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Testing for leverage effects in the returns of US equities

Christophe Chorro [a], Dominique Guégan [b], Florian Ielpo [c,*], Hanjarivo Lalaharison [d]

[a] University Paris 1 Panthéon-Sorbonne, Centre d'Economie de la Sorbonne and Labex ReFi, 106 bd de l'hopital, 75013, Paris, France
[b] IPAG Business School, University Paris 1 Panthéon-Sorbonne, CES and Labex ReFi, 106 bd de l'hopital, 75013, Paris, France
[c] Centre d'Economie de la Sorbonne, France
[d] Université d'Antananarivo, Faculté des sciences, Mention Mathématiques et Informatique, Madagascar

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ABSTRACT

This article questions the empirical usefulness of leverage effects to forecast the dynamics of equity returns. In sample, we consistently find a significant but limited contribution of leverage effects over the past 25 years of S&P 500 returns. From an out-of-sample forecasting perspective and using a variety of different models, we find no statistical or economical value in using leverage effects, provided that an asymmetric and fat-tailed conditional distribution is used. This conclusion holds both at the index level and for 70% of the individual stocks constituents of the equity index.

1. Introduction

An accurate description of the dynamics of the stock index returns requires a mix between a time varying volatility structure and an asymmetric and fat-tailed distribution. That is the conclusion of a long stream of research papers published over the past decades. The time varying volatility structure accounts for the potential changes in the level of risk in financial markets while the conditional distribution deals with the rare occurrence of extreme events, usually seen as jumps. Such an approach turned out to be both successful when applied in continuous – as in Bates (1996)'s extension of Heston (1993)'s work – and in discrete time models—as in Christoffersen et al. (2006, 2010), Badescu et al. (2008, 2011), Chorro et al. (2010, 2012) or Guégan et al. (2013). The estimation of such models is a complex matter as components in the volatility structure and in the conditional distribution can impact the model implied density in a very similar way. The asymmetric past return to volatility feedback effect in discrete time models usually refereed to as "leverage effect" can have a similar impact to that of the asymmetry in the returns' conditional distribution. Building on a recursive numerical implementation of the maximum-likelihood estimation presented in Section 2.6.3 of Chorro et al. (2016), this article aims at disentangling both effects and then assesses whether leverage effects are a necessary modeling feature or not. Our focus here is on a commonly used dataset in financial econometrics empirical experiments: the returns on the S&P500. Our results suggest that the importance of the leverage effect has actually been probably overstated in the literature: it is useful when working with a Gaussian conditional distribution, but loses a significant part of its usefulness when using non-Gaussian conditional distributions. Leverage effects are found to be statistically significant in-sample but loses their appeal when it comes to forecast the density of returns out-of-sample whenever an asymmetric distribution is used for residuals.

* Corresponding author.
E-mail addresses: cchorro@univ-paris1.fr (C. Chorro), dguegan@univ-paris1.fr (D. Guégan), fielpo@univ-paris1.fr (F. Ielpo), lalaharisonh@gmail.com (H. Lalaharison).

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Leverage effects consist in an asymmetric reaction of volatility to past returns, volatility rising more rapidly when returns are negative than positive (see Aydemir et al., 2006). This stylized fact first highlighted in Black (1976) and Christie (1982) is usually explained in two ways: first, an increase in volatility should coincide with a higher expected return – as prices drop – when the price of risk is constant. Second, a drop in the price of a stock increases the underlying company's financial leverage and the volatility of its stock increases as a response to this increase in the firm's risk. Nevertheless, the lack of consensus surrounding the rationale behind the leverage effect is important as illustrated by the various contributions of Schwert (1989), Campbell and Hentschel (1992), Duffee (1995), Bekaert and Wu (2000), Figlewski and Wang (2000), Wu (2001), Aydemir et al. (2006) and Bae et al. (2007). Regardless of the conclusions raised in each of these articles concerning the economic origin of the phenomenon, they unanimously acknowledged the empirical existence of leverage effects in individual stocks. Now, when aggregating these firm-specific phenomenon into equity indices, it is unsure whether the volatility feedback or the financial argument hold as idiosyncratic risk is getting diversified. Still, a significant number of articles maintain an asymmetric component in their modeling of volatility usually in order to generate time varying negative skewness. Examples of these contributions are Poon and Granger (2003), Awartani and Corradi (2005), Corsi and Reno (2012), Bandi and Reno (2012) and Hansen et al. (2012). In the continuous time literature, a similar case can be made out of various extensions of the Heston (1993)'s model where the leverage effect component is used to generate asymmetric implied volatility surfaces as extracted from option prices. Leverage effects probably turned out to be a useful component improving continuous and discrete time financial models' ability to fit the observed distribution of returns (Awartani and Corradi, 2005) or to match the observed price of options on stock indices (Christoffersen and Jacobs, 2004) especially when the model's conditional distribution is Gaussian and thus does not incorporate any asymmetry or fat tails. Alternatively, a properly selected conditional distribution can provide an interesting goodness-of-fit of the returns' distribution as well (see e.g. Wang et al., 2001). Giot and Laurent (2004) and (Curto et al., 2009), somewhat in a very comparable way to that of the leverage effect.

Thus, the theoretical economic reliability of leverage effects in the dynamics of stock index returns and the possibility to use alternative flexible distributions cast doubts on the necessity of a leverage component in conditional volatility structures. This article aims to question its empirical usefulness using 25 years of S&P 500 returns. Following Badescu et al. (2008, 2011) and Chorro et al. (2010, 2012), we combine three classical asymmetric GARCH specifications used in the financial literature, namely, the Exponential GARCH (EGARCH) introduced by Nelson (1991), the Asymmetric Power ARCH model (APARCH) of Ding et al. (1993) and the GJR-GARCH introduced in Glosten et al. (1993), with two families of conditional distributions that are able to generate various levels of skewness and kurtosis: the Generalized Hyperbolic distribution as introduced by Barndorff-Nielsen (1977) and the mixture of two Gaussian distributions (see e.g. Behboodian, 1970). By Combining these two components, we want to be able to test the real impact of the leverage coefficient once one of those conditional distributions is employed.

We both test the statistical significance of leverage in the dynamics of the S&P 500's returns based on in- and out-of-sample approaches. Our conclusions unfold as follows: first, we find that leverage effects account for around 20% of the returns' total skewness: it is statistically significant but it does not dominate the asymmetry in the returns on the S&P500 index. Second, by performing in-sample Hansen (1992)'s test, we consistently accept the hypothesis that the parameter driving the leverage effect in the asymmetric GARCH models can be set to zero. Finally, we consistently find that leverage effects do not statistically improve the out-of-sample forecast accuracy of our time series models when using the Amisano and Giacomini (2007)'s test methodology when the conditional distribution is asymmetric. All results are stable when splitting the sample to check for the robustness of our findings. Hence, our results indicate that modeling the S&P 500's returns through an asymmetric GARCH model is not statistically relevant as long as the conditional distribution is flexible enough to capture the behavior of the returns' distribution's tails—all the more when the user wants to forecast returns out-of-sample. Finally, when testing for leverage effects on the components of the S&P 500 index, we find that 70% of stocks do not exhibit a statistically significant leverage effect parameter. We also ran a series of robustness checks assessing whether our findings would still hold for a GARCH-type with a more flexible time varying leverage component or using a non-parametric estimation of volatility combined with an alternative bivariate volatility model closer to the spirit of a stochastic volatility model. Moreover, we provide a risk analysis application questioning the importance the asymmetric past return to volatility feedback in VaR computations. All the results obtained are confirming the main statement of this article: leverage effects lose a significant part of their interest when using the non-Gaussian distributions described earlier.

The article is organized as follows. Section 2 presents the models and the tests used to detect or not leverage effects. Section 3 details the empirical results. Section 4 analyzes the outcomes of a series of robustness checks. Section 5 concludes.

2. Methodology

In this section we briefly present the classical asymmetric GARCH models we used in the empirical part of this article and the two statistical tests selected to question the relevance of leverage parameters in non-Gaussian environment.

2.1. Modeling S&P500 log-returns with asymmetric GARCH processes and non-Gaussian innovations

Let $(Y_t)_{t\in\{1,\ldots,T\}}$ be a sequence of random variables, defined on a probability space $(\Omega, \mathcal{A}, \mathbb{P})$, representing the daily log-returns of the S&P500 index that we model through a class of related GARCH(1,1) processes:

$$Y_t = \sqrt{h_t} z_t, \quad z_0 = x \in \mathbb{R}, \tag{1}$$

$$h_t = F_{\theta^V}(z_{t-1}, h_{t-1}) \tag{2}$$

where $(z_t)_{t\in\{1,\ldots,T\}}$ is a sequence of independent and identically distributed real random variables with a density d_{θ^D} that depends on a set of parameters θ^D and where F_{θ^V}, indexed by a set of parameters θ^V, models the volatility in the following way: