
4	0.982*	0.107*	-0.007	0.1668*	0.3093	-0.0021	$3.31 \times 10^{-4*}$
5	0.999*	0.032*	-0.023*	-0.0524	0.1803*	-0.0045	$1.60 \times 10^{-3*}$
6	0.994*	0.067*	-0.019*	0.9940*	0.0687*	-0.0191*	-3.15×10^{-6}
7	0.960*	0.231*	-0.004	0.9511*	0.2511*	-0.0027	2.32×10^{-6}
8	0.832*	0.516*	-0.174*	0.2059*	0.5751*	-0.1660*	$9.77 \times 10^{-5*}$
9	0.993*	0.097*	0.006	0.9830*	0.1342	0.0069	$2.95 \times 10^{-5*}$
10	0.981*	0.149*	-0.010	0.9598*	0.1766	-0.0177*	$1.53 \times 10^{-5*}$
11	0.981*	0.120*	-0.005	0.9688*	0.150	-0.003	$8.22 \times 10^{-6*}$
12	0.936*	0.414*	-0.035*	0.7333*	0.5376	0.0447*	$9.75 \times 10^{-4*}$
13	0.994*	0.080*	-0.002	0.9822*	0.1257	-0.0037	$1.48 \times 10^{-5*}$
14	0.975*	0.128*	-0.023*	0.9809*	0.1110*	-0.0238*	-7.85×10^{-6}
15	0.996*	0.091*	-0.018*	0.9956*	0.0906	-0.0168*	-3.61×10^{-7}
16	0.996*	0.063*	-0.019*	-0.0581	0.4034	0.0182	$1.51 \times 10^{-4*}$
17	0.984*	0.153*	-0.047*	0.9847*	0.1239*	-0.0361*	-6.42×10^{-6}
18	0.972*	0.154*	0.004	0.0512	0.2888	-0.0745*	$2.18 \times 10^{-4*}$
19	0.999*	0.050*	-0.011*	0.0985*	0.3785	-0.0211	$2.18 \times 10^{-3*}$
20	0.991*	0.144*	-0.127*	0.9907*	0.1446*	-0.0279*	-2.04×10^{-7}

Notes: V_t is trading volume in day t. * indicates significance at the 5 % level.

Table 5 reports the parameters estimated the EGARCH(1,1) model augmented with TPI-V variables. In four of the sixteen, in which contemporaneous trading volume is positive and statistically significant under the GARCH(1,1) specification, the results under the EGARCH specification reveal that contemporaneous trading volume is not statistically significant. However, δ_2 and δ_3 are positive and statistically significant at the 5 per cent level in sixteen and eleven stocks respectively. Both coefficients δ_2 and δ_3 are positive and statistically significant in twelve stocks and in eleven of them the effect of V_t^{TP+} is greater on conditional volatility than that of V_t^{TP-}. In other words, the asymmetric GARCH model process does not eliminate the explanatory power of TPI-V variables in a majority of the stocks. Overall, seventy-five per cent of the stocks reveal that the effect of TPI-V variables on conditional volatility is asymmetric even after controlling for asymmetric information from the previous period.

5.3 Non-Trading Period Indicator-Volume Variables

5.3.1 Performance under the GARCH specification

The parameters estimated in the GARCH(1,1) model with NTPI-V variables are given in Table 6. The results reveal that NTPI-V variables generally do not reduce volatility

Table 5. EGARCH(1,1) parameters estimated with trading period indicator-volume variables

Variance equation of the estimated model is

$$log(\sigma_t^2) = \omega + \beta_2 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-}$$

Stock No.	α_2	γ	b_2	δ_5	δ_6	H_1: $\delta_5 > \delta_6$
1	0.3837*	-0.0453	0.4646*	$1.48 \times 10^{-5*}$	$4.26 \times 10^{-6*}$	Y
2	0.1331*	-0.008	0.9951*	2.18×10^{-8}	4.53×10^{-7}	N
3	0.1467*	-0.0248*	0.9832*	$1.67 \times 10^{-6*}$	8.74×10^{-8}	N
4	0.3000*	-0.0301	0.0965*	$4.58 \times 10^{-4*}$	$2.32 \times 10^{-4*}$	Y
5	0.1750*	0.0134	-0.078^{3*}	$2.44 \times 10^{-3*}$	$1.12 \times 10^{-3*}$	Y
6	0.0709*	-0.0289*	0.9950*	$1.85 \times 10^{-5*}$	$-3.01 \times 10^{-5*}$	Y
7	0.2483*	0.0010	0.9522*	-1.15×10^{-7}	4.25×10^{-6}	N
8	0.5532*	-0.1507*	0.1740*	$1.15 \times 10^{-4*}$	$9.02 \times 10^{-5*}$	Y
9	0.1380*	-0.0013	0.9813*	$6.05 \times 10^{-5*}$	$5.96 \times 10^{-6*}$	N
10	0.1733*	-0.0296*	0.9601*	$2.53 \times 10^{-5*}$	$3.95 \times 10^{-6*}$	Y
11	0.1548*	-0.0068	0.9667*	$1.12 \times 10^{-5*}$	5.86×10^{-6}	Y
12	0.5333*	0.0279	0.7618*	$1.02 \times 10^{-3*}$	$6.99 \times 10^{-4*}$	Y
13	0.1484*	-0.0157*	0.9746*	$6.17 \times 10^{-5*}$	-1.46×10^{-5}	Y
14	0.3848*	-0.0825*	0.6817*	$2.49 \times 10^{-4*}$	$1.19 \times 10^{-4*}$	Y
15	0.3002*	-0.0467*	-0.1200*	$1.57 \times 10^{-4*}$	$4.96 \times 10^{-5*}$	Y
16	0.4168*	0.0217	-0.0547	$2.22 \times 10^{-4*}$	$7.21 \times 10^{-5*}$	Y
17	0.1262*	-0.0436*	0.9894*	$1.15 \times 10^{-5*}$	-1.14×10^{-5}	Y
18	0.3092*	-0.0794*	0.1417*	$2.71 \times 10^{-4*}$	$1.36 \times 10^{-4*}$	Y
19	0.4873*	-0.0526*	0.2951*	$2.61 \times 10^{-3*}$	-9.50×10^{-6}	Y
20	0.1505*	-0.0309*	0.9896*	2.96×10^{-6}	-3.86×10^{-7}	N

Notes: $V_t^{TP+} = TPI_{1t} V_t$ and $V_t^{TP-} = TPI_{2t} V_t$ where V_t is the trading volume in day t is, TPI_{1t}

$$TPI_{1t} = \begin{cases} 1 \text{ if } P_t^{open} < P_t^{close} \\ 0 \quad \text{otherwise} \end{cases}, TPI_{2t} = \begin{cases} 1 \text{ if } P_t^{open} \geq P_t^{close} \\ 0 \quad \text{otherwise} \end{cases}, P_t^{open}$$

is the opening price on day t and P_t^{close} is the closing price on day t. Columns 5 and 10 report Wald test results of H_0: $\delta_5=\delta_6$ against H_1: $\delta_5>\delta_6$ with Y indicating rejection of the null hypothesis in favour of the alternative at the 5 % level. * indicates significance at the 5 % level.

persistence compared to GARCH(1,1) model with contemporaneous trading volume. In this case in twelve out of the twenty stocks $\alpha_1+\beta_1$ is higher than that under the GARCH(1,1) with trading volume.

Comparison of the results in Tables 3 and 6 reveal that in fifteen stocks TPI-V variables (V_t^{T+} and V_t^{T-}) induce greater reduction in persistence in volatility than NTPI-V variables (V_t^{N+} and V_t^{N-}) suggesting that TPI-V variables may explain conditional volatility better than NTPI-V variables. Table 6 entries reveal further that in twelve stocks the coefficients of V_t^{NTP+} and V_t^{NTP-} and (δ_7 and δ_8) are not different from each other at the 5 per cent level of test. In five of the other eight stocks, δ_7 is less than δ_8 and in the other three stocks, δ_7 is greater than δ_8. The evidence here suggests, that in general, NTPI-V variables may not explain conditional volatility and in the stocks where NTPI-V variables do explain conditional volatility, there is weak evidence that the effect of non-trading period bad news induced trading volume is more likely to be greater on conditional volatility than with good news in the non-trading period.

Table 6. GARCH(1,1) parameters estimated with previous trading period indicator-volume variables

Variance equation of the estimated model is $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \delta_7 V_t^{NTP+} + \delta_8 V_t^{NTP-}$

Stock No.	α_1	β_1	$\alpha_1+\beta_1$	δ_7	δ_8	$H_1: \delta_7 \neq \delta_8$	$H_1: \delta_7 < \delta_8$
1	0.0550*	0.9281*	0.9831	1.21×10^{-7}	$7.52 \times 10^{-7*}$	N	N/R
2	0.0659*	0.9278*	0.9937	-1.32×10^{-6}	$6.27 \times 10^{-6*}$	Y	Y
3	0.0760*	0.9022*	0.9782	4.41×10^{-7}	$3.35 \times 10^{-6*}$	Y	Y
4	0.1305*	0.0346	0.1651	$1.17 \times 10^{-3*}$	$1.20 \times 10^{-3*}$	N	N/R
5	0.0944*	0.0053	0.0997	$5.66 \times 10^{-3*}$	$6.24 \times 10^{-3*}$	N	N/R
6	0.0306*	0.9665*	0.9971	-3.58×10^{-7}	-2.07×10^{-5}	N	N/R
7	0.2806*	0.4761*	0.7567	$1.72 \times 10^{-4*}$	$1.14 \times 10^{-4*}$	Y	N
8	0.4252*&	0.0319*	0.4571	$2.42 \times 10^{-4*}$	$2.41 \times 10^{-4*}$	N	N/R
9	0.0514*	0.9378*	0.9892	-4.69×10^{-5}	$1.75 \times 10^{-4*}$	Y	Y
10	0.1530*	0.6819*	0.8349	$1.70 \times 10^{-4*}$	$3.54 \times 10^{-4*}$	Y	Y
11	0.1698*	0.1150*	0.2848	$9.44 \times 10^{-4*}$	$9.51 \times 10^{-4*}$	N	N/R
12	0.3284*	0.4532*	0.7816	$5.08 \times 10^{-3*}$	$4.28 \times 10^{-3*}$	N	N/R
13	0.0922*	0.8659*	0.9582	$3.49 \times 10^{-4*}$	$2.21 \times 10^{-4*}$	N	N/R
14	0.0599*	0.9190*	0.9789	-3.18×10^{-5}	4.39×10^{-5}	N	N/R
15	0.0293*	0.9681*	0.9974	$-4.3 \times 10^{-6*}$	7.88×10^{-7}	N	N/R
16	0.2362*	0.0800*	0.3162	7.41 x10-4*	$8.65 \times 10^{-4*}$	N	N/R
17	0.2008*	0.0191	0.2199	$1.48 \times 10^{-3*}$	$-3.3 \times 10^{-5*}$	Y	N
18	0.1074*	0.5379*	0.6454	-2.65×10^{-4}	-3.41×10^{-5}	N	N/R
19	0.2707*	0.2412*	0.5119	$1.27 \times 10^{-2*}$	$2.19 \times 10^{-2*}$	Y	Y
20	0.1419*	0.5444*	0.6863	$-3.3 \times 10^{-4*}$	$-3.0 \times 10^{-5*}$	Y	N

Notes: $V_t^{NTP+} = PPI_{1t-1}V_t$ and $V_t^{PP-} = TPI_{2t-1}V_t$ where V_t is the trading volume in day *t*, $NPI_{1t-1} = \begin{cases} 1 \text{ if } P_{t-1}^{close} < P_t^{open} \\ 0 \quad \text{otherwise} \end{cases}$, $PPI_{2t-1} = \begin{cases} 1 \text{ if } P_{t-1}^{close} \geq P_{t-1}^{open} \\ 0 \quad \text{otherwise} \end{cases}$, P_t^{open} is the opening price on day t and P_{t-1}^{close} is the closing price on day *t*-1. Columns 5 and 10 report Wald test results of H_0: $\delta_7 = \delta_8$ against H_1: $\delta_7 \neq \delta_8$ with Y indicating rejection of the null hypothesis in favour of the alternative at the 5 per cent level. * indicates significance at the 5 % level. N/R indicates that the hypothesis test of H_0: $\delta_7 = \delta_8$ against H_1: $\delta_7 < \delta_8$ is not relevant.

5.3.2 Performance under the EGARCH specification

Under the EGARCH specification, the coefficient of NTP-IV variables δ_9 and δ_{10} is not different from each other in half the stocks. In the ten stocks where δ_9 and δ_{10} are significantly different from each other, we find that δ_9 is less than δ_{10} at the 5 per cent level of test.[15] In other words when non-trading period news induced trading volume does affect conditional volatility, the evidence that V_t^{NTP-} may have a greater effect on conditional volatility than V_t^{NTP+} is strong. It appears that trading volume together with news in the non-trading period may affect conditional volatility differently from trading volume with news from the trading period. Specifically, conditional volatility is more likely to be affected by trading volume with bad news in the non-trading period than good news

[15] In two of these ten stocks, the coefficient of V_t^{NTP-} is not different from zero at the 5 per cent level. In eight stocks the coefficient of V_t^{NTP+} is negative and in two of them the coefficient is not different from zero.

in the non-trading period and by trading volume with good news in the trading period than with bad news in the trading period.

The findings here shed light on the link between trading volume and price changes in a conditional volatility framework. Previous studies reveal that there is no strong evidence of contemporaneous association between stock returns and trading volume. For example, Mester *et al.* (2003) reveal weak evidence and De Medeiros and Van Doornik (2006) find no evidence to support a contemporaneous association between stock returns and trading volume. We uncover that the type of stock return in the trading period and in the non-trading period together with trading volume may affect conditional volatility differently. Rogalski (1978) on the other hand found evidence that stock prices and trading volume are dependent according to the Granger criteria - sample cross-correlations are non-zero at lag zero (Granger, 1969). Granger criteria imply three possibilities: volume causes price change, price change causes volume and there is feedback between volume and price change. Therefore, it is not possible for Rogalski (1978) to distinguish between contemporaneous feedback and unidirectional causality. We provide a method to accommodate the overall direction of price changes together with trading volume and determine its effect on conditional volatility.

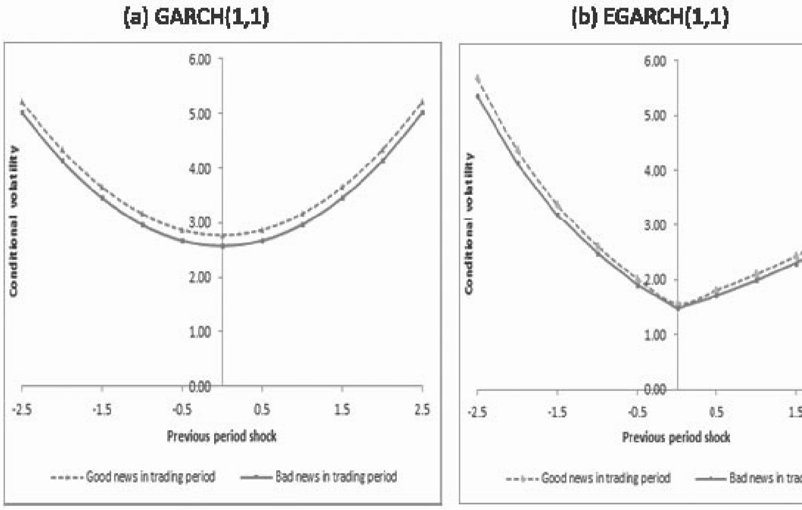
5.4 News Impact Curves

Here we illustrate the asymmetric effect of good and bad news induced trading volume on conditional volatility estimated in the GARCH(1,1) model and in the EGARCH model through a plot of the news impact curves. The news impact curves for the GARCH and EGARCH processes with trading period news induced trading volume are derived in the Appendix. Under the GARCH(1,1) specification, there are two symmetric curves corresponding to good news and bad news in the trading period. Their equations are given by (a2) and (a3). Under the EGARCH specification, (a7) and (a11) give the news impact curve corresponding to good news in the trading period and (a8) and (a12) give the news impact curve corresponding to bad news in the trading period. In (a2), (a7) and (a11), we use average $\{V_t^{TP+}\}$ for $\{V_t^{TP+}\}$ and in (a3), (a8) and (a12), we use average $\{V_t^{TP-}\}$ for $\{V_t^{TP-}\}$.[16] In all news impact curves σ_{t-1}^2 is substituted with the unconditional variance of daily returns.

Panel (a) of Figure 1 gives the plots of conditional volatility σ_t^2 against impact ε_{t-1} under the GARCH(1,1) specification and Panel (b) of Figure 1 gives the same under the EGARCH specification for stock 8.[17] Panel (a) highlights (i) the expected symmetric impact of previous period news and (ii) that the current period good news induced trading volume has a greater impact than bad news induced trading volume on GARCH(1,1) conditional volatility. Panel (b) illustrates (i) the asymmetric effect of previous period news captured in the EGARCH(1,1) model and shows that bad news in the previous period may have a greater impact on conditional volatility than good news in that period. The asymmetric

[16] Average $\{V_t^{TP+}\}$ is the average trading volume on the days where the overall price movement over the trading day is positive. Average $\{V_t^{TP-}\}$ is the average trading volume on the days where the overall price movement over the trading day is non-positive.

[17] The skewness and kurtosis of stock 8 is the highest among the sampled stocks.



Notes: Good (bad) news is associated with an overall upward (downward) price movement. The equation of the news impact curve for the GARCH(1,1) model with good news induced trading volume is given by $\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \delta_2 V_t^{TP+}$ and with bad news induced trading volume is given by $\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \delta_3 V_t^{TP-}$. The equations of the news impact curves under the EGARCH(1,1) specification with positive innovation and under good news in the trading period is given by $\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+}) exp\left[\left(\frac{\alpha_2+\gamma}{\sigma_{t-1}}\right)\varepsilon_{t-1}\right]$ and under bad news in the trading period the equation is given $\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2+\gamma}{\sigma_{t-1}}\right)\varepsilon_{t-1}\right]$. The corresponding equations under the EGARCH(1,1) specification with negative innovation are given by

$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+}) exp\left[\left(\frac{\alpha_2-\gamma}{\sigma_{t-1}}\right)|\varepsilon_{t-1}|\right]$

and $\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2-\gamma}{\sigma_{t-1}}\right)|\varepsilon_{t-1}|\right]$.

Figure 1. *News impact curves for stock 8 under the GARCH(1,1) and the EGARCH(1,1) specification with trading period price movement induced trading volume*

effect of good and bad news-induced contemporaneous trading volume is also evident in Panel (b) where the current period good news induced trading volume has a greater impact on conditional volatility than bad news induced trading volume.

6. Robustness Check

When we model previous period price movement information with trading volume, we find that previous period upward and downward price movement has no asymmetric effect on conditional volatility of stock returns. Financial return series are generally considered to be heavy-tailed and skewed and therefore the assumption of normality in the returns in asset pricing models is a concern. When we follow Arago and Nieto (2005) and use General Error Distribution as an alternative, the results are consistent with that observed under the normal distribution error specification. Another concern is treatment of trading volume as an exogenous variable (Karpoff 1987). Harvey (1989) points out that lagged values of the endogenous variable may be used because they may be classified as pre-determined. When we repeat the analysis with lagged indicator-volume variables in

Table 7. EGARCH(1,1) parameters estimated with previous trading period indicator-volume variables

Variance equation of the estimated model is

$$log(\sigma_t^2) = \omega + \beta_1 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_9 V_t^{NTP+} + \delta_{10} V_t^{NTP-}$$

Stock No.	α_2	γ	β_1	δ_9	δ_{10}	H_1: $\delta_9 \neq \delta_{10}$	H_1: $\delta_9 < \delta_{10}$
1	0.0697*	-0.0231*	0.9942*	-3.7 x10-7*	4.21 x10-7*	Y	Y
2	0.1305*	-0.0079	0.9942*	-2.1 x10-6*	5.18 x10-6*	Y	Y
3	0.1449*	-0.0113	0.9820*	-4.02 x10-7	2.67 x10-6*	Y	Y
4	0.3094*	-0.0025	0.1647*	3.29 x10-4*	3.39 x10-4*	N	N/R
5	0.1788*	-0.0048	-0.0598	1.62 x10-3*	1.57 x10-3*	N	N/R
6	0.0671*	-0.0200*	0.9948*	-1.4 x10-5*	9.26 x10-6	Y	Y
7	0.2338*	-0.0008	0.9590*	-8.49 x10-7	4.40 x10-6	N	N/R
8	0.5763*	-0.1677*	0.2063*	9.92 x10-5*	9.62 x10-5*	N	N/R
9	0.1100*	-0.0036	0.9893*	-2.47 x10-5	5.73 x10-5*	Y	Y
10	0.1244*	-0.0236*	0.9754*	-5.41 x10-6	3.24 x10-5*	Y	Y
11	0.1385*	-0.0028	0.9729*	3.43 x10-6	1.04 x10-5*	N	N/R
12	0.5030*	0.0244	0.8042*	6.96 x10-4*	7.41 x10-4*	N	N/R
13	0.1389*	-0.0032	0.9768*	4.42 x10-5*	8.79 x10-6	N	N/R
14	0.1162*	-0.0259*	0.9801*	-2.4 x10-5*	1.65 x10-5	Y	Y
15	0.0924*	-0.0148*	0.9941*	-3.5 x10-6*	1.70 x10-6*	Y	Y
16	0.4227*	0.0069	0.2152*	1.22 x10-4*	1.39 x10-4*	N	N/R
17	0.1234*	-0.0361*	0.9847*	-6.8 x10-6*	-6.3 x10-6*	N	N/R
18	0.2319*	-0.0067	0.8762*	1.33 x10-5*	4.49 x10-5*	Y	Y
19	0.4323*	-0.0112	0.3914*	1.28 x10-3*	2.23 x10-3*	Y	Y
20	0.1400*	-0.0276*	0.9915*	-2.80 x10-6	-8.84 x10-8	N	N/R

Notes: $V_t^{NTP+} = PPI_{1t-1} V_t$ and $V_t^{PP-} = TPI_{2t-1} V_t$ where V_t is the trading volume in day t, $NPI_{1t-1} = \begin{cases} 1 \text{ if } P_{t-1}^{close} < P_t^{open} \\ 0 \quad \text{otherwise} \end{cases}$, $PPI_{2t-1} = \begin{cases} 1 \text{ if } P_{t-1}^{close} \geq P_{t-1}^{open} \\ 0 \quad \text{otherwise} \end{cases}$, P_t^{open} is the opening price on day t and P_(t-1)^close is the closing price on day t-1. Columns 5 and 10 report Wald test results of H_1: δ_9=δ_10against H_1:$\delta_9 \neq \delta_{10}$with Y indicating rejection of the null hypothesis in favour of the alternative at the 5 per cent level. * indicates significance at the 5 per cent level. N/R indicates that the hypothesis test of H_0: $\delta_9 = \delta_{10}$ against H_1:$\delta_9 < \delta_{10}$ is not relevant.

the GARCH(1,1) model they are not statistically significant in the majority of stocks. When we repeat the investigation in two sub-sample periods, January 2000 to June 2005 and July 2005 to April 2011, the results in both sub-sample periods are consistent with our findings with data in the full sample period. When we account for a financial crisis period by introducing a dummy variable, our conclusions remain largely unchanged.

