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Do negative and positive equity returns share the same volatility dynamics?

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ABSTRACT

This paper investigates whether positive and negative returns share the same dynamic volatility process. The well established stylized facts on volatility persistence and asymmetric effects are re-examined in light of such dichotomy. To analyze the dynamics of down and up volatilities estimated from daily returns I use a bivariate generalization of the standard EGARCH model. As a robustness check, I also investigate various specifications of down and up realized measures estimated from high-frequency data. The empirical findings point to the existence of a marked diversity in the volatilities of positive and negative daily returns in terms of persistence and sensitivity to good and bad news. A simple forecasting exercise highlights the striking performance of the proposed approach even during the crisis period.

1. Introduction

The modeling and forecasting of volatility has received significant attention in the financial-economic literature due to its relevance in areas such as portfolio management and selection, risk analysis and hedging and the pricing of assets and derivatives. Since Engle's (1982) ARCH and Bollerslev's (1986) GARCH, the study of volatility has witnessed a multitude of contributions ranging from the parametric to the nonparametric and from the discrete to the continuous time modeling. Particular attention has been devoted to the modeling of the news impact curve, that is the reaction of future volatility to negative and positive return shocks. Among the first parametrizations capturing the asymmetric response of volatility to the arrival of news are the EGARCH of Nelson (1991), the GJR-GARCH of Glosten et al. (1993) and the GTARCH of Zakoian (1994). For a literature review of GARCH models see Andersen et al. (2006).

El Babsiri and Zakoian (2001) introduce the concept of contemporaneous asymmetry in conditional heteroskedasticity models and accordingly decompose the primitive innovations into negative (down) and positive (up) shocks. Treating the volatility of negative and positive returns as distinct processes, although not necessarily independent, has its economic motivation in the fact that for investors with long (short) positions risk is clearly associated with down (up) movements of the asset's price but not necessarily with up (down) movements. Failure to separate the two aspects of volatility results in biased measures and forecasts whenever the down and up components do not coincide. On the other hand, distinguishing between down and up moves allows for *"different volatility processes for down and up moves in equity market [returns] (contemporaneous asymmetry)"* and *"asymmetric reactions of these volatilities to past negative and positive changes [in returns] (dynamics asymmetry or leverage-effect)"*. El Babsiri and Zakoian (2001) model the contemporaneous asymmetries with an *ad hoc* generalization of the univariate GTARCH (already capturing dynamic asymmetries) specification. In their study of the CAC 40 stock index they find that bad news increase future down and up volatilities significantly more than good news.[2] Furthermore, they find that current down and up volatilities substantially enter with

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[2] Throughout the paper, good and bad news are defined as return realizations respectively above and below their conditional expectation.

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the same coefficients in both equations of future down and up volatilities.

More recently, the availability of high-frequency data has stimulated a growing literature interested in the nonparametric estimation of the latent volatility process and in the decoupling of discontinuous *jumps* from the continuous component. In this framework, Barndorff-Nielsen et al. (2010) spell out the theory of realized semivariances, that is the realized variance of negative and positive intradaily returns. Using intradaily down variance as explanatory variable in a study of General Electric share prices, they find that *"for non-leveraged based GARCH models, downside realized semivariance is more informative than the usual realized variance statistic"*. However, when *"a leverage term is introduced it is hard to tell the difference"*. Stronger evidence favoring the intradaily down and up dichotomy of explanatory variables is found in Chen and Ghysels (2011). Modeling realized measures of volatility as functions of intradaily returns measured over some time intervals, they achieve the down and up decomposition of the explanatory variables with the exception of the jump component. In their study of the Dow Jones cash market and S&P500 futures market, they find that *"moderately good news reduce volatility"* while *"both very good news (unusual high positive returns) and bad news (negative returns) increase volatility, with the latter having a more severe impact"*.

Patton and Sheppard (2011) extend the use of intradaily down and up semivariances as predictors of future realized measures by introducing *signed jump variation*, defined as the difference between positive and negative realized semivariances. From a panel regression of 105 individual stocks and the S&P500 index they measure the average effects of the explanatory variables on standard measures of volatility. They conclude that intradaily down volatility *"is much more important for future volatility"* than intradaily up volatility. Furthermore, based on their definition of negative and positive jumps, they find that the former *"lead to significantly higher future volatility"* while the latter *"lead to significantly lower volatility"*.

Building on the work of El Babsiri and Zakoian (2001), this paper studies the volatility dynamics of negative and positive returns. In contrast to standard modeling, this class of volatility processes allows for time periods characterized by down and up movements of different magnitudes. Here the UD-EGARCH, a generalization of Nelson's (1991) EGARCH model, is proposed. The main differences with respect to the GTARCH generalization of El Babsiri and Zakoian (2001) are: the possibility for the realizations to have a negative impact on the volatilities without compromising their positivity and the complete separation of the model's memory parameters from the loadings of the realizations.

Stylized facts on volatility persistence and asymmetric effects are re-examined in light of the down and up dichotomy for nine major world indices. Particular attention is paid to the analysis of the memory of down and up processes. Notably, the relevance of this aspect is due to the fact that, if undetected, different levels of persistence will give investors either a false sense of calmness or a false sense of activity, resulting, among others, in costly under- and over-estimated risk exposures. Memory of the down and up processes is elicited in terms of half-lives of the shocks.

The empirical findings point to the existence of marked diversities in down and up volatilities in terms of persistence and response to good and bad news. The robustness of the In-Sample (henceforth IS) findings is evaluated by assessing their stability Out-Of-Sample (henceforth OOS). Additional robustness checks are conducted in the specific case of the S&P500 index using high-frequency observations. All results highlight significant gains in the IS estimations and OOS predictions from the separate treatment of the two aspects of volatility. Sizable gains have been identified in the measurement and prediction of volatilities for all indices for the time periods considered. Specifically, the reduction of OOS mean-squared-errors ranges between 6% to 70% and 11% to 45% (depending on the benchmark measure) and averages at more than 25%.

The paper is organized as follows. Section 2 presents the Low-Frequency Analysis: Volatility Specification (2.1), Data (2.2), Findings (2.3), Predictions and Stability (2.4). The High-Frequency Analysis is presented in Section (3): Volatility Specifications (3.1), Data (3.2) and Findings (3.3). Section 4 concludes.

2. Low-Frequency Analysis

2.1. Volatility Specification

A stochastic process y_t may be described in terms of its location and scale:

$$y_t = \mu_t + \epsilon_t$$
$$\epsilon_t = h_t^{1/2} \cdot z_t \tag{1}$$

where μ_t is a function describing the evolution of the mean conditional on the information set $\mathcal{I}_{t-1}$,[3] h_t is the conditional variance of the process y_t and z_t is a zero-mean, unit-variance and serially uncorrelated innovation.

In the standard decomposition of Eq. (1), the primitive shocks z_t are scaled by the process h_t regardless of their sign: no distinction is made between good and bad contemporaneous news. However, negative and positive innovations need not be subject to the same amplification dynamics. Specifically, the return process y_t may exhibit large (small) down movements and small (large) up movements over a certain period of time. To allow for two distinct scale factors, redefine ϵ_t by:

$$\epsilon_t = \begin{cases} h_{U,t}^{1/2} \cdot z_t & \text{if } z_t > 0 \\ h_{D,t}^{1/2} \cdot z_t & \text{otherwise} \end{cases} \tag{2}$$

with:

$$\mathbb{E}[z_t^2 | z_t < 0] = 1 \quad \text{and} \quad \mathbb{E}[z_t^2 | z_t > 0] = 1 \tag{3}$$

$h_{D,t}^{1/2}$ and $h_{U,t}^{1/2}$ are the volatilities amplifying and compressing negative and positive innovations, respectively. z_t is a zero-mean and serially uncorrelated innovation satisfying the conditions in (3). These are the down and up counterparts of the standard identification condition for which primitive shocks have unit variance. It is straightforward to see that the equations in (3) imply $\mathbb{E}[z_t^2] = 1$. It must be noted that with distinct $h_{D,t}$ and $h_{U,t}$ processes additional assumptions[4] are needed to guarantee a zero conditional expectation of the shock ϵ_t. In other words, the clear-cut distinction between mean and variance of Eq. (1) becomes fuzzy once the constraint $h_D = h_U$ is relaxed. Further study of this salient connection between

[3] The information set is defined as usual: $\mathcal{I}_t,\ t \in \mathcal{Z}^+$ is an increasing filtration of σ-fields ($\mathcal{I}_{t-1} \subset \mathcal{I}_t,\ \forall t$) such that $\mathcal{I}_t$ summarizes the information provided by the observation of variables of interest up to time t. For purely dynamic specifications such as conditional volatility models it is enough to define the information set generated by past realizations of the returns $y_t : \mathcal{I}_t = \{y_1, \ldots, y_t\}$.

[4] For the conditional expectation of ϵ_t:

$$\mathbb{E}[\epsilon_t | \mathcal{I}_{t-1}] = h_{U,t}^{1/2}\mathbb{E}[z_t | z_t > 0] \cdot \mathbb{P}(z_t > 0) + h_{D,t}^{1/2}\mathbb{E}[z_t | z_t \leqslant 0] \cdot \mathbb{P}(z_t \leqslant 0)$$

to be zero it is sufficient to specify the probability of observing an up movement $\mathbb{P}(z_t > 0)$ that offsets the movements in the down and up volatilities. For the unconditional expectation of ϵ_t:

$$\mathbb{E}[\epsilon_t] = h_U^{1/2}\mathbb{E}[z | z > 0] \cdot \mathbb{P}(z > 0) + h_D^{1/2}\mathbb{E}[z | z \leqslant 0] \cdot \mathbb{P}(z \leqslant 0)$$

to be zero it is sufficient to specify either $\mathbb{P}(z > 0)$ or the pair $h_U^{1/2},\ h_D^{1/2}$ so that $\mathbb{E}[\epsilon_t] = 0$.