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Modeling time-varying skewness via decomposition for out-of-sample forecast

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ABSTRACT

This paper models the time-varying skewness via a return decomposition framework which splits a return into the product of absolute return and its sign. Specifically, the nonlinear dependence between absolute returns and signs is characterized by a dynamic copula function which governs a dynamic skewness process of financial returns. The importance of modeling the time-varying skewness is evaluated via out-of-sample forecasts for the US excess stock returns, in terms of both statistical significance and economic relevance. I find that the skewness timing of the proposed time-varying dependence models yields an average gain in the returns of around 195 basis points per year over the forecast sample period. Statistically, the fluctuation test shows strong evidence that the forecasting performance of the decomposition models is unstable over the sample time path. In this regard, a forecast combination, being more robust to structural instability than the individual forecasts, performs significantly better than the benchmarks out-of-sample.

1. Introduction

Recently, Anatolyev and Gospodinov (2010, AG) took an alternative approach to the prediction of excess stock returns: instead of trying to identify better predictors, they looked for better ways of using predictors. They accomplished this by modeling the individual multiplicative components of excess stock returns and combining the information in the components so as to recover the conditional expectation of the original variable of interest. Let r_t denote the excess stock return at time t. Specifically, AG's approach utilizes a return decomposition given by

$$r_t = |r_t|\text{sign}(r_t), \tag{1.1}$$

which Christoffersen and Diebold (2006) also called "an intriguing decomposition". The joint distribution of the multiplicative components in Eq. (1.1) is obtained by combining a multiplicative error model for absolute returns, a dynamic binary choice model for signs, and a copula function for their interaction.

AG's decomposition models are able to incorporate important nonlinearities in excess return dynamics that cannot be captured in the standard predictive regression setup. However, their approach is rather restrictive, as the dependence between absolute returns and signs is constant over sample periods. The constant dependence also imposes a constant skewness on the excess returns. The literature has recognized that returns may in fact be characterized better by a conditional distribution with time-varying asymmetry. Some of the results from AG's constant decomposition models are difficult to interpret, given that the distribution of excess returns might be time-varying. For instance, their constant copula structure may give an averaging of symmetric and asymmetric distributions of excess returns over a sample period, meaning that a high degree of return asymmetry in some subperiods cannot be distinguished clearly from small asymmetry or symmetry

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in other subperiods.[1] This may result in the conditionally weak dependence between multiplicative components found by AG. In this sense, a time-invariant dependency structure may miss the important distribution timing of excess returns during events such as economic recessions and financial crises.

In addition, the time-varying return skewness can be characterized naturally by dynamic dependence between the absolute returns and signs. If the excess return at time t is distributed around zero, its predictability might be statistically small; nonetheless, it can be improved if time-varying skewness is present and modeled.[2] As pretesting for the US excess stock returns, the test statistics of Busetti and Harvey (2011) in Section 3 provide significant evidence of dynamic tail dependence and asymmetry. Thus, a time-varying process of dependence between absolute returns and signs is desirable for improving the predictability of excess returns.

Recent studies have also found time-varying skewness to be important in asset pricing and allocation. Harvey and Siddique (1999, 2000a,b) show that the inclusion of autoregressive conditional skewness affects the persistence of the variance and helps explain the time-variation in the ex ante market risk premiums and the cross-sectional variation of expected returns across assets. Leon, Rubio, and Serna (2005) estimate the time-varying skewness and kurtosis using a Gram–Charlier series expansion of the normal density function for the error term. It is found that specifications which allow for time-varying skewness and kurtosis outperform specifications with constant third and fourth moments. Jondeau and Rockinger (2003) use the generalized Student-t distribution with an autoregressive specification of the parameters to demonstrate the importance of time-varying asymmetry parameters.

However, these studies are concerned mainly with the in-sample fit of time-varying skewness. An exception is that of Jondeau and Rockinger (2012), who study the importance of time-varying higher moments in out-of-sample asset allocation. Their results show that an investor could receive sizable benefits from distribution timing compared to volatility timing.

In this paper, I propose a new approach to modeling the time-varying skewness, the model performance of which is evaluated based on out-of-sample forecasts of the US excess stock returns, in terms of both statistical significance and economic value. Specifically, I extend AG's constant decomposition model by characterizing the joint distribution as a time-varying copula function.[3] In this way, the nonlinear temporary interdependence between absolute returns and signs, which governs the dynamic skewness processes of returns, is estimated by the dynamic copula function simultaneously with marginals. Importantly, this approach provides a flexible way to estimate the time-varying skewness, in that the joint distribution is specified in three components, namely a copula function with two marginals, whereas conventional approaches assume a single distribution for returns. Hence, the proposed dynamic decomposition model is expected to capture both important hidden nonlinearities and the time-varying distributional natures of excess returns.

Besides modeling the time-varying skewness in out-of-sample forecasts, this paper also differs from AG's work in several important ways. (1) The out-of-sample forecast period is extended to cover the recent financial crisis of 2007–2009, which has attracted a tremendous amount of research interest in both the economic and financial literature. (2) The fluctuation tests and the decomposition of forecast performances, proposed by Giacomini and Rossi (2010) and Rossi and Sekhposyan (2011) respectively, show strong statistical evidence of the instability of forecast performances over the sample time paths. This finding reconciles the insignificant results on average forecast performances from AG's constant decomposition models. Interestingly, a forecast combination, being more robust to structural instability than the individual forecasts, performs significantly better than the benchmarks out-of-sample. (3) The economic value of the skewness timing presents substantial benefits from modeling time-varying skewness. The skewness timing of the proposed time-varying dependence models yields an average gain in the returns of around 195 basis points per year over the forecast sample period. By comparison, the forecast results show in addition that investors were willing to pay an extra 442 basis points of the returns per year over and above the volatility timing in order to acquire skewness timing information for their portfolios during the recent financial crisis of 2007–2009.

The rest of the paper is organized as follows. Section 2 presents the proposed methodology for modeling time-varying skewness, which is then followed by a discussion of forecasting and simulation methods for conditional mean forecasts. