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A test of asymmetric comovement for state-dependent stock returns☆

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ABSTRACT

I propose a test of asymmetric stock return comovement across states. The test can be viewed as a variation of Kendall's τ conditional on the state and has an asymptotic χ^2-distribution. A refined version of the test is derived based on the Markov chain theory of regenerative cycles which substantially improves finite sample size and power properties. I show that the test has power against local alternatives, which is nonetheless compromised due to a finite sample convergence bound put on the implied local alternative data generating process. I evaluate the new test against traditional correlation-based measures and demonstrate power attrition of a state-free tail dependence test as parameter values are varied. Broad market-based ETFs and international indices are studied and in most cases there is no compelling evidence for asymmetric comovement across states. A list of related tests is given as an extension at the end.

1. Introduction

Ever since excess kurtosis and sporadic peaks in stock returns were recognized in the economic profession five decades ago, a central theme in financial econometrics has been the study of the temporal and distributional characteristics of asset returns. One late comer that has recently turned quite a few heads is stock return comovement, about which a shared feeling is that comovement is asymmetric conditional on volatilities and returns.

One strand of research has focused on tail comovement, or more generally, the characterization of upside and downside dependence structure. Theoretical contributions made in this direction have used copulas (Patton, 2006) and multivariate extreme value theory (Stărică, 1999; Longin and Solnik, 2001). Correlation-based measures have also received close attention in the international financial market; see Ramchand and Susmel (1998); Ang and Chen (2002), and Syllignakis and Kouretas (2011). As the study of tail dependence typically does not differentiate between different states, the link between comovement differential across states and tail dependence (without respect to the states) is not well understood. The notion of state is most easily seen through the lens of vastly different volatilities and mean returns, so an interesting question to ask is whether comovement is significantly higher in the volatile and low return periods.

The importance of modeling asymmetric comovement across states can be seen via a somewhat overlooked fact in the literature: asset return comovement is not necessarily higher in the left tail. Karolyi and Stulz (1996) speak in terms of large "absolute

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returns" and Patton (2006) finds that in the post-euro era, the dependence structure between two exchange rate returns (DM-USD and Yen-SD) has gone from significantly asymmetric in the negative direction to weakly asymmetric in the positive direction. Longin and Solnik (1995) fit a threshold GARCH model to monthly market returns and find that conditional correlation tends to increase in periods of high turbulence but is no more sensitive to negative than to positive shocks. In this respect, economic theory does not give a unified answer either. Ribeiro and Veronesi (2002) model news in bad times as more informative about the true state of the economy, which then predicts that during volatile periods of more uncertainty about the future, cross-market correlation tends to be higher. By contrast, Simsek (2011) studies the role of financial innovation in portfolio risk diversification and finds that when large belief disagreements exist among traders, financial innovation tends to increase average portfolio volatility and decrease average portfolio comovement. In view of regime-switching models, this suggests that when states are ignored, comovement asymmetry conditional on, say, exceeding certain threshold of return, may be a natural result of pooling returns from state-dependent distributions.

Previous authors have used popular models such as the DCC, GARCH-M, and regime-switching GARCH, yet results are mixed and existent tests are mostly based on pairwise correlation which is inappropriate for nonlinear dependence structures. In copula-based models, researchers have frequently relied on Goodness-of-fit-type tests for lack of a direct test of asymmetric comovement. The test I propose takes a probabilistic form to which the closest predecessor is the state-free tail-dependence test of Li (2014). They differ, however, in four important aspects. First, I construct a test of symmetric state-dependent comovement and prove the asymptotic results by exploiting the structure of a Markov chain. Second, I show in Section 5.3 that the power of Li's test is sensitive to certain model parameters. Third, I examine the local power property of the test and map it into local data generating processes. Further, I construct a refined version of the test based on the Markov regenerative cycle theory and apply the test to ETFs and international market indices. To facilitate comparison with a Wald test of correlation equality, I estimate the variance and correlation separately in a model that allow both of them to switch.

In the next section, I first lay out the model specification and give a summary of the test procedure. In Section 3, I present the main asymptotic results for the test, the proofs of which are given in the appendix. I then analyze the power of the test in Section 4 where it is shown that the test has nonnegligible power against local alternatives and is invariant in the meta-elliptical family. Numerical studies are given in Section 5 followed by a list of extensions. Section 7 concludes.

2. Model and test procedure

In a study of asymmetric correlations of portfolio returns, Ang and Chen (2002) demonstrate that a mixture of normal model is very good at matching the empirical correlation asymmetries in the data. Rydén et al. (1998) and Timmermann (2000) show that a Gaussian Markov-switching model can significantly expand the model's scope for well-established financial return patterns and higher order distributional characteristics such as asymmetry, fat tails, volatility dynamics and infrequent breaks in the conditional mean or variance. For these reasons, I consider the data generating process to be multivariate normal and governed by an m-state Markov-switching structure.

The current DGP is a useful way to capture the centerpiece of the test which can easily accommodate many other interesting variations with a switching structure. This is because the test is invariant in a much larger family of DGP's (Section 4.3) and enjoys certain robustness to the specification of state-dependent variances and means (see Remark 1). It can also be viewed as a quasi-MLE approximation to more elaborate models. The procedure contains two separable steps: the goal of step one is to identify the true state and to estimate the stationary state distribution, after which step two is model-free. As such, it can be used for DGP's with switching in the mean or variance, switching GARCH in the variance, duration in the mean or variance, time-varying transition probability that only depends on current information, or a combination of these. The nonparametric nature of step two together with the aforementioned robustness properties implies that state classification in the first step is crucial to the implementation of the test. Experiment with more complicated models such as the Markov-switching GARCH burdens estimation and strains numerical stability with little gain in state identification. On balance, the Gaussian Markov-switching framework performs well in terms of state identification.

2.1. Model specification

Consider the multivariate return process $\{x_1, x_2, \ldots, x_n\}$ generated by $x_t = \mu_{s_t} + \sum_{s_t}^{1/2} z_t$, where s_t is the state at time t, z_t ~ iid $N(0,1)$, and μ_{s_t} and $\sum_{s_t}$ are the state-dependent mean vector and covariance matrix. $\{x_t\}$ is governed by an m-state Markov chain with the *transition probability matrix* Γ. In what follows, let $P(\cdot)$ be the probability measure and let $P(x_t|s_t)$ denote the conditional probability of observing r_t given state s_t. π is the initial state distribution; $x^{(t)}$ and $s^{(t)}$ represent the histories of observations and states up to time t. Treating the unobserved states as missing data one gets,

$$L(T) = P\left(\boldsymbol{X}^{(\boldsymbol{T})} = \boldsymbol{x}^{(T)}\right) = \sum_{s_1, s_2, \ldots, s_n \in \{1, \ldots m\}} P\left(\boldsymbol{X}^{(\boldsymbol{T})} = \boldsymbol{x}^{(T)}, \boldsymbol{S}^{(T)} = \boldsymbol{s}^{(T)}\right),$$

and by the strong Markov property, a particular realization of states contributes to the likelihood by as much as.

$$P\left(\boldsymbol{X}^{(\boldsymbol{T})} = x^{(T)}, \boldsymbol{S}^{(T)} = \boldsymbol{s}^{(T)}\right) = \pi(s_1)P(x_1|s_1)P(s_2|s_1)P(x_2|s_2) \ldots P(s_n|s_{n-1})P(x_n|s_n).$$