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A common jump factor stochastic volatility model

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ABSTRACT

We introduce a new multivariate stochastic volatility model, based on the presence of a latent common factor with random jumps. The common factor is parameterized as a permanent component using a compound binomial process. This model can capture common jumps in the latent volatilities between markets, with particular relevance in the presence of crises and contagion in emerging markets.

1. Introduction

The modeling of volatility in financial assets is a key topic in financial economics. Volatility is an essential input for asset pricing, risk management and portfolio management. Due to the importance of this measure there is an extensive literature proposing models to capture the conditional volatility patterns. In this work we focus on stochastic volatility models. The most common form of discrete time stochastic volatility (SV) model is the log-normal formulation, which can be specified as:

$$y_t = exp\left(\frac{h_t}{2}\right)\varepsilon_t \tag{1}$$

$$h_{t+1} = \alpha + \phi h_t + \sigma_\upsilon \upsilon_t, \tag{2}$$

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where y_t is the observed series, h_t is the latent volatility process, ε_t and υ_t are independent standard Gaussian processes and α, ϕ, and σ_υ are parameters.

While SV models have generally a good fit to the data, when we assume that the innovation process υ_t is from a continuous Gaussian variable the probability of large variations in the volatility process is small. In this respect the standard SV models may be inadequate to capture the behaviors seen in financial assets, especially in emerging markets. In these markets we often observe sudden and large changes in the volatility and in the patterns of transmission of shocks between markets (contagion), as discussed in Allen and Gale (2000) or Billio and Caporin (2005).

Another important problem with SV models is the possibility of changing parameters in the volatility process. In this situation the structural changes can lead to incorrect results, especially spurious persistence patterns, as discussed in Hwang et al. (2007) and Messow and Krämer (2013). To circumvent this problem were formulated some alternative specifications of the SV model. Hwang et al. (2007) introduce a version of the SV model allowing for the possibility of Markov switching regimes. An alternative formulation of the SV model with the possibility of level changes has been proposed in Qu and Perron (2013). In this model the volatility process is decomposed into two factors, one factor being a first order autoregressive process, and the other factor an permanent process for the mean level of volatility, formulated as a compound binomial process subjected to random discontinuous jumps. This formulation is not subject to the usual limitations of models with Markov regime changes, such as the use of a fixed number of regimes.

We propose a new multivariate stochastic volatility model, using a decomposition of permanent and transitory components similar to the proposed in Qu and Perron (2013), where the permanent component is related to the simultaneous jumps (co-jumps) in the volatility process of distinct markets.

Our work is related to the literature on co-jumps in financial markets. An important example is the relationship between jumps in the stock index and co-jumps in the active participants of the index, as discussed for example in Clements and Lia (2013), verifying the occurrence of co-jumps for a group of 20 large US stocks. The importance of jumps and co-jumps in stock market diversification is also discussed in Bollerslev et al. (2008), which analyze the jump process for a total of 40 large capitalization stocks. This evidence of simultaneous jumps is also found in Gilder et al. (2014), who find evidence of co-jumps for 60 liquid stocks in the TAQ database. The results indicate that market-level news can generate simultaneous large jumps in individual stocks and the association between systematic co-jumps in stock prices and Federal Funds Target Rate announcements. Similar evidence of joint jumps were obtained in Bormettia et al. (2013) using a set of 20 high cap stocks traded at the Italian Stock Exchange, finding high frequency price co-jumps. In the same study the authors point out that the existence of automated mechanisms of high frequency trading can also lead to the existence of joint price jumps, as shown in the synchronization effect observed in Flash Crash of May 6, 2010. According to SEC-CFTC, the crash began with a rapid price decline in the E-mini S&P 500 market and soon the negative jump in prices was propagated towards ETFs and derivative markets.

This model is also especially interesting to capture the patterns of volatility in emerging markets, as will be discussed in more detail in Section 3. To show the application of this new SV model we perform the simultaneous modeling of stochastic volatilities of daily exchange rates of Brazilian Real/Dollar and Turkish Lira/Dollar in the period 2006–2014.

2. Common jump factor SV model

The model proposed in this work is based on a multivariate extension of the random jumps in the level proposed in Qu and Perron (2013). The proposed parameterization is obtained by introducing a specific transitory factor for each observed series in the model, and the latent volatility is a combination of this autoregressive factor with a common factor for all series, modeled as a compound binomial process. Thus we can specify the proposed model, at a bivariate specification, by the following equations: