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The effects of trading activity on market volatility

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The paper re-examines the question of excessive implied persistence of volatility estimates when GARCH-type models are used. Ten actively traded US stocks are considered and as already established in the literature, when volume traded is inserted in the GARCH(1,1) or EGARCH(1,1) models for returns, the estimated persistence is decreased. Since volume is affected also by within-the-day price movements and hence is not weakly exogenous relative to returns, alternative proxies for trading activities are suggested. It is concluded that the difference between the opening price and the closing price of the previous day accounts also for most of the persistence in the autoregressive conditional heteroskedasticity.

Keywords: GARCH, persistence, market efficiency

1. INTRODUCTION

A well-established result in the literature is that the degree of serial linear correlation in returns on securities is very weak and can at best be approximated by a low order linear autoregressive process. On the other hand, returns exhibit non-normality and volatility clustering which tend to disappear as the frequency of observation of the data decreases. The question remains open as to whether the analysis should focus on modelling nonlinearities in the mean (as suggested by, for example, the neural network literature, Trippi and Turban, 1993, or the literature on chaos, Brock *et al.*, 1991), or, rather, characterize the behaviour of second moments of returns, giving account of the dynamics of volatility clustering.

In the latter stream of research, GARCH-type processes are very popular (Bollerslev *et al.,* 1994) since they capture various aspects of the volatility behaviour, including possible asymmetries according to whether the innovations are positive or negative. On the downsides of these models, the implied persistence of their estimates is too high to be reconciled with the observed behaviour of squared returns. From a more theoretical point of view, these are

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merely statistical models which do not provide any clear-cut explanation of what market behaviour determines volatility clustering.

Efforts have been made to insert some modifications in the basic GARCH scheme that would allow for a reduction of the degree of persistence implied by the estimates. For example, by positing the existence of high/low volatility regimes and that the passage from one phase to another is abrupt and is ruled by a first-order Markov process, the Markov Switching ARCH model of Hamilton and Susmel (1994) manages to reduce the volatility persistence. Although this approach is appealing, it concentrates on the effects of large innovations but still lacks a deeper explanation of why such innovations are so important as to give rise to the switch between regimes.

Clark (1973) and Tauchen and Pitts (1983) suggested a model whereby conditional heteroskedasticity (although serially uncorrelated) is generated by the sum of a random number of homoskedastic within-the-day innovations. Lamoureux and Lastrapes (1990a) resume the flavour of the model and derive volatility clustering by assuming that the number of price movements is autocorrelated. On the practical side, this number is unobservable and must be proxied. Lamoureux and Lastrapes adopt a variable, measuring the total volume of stocks traded during the same day. As the authors admit, the reduction in persistence within a GARCH(1,1) obtained by them is based on the crucial assumption that the volume variable can be considered as weakly exogenous relative to the returns and hence can act as a mixing variable for the total movements of stock prices. In a later paper (1994) the same authors consider endogenizing the volume in a state-space representation where the mean and variance of the two measurement equations (for returns and volume) depend on a latent factor related to the flow of information reaching the market during the day.

As noted by several authors, the economic basis for such an investigation is fairly scant, although the statistical appeal is quite interesting. In this paper we will not attempt to provide such a basis, but will maintain the same reference model for generating conditional heteroskedasticity, investigating the information content of other proxies for the mixing variable, and checking their impact on the persistence of GARCH effects. Our results show that there exist alternatives which reduce measured persistence and are more interpretable than contemporary volume on the way news propagates through the market.

The paper is organized as follows: in Section 2 we present the standard GARCH and EGARCH models and point out how the results on ten actively traded US stocks show high persistence in the estimated volatility. In Section 3 we introduce concepts related to market activity and its impact on volatility, by recalling (and reproducing) the results of Lamoureaux and Lastrapes (1990a), and by suggesting alternative proxies which have more of an *ex-ante* motivation. We suggest an overnight indicator (ONI) which represents the surprise intervening between the closing of one day and the opening of the following day and is capable of a substantial reduction in the estimated persistence. Concluding remarks follow.

2. PERSISTENCE AND ASYMMETRY IN VOLATILITY

The model we are working with is a univariate model for daily returns r_t in which the dynamics for the mean is limited to a linear autoregression typically of a low order[1]

$$r_t = \mu + \Phi(L)r_{t-1} + \varepsilon_t, \qquad t = p+1, \ldots, T$$

where $\Phi(L)$ is a polynomial in the lag operator L, i.e. $\Phi(L) = \phi_1 + \phi_2 L + \ldots + \phi_p L^{p-1}$. The error term ε_t describes the unpredictable component of the returns. A common assumption about its behaviour is that it follows a GARCH-type process, namely that

$$\varepsilon_t | I_{t-1} \sim \mathcal{N}(0, \sigma_t^2)$$

where I_{t-1} is the information available at time $t-1$ and σ_t^2 follows a process

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

in the GARCH(1,1) representation (Bollerslev, 1986), and

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{2/\pi}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

in the Nelson (1991) exponential GARCH (EGARCH(1,1)) representation.

One of the characteristics of both models is that they capture the stylized facts of volatility clustering, while the EGARCH specification is more flexible and is suitable to capture asymmetric or leverage effects (Engle and Ng, 1993) in the behaviour of the conditional variance relative to positive or negative innovations, when $\gamma_2 \neq 0$.[2]

An important feature of the estimated models is the degree of implied persistence of the conditional volatility: for the GARCH(1,1) model it is measured as $\alpha_1 + \beta_1$, while for the EGARCH(1,1) model it is represented by β. As already mentioned, one of the downsides of these models is that the estimated persistence in practice is too high to reproduce the observed behaviour of the volatility (which seems to absorb innovations much more rapidly).

For the empirical illustration, we chose 10 stocks available to us among the ones listed by Lamoureux and Lastrapes (1990a) on a sample from 2 January 1985 to 1 December 1995.[3] In the Appendix we detail the symbols used in the tables.

[1] In other words, in what follows, we will not deny the importance of the research focusing on nonlinearities in the equation for the mean, but we will concentrate on the characterization of the behaviour of returns' conditional second moments by also assuming that the analysis of interest can be limited to a univariate framework where no other variables can be used in predicting mean returns.

[2] Alternative, equivalent, models for asymmetric effects are the ones proposed by Glosten *et al.* (1993) or Rabemananjara and Zakoïan (1993).

[3] We are not taking into account the issue of possible structural breaks in the process as being responsible for the estimated persistence (as in Lamoureaux and Lastrapes, 1990b). In view of the comparison between our results and those of Lamoureaux and Lastrapes (1990a – on shorter samples) this does not seem to be an issue.

Table 1. GARCH(1,1) estimation

Company	α_1	β_1	$\alpha_1 + \beta_1$
AAL	0.077*	0.857*	0.934
	(0.006)	(0.014)	
BMY	0.087*	0.888*	0.975
	(0.007)	(0.010)	
EC	0.103*	0.650*	0.753
	(0.012)	(0.044)	
HRS	0.239*	0.529*	0.768
	(0.012)	(0.030)	
LOR	0.092*	0.804*	0.896
	(0.008)	(0.021)	
MDT	0.092*	0.817*	0.909
	(0.010)	(0.021)	
NOC	0.040*	0.949*	0.989
	(0.003)	(0.004)	
PWJ	0.071*	0.880*	0.951
	(0.004)	(0.009)	
SBR	0.126*	0.846*	0.972
	(0.009)	(0.009)	
WGO	0.090*	0.880*	0.970
	(0.004)	(0.005)	

The results for the Maximum Likelihood estimation of our GARCH(1,1) model[4] (Table 1) show that there is a high level of persistence across all stocks, ranging from 0.753 to 0.989. Most estimated persistences are higher than 0.9.

The estimated EGARCH (Table 2) shows that besides a similar degree of persistence to the GARCH model, the asymmetry parameter is almost always significantly different from zero (the exception being HRS) and with the expected negative sign.

Having assessed a benchmark against which we can judge later results, the research question tackled in the next section is whether there are variables which can be found responsible for the persistence and/or the asymmetry in the class of models considered.

3. TRADING ACTIVITY AND VOLATILITY

Although a thorough explanation of what mechanisms determine autoregressive conditional heteroskedasticity is still lacking in the literature, various efforts have been put into finding correlations between the conditional variance and other variables in the information set. One model commonly used follows Clark (1973) and Tauchen and Pitts (1983), and assumes that ε_t can be thought of as a sum of identical and independently distributed within-the-day price variations, namely

[4] In most cases, this specification seems an appropriate one, judging by the customary residual diagnostics.

Table 2. EGARCH(1,1) estimation

Company	$\log(\alpha_{t-1}^2)$	$\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}}$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$
AAL	0.898*	0.199*	–0.030*
	(0.015)	(0.014)	(0.008)
BMY	0.968*	0.182*	–0.027*
	(0.005)	(0.015)	(0.009)
EC	0.777*	0.205*	–0.042*
	(0.027)	(0.018)	(0.011)
HRS	0.746*	0.428*	0.019
	(0.022)	(0.018)	(0.012)
LOR	0.946*	0.145*	–0.043*
	(0.009)	(0.012)	(0.007)
MDT	0.931*	0.173*	–0.038*
	(0.011)	(0.015)	(0.009)
NOC	0.982*	0.116*	–0.018*
	(0.003)	(0.011)	(0.006)
PWJ	0.924*	0.215*	–0.042*
	(0.010)	(0.013)	(0.008)
SBR	0.958*	0.224*	–0.026*
	(0.004)	(0.013)	(0.006)
WGO	0.909*	0.242*	–0.027*
	(0.007)	(0.010)	(0.006)

$$\varepsilon_t = \sum_{i=1}^{n_t^*} \delta_{it}$$

where n_t^* indicates the number of trades in day t, from close at $t-1$ to close at t, and δ_{it} are destributed with zero mean and constant variance σ^2. Therefore, ε_t is heteroskedastic since it has variance equal to $n_t^{*2}\sigma^2$. By assuming that n_t^* is autocorrelated (as in Lamoureux and Lastrapes, 1990a), autoregressive conditional heteroskedasticity arises.

3.1. Contemporaneous volume

Lamoureaux and Lastrapes (1990a) specify a GARCH-cum-volume model for the conditional variance in which contemporaneous volume is taken to be a proxy for the number of trades within the day n_t^*. The volume of stocks exchanged is a (positive valued) variable (expressed in our case as millions of shares traded) which is often used by technical analysts to assess the strength of a local trend reversal. Therefore it can represent an indicator of consensus (or lack thereof) about the direction the stock price is taking as a consequence of a new piece of information. The models estimated are therefore modified to be

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \beta_2 vol_t$$

for the GARCH(1,1) model; by analogy and to favour comparisons of asymmetry, we augment the EGARCH model to include also volume and to read

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \beta_2 \log(vol_t) + \alpha\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{2/\pi}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The results are shown, respectively, in Tables 3 and 4. As in Lamoureux and Lastrapes (1990a), for the GARCH model we gain a general substantial reduction in the estimated persistence with values lower than the counterparts in Table 1.

For the EGARCH model, the picture is quite similar, since the persistence is very low (close to zero) with a significant coefficient on the volume variable. The interesting result is that asymmetry disappears from most stocks.

3.2. Alternative proxies

The results obtained in this framework rest on the crucial assumption that the volume is weakly exogenous with respect to the returns, which is possibly a strong hypothesis in view of the fact that if the price movements within the day go mainly in one direction creating a local trend, they may attract further trades and therefore affect volume. In other words, some problems arise since contemporaneous volume has too much information in common with the

Table 3. GARCH(1,1) estimation with volume

Company	α_1	β_1	$\alpha_1 + \beta_1$	Vol
AAL	0.077*	0.010	0.087	0.002*
	(0.017)	(0.011)		(0.000)
BMY	0.127*	0.799*	0.926	0.0001*
	(0.013)	(0.019)		(0.0000)
EC	0.184*	0.078*	0.262	0.001*
	(0.021)	(0.020)		(0.000)
HRS	0.186*	0.050	0.236	0.001*
	(0.019)	(0.029)		(0.000)
LOR	0.156*	0.126*	0.282	0.0005*
	(0.017)	(0.035)		(0.0000)
MDT	0.089	–0.057*	0.032	0.0003*
	(0.019)	(0.017)		(0.0000)
NOC	0.117*	–0.031	0.086	0.002*
	(0.014)	(0.019)		(0.000)
PWJ	0.110	0.103	0.213	0.001*
	(0.017)	(0.005)		(0.000)
SBR	0.126*	0.088*	0.214	0.012*
	(0.022)	(0.030)		(0.000)
WGO	0.127*	–0.055*	0.072	0.009*
	(0.016)	(0.019)		(0.000)

Table 4. EGARCH(1,1) with volume

Company	$\log(\alpha_{t-1}^2)$	$\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}}$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	Vol
AAL	0.065	0.231*	–0.030	0.645*
	(0.034)	(0.034)	(0.022)	(0.020)
BMY		0.361*	0.040*	0.957*
		(0.033)	(0.017)	(0.041)
EC	0.057*	0.259*	–0.076*	0.720*
	(0.023)	(0.031)	(0.020)	(0.018)
HRS	0.077*	0.337*	–0.004	0.787*
	(0.030)	(0.031)	(0.019)	(0.026)
LOR	0.205*	0.299*	–0.030	0.643*
	(0.040)	(0.034)	(0.021)	(0.030)
MDT	0.070	0.232*	–0.049	0.896*
	(0.036)	(0.041)	(0.025)	(0.036)
NOC	0.031	0.271*	–0.020	0.748*
	(0.033)	(0.032)	(0.022)	(0.028)
PWJ		0.290*	–0.034	0.671*
		(0.031)	(0.021)	(0.019)
SBR	0.173*	0.290*	0.035	0.567*
	(0.029)	(0.036)	(0.025)	(0.020)
WGO	–0.240*	0.285*	–0.037*	0.536*
	(0.027)	(0.025)	(0.018)	(0.016)

returns and hence the squared returns it is related to. For this reason, without going into the model modification suggested by Lamoureux and Lastrapes (1994) for a joint modelling of returns and volume depending on a common latent factor, we could suggest as a proxy for the number of trades at time t the volume observed at time $t-1$. Since volume is autocorrelated, we can expect to get a similar result. Tables 5 and 6 show that this is not necessarily so, since the lagged volume is significant in just four out of the ten stocks (sometimes with the 'wrong' sign), although there is a reduction in volatility persistence, even if less pronounced. In the case of WGO a nonsignificant volume determines an unacceptable value for the estimated persistence.

Also for the EGARCH model (Table 6), the performance of lagged volume is quite disappointing, since it does not reduce persistence, it is not significant in six out of the ten stocks, and it does not alter the initial results on asymmetry.

As a substitute to lagged volume we suggest the use of an indicator of previous day volatility expressed as the difference between the highest and the lowest price (dubbed IDV for intra-day volatility) as an indicator, again, of the vivaciousness of trade at $t-1$ and the possible spillover effects onto the next day. The variable is always significant and the results are supportive of the hypothesis that persistence can be partially absorbed by such movements

Table 5. GARCH(1,1) estimation with lagged volume

Company	α_1	β_1	$\alpha_1 + \beta_1$	Vol(–1)
AAL	0.078*	0.794*	0.872	0.0001*
	(0.007)	(0.022)		(2.7×10^{-5})
BMY	0.136*	0.752*	0.888	$-5.1\times10^{-6*}$
	(0.010)	(0.021)		(2.0×10^{-6})
EC	0.081*	0.675*	0.756	-5.1×10^{-6}
	(0.011)	(0.049)		(6.4×10^{-5})
HRS	0.247*	0.482*	0.729	7.7×10^{-5}
	(0.013)	(0.032)		(4.6×10^{-5})
LOR	0.149*	0.598*	0.747	$-6.7\times10^{-5*}$
	(0.019)	(0.039)		(4.5×10^{-6})
MDT	0.096*	0.805*	0.901	3.6×10^{-7}
	(0.011)	(0.023)		(4.2×10^{-6})
NOC	0.040*	0.949*	0.982	-6.2×10^{-6}
	(0.003)	(0.004)		(7.6×10^{-6})
PWJ	0.083*	0.849*	0.932	1.3×10^{-5}
	(0.006)	(0.013)		(1.2×10^{-5})
SBR	0.129*	0.830*	0.959	0.0003*
	(0.009)	(0.011)		(0.0001)
WGO	0.914*	0.878*	1.792	4.3×10^{-5}
	(0.004)	(0.005)		(4.6×10^{-5})

better than by lagged volume since now the estimated persistence is smaller (Table 7), ranging from 0.683 to 0.894.

The EGARCH specification (Table 8) shows also a significant effect for the IDV variable, accompanied by a reduction in persistence, but maintains asymmetry (with one exception, HRS).

Another specification requires the assumption of ε_t being the sum of i.i.d. random variables to be lifted. In fact, for example, if we simplify matters and assume both μ and $\Phi(L)$ are equal to zero, ε_t coincides with the daily return r_t. Such a return is the outcome of at least two separate mechanisms at work between two closings of the markets, that is the difference observable between the opening price at t relative to the closing price at $t-1$ (let us denote it as δ_{1t}), and the net outcome of the trading activity during day t. As a single movement, the former is much stronger than each subsequent movement.

Therefore, we will assume that $n_t^* = n_t + 1$, where n_t is the number of trades from open to close, and hence we can write

$$\varepsilon_t = \delta_{1t} + \sum_{i=2}^{n_t} \delta_{it}$$

Accordingly, we assume that δ_{1t} and the other δ_{it}, $i = 2, \ldots, n_t$ have different characteristics. The innovation at the opening of the markets represents the

Table 6. EGARCH(1,1) with lagged volume

Company	$\log(\alpha^2_{t-1})$	$\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}}$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	Vol(–1)
AAL	0.836*	0.170*	–0.038*	0.064*
	(0.024)	(0.016)	(0.009)	(0.010)
BMY	0.968*	0.185*	–0.028*	–0.006
	(0.005)	(0.016)	(0.010)	(0.006)
EC	0.751*	0.221*	–0.050*	–0.039*
	(0.033)	(0.020)	(0.013)	(0.009)
HRS	0.746*	0.433*	0.020	–0.009
	(0.022)	(0.019)	(0.012)	(0.011)
LOR	0.945*	0.145*	–0.044*	0.002
	(0.009)	(0.013)	(0.007)	(0.006)
MDT	0.912*	0.179*	–0.041*	0.015
	(0.014)	(0.017)	(0.009)	(0.009)
NOC	0.981*	0.122*	–0.018*	–0.003
	(0.003)	(0.012)	(0.006)	(0.003)
PWJ	0.798*	0.285*	–0.056*	0.040*
	(0.023)	(0.020)	(0.012)	(0.009)
SBR	0.950*	0.221*	–0.024*	0.015*
	(0.005)	(0.013)	(0.006)	(0.004)
WGO	0.922*	0.229*	–0.026*	–0.006
	(0.006)	(0.009)	(0.006)	(0.004)

accumulation of information absorption during market closure and is bound to have an important impact on the market during the day.[5]

The proxy to build in the volatility model is therefore the variable *ONI* (overnight indicator) which is built as

$$ONI_t = \left| \log \frac{\text{open}_t}{\text{close}_{t-1}} \right|$$

Since we are evaluating returns as differences between closing prices, we suggest that from the viewpoint of the so-called end-of-the-day traders, the difference between the opening price of a day and the closing price of the day before represents an interesting indicator of the number of trades during the day, and therefore may act as a variable on the basis of which the decision whether or not to engage in a trade during the day can be made. As a result, it is a good candidate to capture the persistence in the conditional heteroskedasticity.