7. Concluding Remarks

This study investigates the effect of price movement (an information variable) induced trading volume (a proxy for the rate of information arrival) on GARCH-type conditional volatility in twenty actively traded Australian stocks. The proposed new proxies for information arrival tend to reduce persistence in volatility in the returns more than contemporaneous and lagged trading volume. When the overall price movement over the trading period is modelled through contemporaneous trading volume, there is evidence to suggest that an upward price movement is likely to affect conditional volatility more than a downward price movement. The asymmetric effect due to price movement over the overnight non-trading period is opposite to what is uncovered with price movement over the trading period. However, the evidence of asymmetry is not strong in the case with trading period price movement. During the trading period, there is greater incorporation of private information into prices than public information (Chordia *et al.* 2011). Therefore, good news in the trading period is likely to affect volatility more than bad news. Open price, on the other hand is more likely to be influenced by uninformed noise traders and therefore is subject to mispricing. This may be the reason for the observed difference in the sensitivity of volume-volatility relation to the direction of price movement. Overall, in a sample of Australian stocks we find that the direction of price movement has an asymmetric effect on trading volume-volatility relationship. This information becomes useful when forecasting variation in the returns.

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Appendix

A1. News impact curves for the GARCH(1,1) model with TPI-V variables

The GARCH(1,1) model augmented with trading period indicator-volume variables is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_2 V_t^{TP+} + \delta_3 V_t^{TP-} \quad \text{(a1)}$$

When the open price in day *t* is lower than the close price in day *t*, (a1) reduces to

$$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \delta_2 V_t^{TP+} \quad \text{(a2)}$$

and when the open price in day *t* is greater than or equal to the close price in day *t*, (a1) reduces to

$$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \delta_3 V_t^{TP-} \quad \text{(a3)}$$

(a2) and (a3) give the news impact curves when $V_t^{TP-} = 0$ and $V_t^{TP+} = 0$ respectively.

A2. News impact curves for the EGARCH(1,1) model with TPI-V variables

The EGARCH(1,1) model augmented with trading period indicator-volume variables is given by

$$log(\sigma_t^2) = \omega + \beta_2 log(\sigma_{t-1}^2) + \alpha_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-} \quad \text{(a4)}$$

Suppose $\varepsilon_{t-1} > 0$, then

$$log\left(\frac{\sigma_t^2}{\sigma_{t-1}^{2\beta_2}}\right) = \omega + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-} + \left(\frac{\alpha_2 + \gamma}{\sigma_{t-1}}\right) \varepsilon_{t-1} \quad \text{(a5)}$$

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2 + \gamma}{\sigma_{t-1}}\right) \varepsilon_{t-1}\right] \quad \text{(a6)}$$

When the open price in day *t* is lower than the close price in day *t*, (a6) reduces to

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+}) exp\left[\left(\frac{\alpha_2 + \gamma}{\sigma_{t-1}}\right) \varepsilon_{t-1}\right] \quad \text{(a7)}$$

and when the open price in day *t* is greater than or equal to the close price in day *t*, (a6) reduces to

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2 + \gamma}{\sigma_{t-1}}\right) \varepsilon_{t-1}\right] \quad \text{(a8)}$$

(a7) and (a8) are the components of news impact curves under positive innovation when $V_t^{TP-} = 0$ and $V_t^{TP+} = 0$ respectively.

Suppose $\varepsilon_{t-1} < 0$, then

$$log\left(\frac{\sigma_t^2}{\sigma_{t-1}^{2\beta_2}}\right) = \omega + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-} + \left(\frac{\alpha_2 - \gamma}{\sigma_{t-1}}\right) |\varepsilon_{t-1}| \quad \text{(a9)}$$

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+} + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2 - \gamma}{\sigma_{t-1}}\right) |\varepsilon_{t-1}|\right] \quad \text{(a10)}$$

When the open price in day *t* is lower than the close price in day *t*, (a10) reduces to

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_5 V_t^{TP+}) exp\left[\left(\frac{\alpha_2 - \gamma}{\sigma_{t-1}}\right)|\varepsilon_{t-1}|\right] \qquad (a11)$$

and when the open price in day *t* is greater than or equal to the close price in day *t*, (a10) reduces to

$$\sigma_t^2 = \sigma_{t-1}^{2\beta_2} exp(\omega + \delta_6 V_t^{TP-}) exp\left[\left(\frac{\alpha_2 - \gamma}{\sigma_{t-1}}\right)|\varepsilon_{t-1}\ \right] \qquad (a12)$$

(a11) and (a12) are the components of news impact curves under negative innovation when and respectively.