Inserting this variable in the specifications for the conditional variance, we get results supporting the hypothesis that the surprise at the opening relative to

[5] The results in Berry and Howe (1994) (among others) about the clustering and seasonality of information arrival cast some further doubts about the validity of the hypothesis of i.i.d. price movements during the day, but this does not alter the substance of our proposal which follows.

Table 7. GARCH(1,1) estimation with lagged IDV

Company	α_1	β_1	$\alpha_1 + \beta_1$	IDV(–1)
AAL	0.010	0.806*	0.816	0.002*
	(0.010)	(0.019)		(0.000)
BMY	0.064*	0.830*	0.894	0.001*
	(0.009)	(0.020)		(0.000)
EC	0.000	0.676*	0.676	0.006*
	(0.008)	(0.028)		(0.000)
HRS	0.160*	0.376*	0.536	0.005*
	(0.015)	(0.032)		(0.000)
LOR	0.059*	0.681*	0.740	0.003*
	(0.007)	(0.027)		(0.000)
MDT	0.051*	0.720*	0.771	0.002*
	(0.011)	(0.030)		(0.000)
NOC	0.028*	0.655*	0.683	0.005*
	(0.013)	(0.032)		(0.000)
PWJ	0.098*	0.643*	0.741	0.003*
	(0.010)	(0.028)		(0.000)
SBR	0.097*	0.738*	0.835	0.002*
	(0.012)	(0.016)		(0.000)
WGO	0.017	0.681*	0.698	0.009*
	(0.010)	(0.016)		(0.000)

Table 8. EGARCH(1,1) with lagged IDV

Company	$\log(\alpha^2_{t-1})$	$\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}}$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	IDV(–1)
AAL	0.772*	0.071*	–0.034*	0.203*
	(0.031)	(0.024)	(0.010)	(0.029)
BMY	0.887*	0.130*	–0.031*	0.152*
	(0.021)	(0.021)	(0.012)	(0.036)
EC	0.565*	0.026	–0.065*	0.323*
	(0.042)	(0.023)	(0.014)	(0.031)
HRS	0.571*	0.285*	0.007	0.297*
	(0.033)	(0.031)	(0.012)	(0.038)
LOR	0.837*	0.089*	–0.052*	0.184*
	(0.020)	(0.015)	(0.009)	(0.027)
MDT	0.768*	0.097*	–0.056*	0.200*
	(0.028)	(0.023)	(0.013)	(0.027)
NOC	0.658*	0.056	–0.035*	0.361*
	(0.038)	(0.030)	(0.014)	(0.038)
PWJ	0.791*	0.186*	–0.056*	0.157*
	(0.026)	(0.018)	(0.011)	(0.027)
SBR	0.911*	0.217*	–0.020*	0.049*
	(0.015)	(0.015)	(0.007)	(0.007)
WGO	0.884*	0.149*	–0.023*	0.109*
	(0.008)	(0.010)	(0.005)	(0.011)

Table 9. GARCH(1,1) estimation with ONI

Company	α_1	β_1	$\alpha_1 + \beta_1$	ONI
AAL	0.108*	0.097	0.205	0.016*
	(0.021)	(0.058)		(0.001)
BMY	0.129*	0.789*	0.918	0.002*
	(0.013)	(0.019)		(0.000)
EC	0.183*	0.414*	0.597	0.014*
	(0.016)	(0.034)		(0.001)
HRS	0.249*	0.250*	0.499	0.017*
	(0.018)	(0.035)		(0.001)
LOR	0.148*	0.211	0.359	0.017*
	(0.020)	(0.045)		(0.001)
MDT	0.113*	0.181*	0.294	0.030*
	(0.023)	(0.032)		(0.002)
NOC	0.109*	0.141*	0.250	0.022*
	(0.017)	(0.047)		(0.001)
PWJ	0.161*	0.444*	0.605	0.014*
	(0.017)	(0.035)		(0.001)
SBR	0.130*	0.840*	0.970	0.0002
	(0.009)	(0.010)		(0.0001)
WGO	0.125*	0.257*	0.382	0.027*
	(0.016)	(0.001)		(0.001)

the closing is important since ONI is always significant (except for SBR for the GARCH model – Table 9 and for BMY for the EGARCH model – Table 10). The effect is to bring down persistence: in the GARCH case it now ranges from 0.205 to 0.970 (the latter is the estimated value for SBR), with most values between 0.2 and 0.6; for the EGARCH model it ranges from 0.09 to 0.96 (again for SBR) with most values between 0.1 and 0.5.

The results are seemingly worse than those obtained with contemporaneous volume, but, once again, the meaning of the exercise should be clear: we want to take out of the stock returns volatility the component which is due to the surprise between open and previous close price. By so doing persistence in the estimated volatility is reduced.

4. CONCLUSIONS

The structure of GARCH-type models of conditional heteroskedasticity does not manage to capture the quick absorption of large shocks to returns and implies in practice a too high level of persistence of shocks. Even if various explanations have been sought such as the presence of structural breaks in the process (paralleling the debate on unit roots) or the role played by volume in reducing the persistence, a more ‘structural’ explanation of what gives rise to volatility clustering is still lacking. This paper is no exception, as it falls short of

Table 10. EGARCH(1,1) with ONI

Company	$\log(\alpha^2_{t-1})$	$\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}}$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	ONI
AAL	0.126	0.281*	–0.005	0.106*
	(0.068)	(0.030)	(0.019)	(0.006)
BMY	0.968*	0.180*	–0.027*	0.0002
	(0.005)	(0.015)	(0.010)	(0.0021)
EC	0.453*	0.294*	–0.073*	0.111*
	(0.037)	(0.021)	(0.015)	(0.004)
HRS	0.575*	0.474*	0.010	0.074*
	(0.031)	(0.025)	(0.016)	(0.006)
LOR	0.259*	0.355*	0.018	0.112*
	(0.057)	(0.031)	(0.020)	(0.008)
MDT	0.285*	0.320*	–0.096*	0.188*
	(0.032)	(0.041)	(0.024)	(0.009)
NOC	0.092*	0.317*	–0.017	0.156*
	(0.042)	(0.034)	(0.022)	(0.007)
PWJ	0.663*	0.346*	–0.054*	0.059*
	(0.025)	(0.021)	(0.015)	(0.005)
SBR	0.959*	0.218*	–0.025*	–0.006*
	(0.004)	(0.013)	(0.006)	(0.002)
WGO	0.136*	0.307*	–0.056*	0.142*
	(0.039)	(0.025)	(0.018)	(0.006)

providing such an explanation. In our opinion, though, it takes a step in the right direction, since by assessing the role of beginning-of-the-day surprises, relative to the closing price of the previous day, we suggest that these surprises play a major role in the arisal of large returns and of volatility clustering. Such innovations represent accumulated overnight information to which the markets react starting from the opening quotes. Reaching a consensus on the direction the price should take may therefore be a long process which is constantly tested. Our results show that previous day information is much less informative: both lagged volume and an indicator of intra-day volatility (the difference between the highest and the lowest price observed) serve a smaller role.

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APPENDIX

Symbol legend

Symbol	*Company*
AAL	Alex & Alex
BMY	Brist. Meyers
EC	Engelhard
HRS	Harris Corp.
LOR	Loral
MDT	Medtronic
NOC	Northrop
PWJ	Paine-Webber
SBR	Sabine
WGO	Winnebago

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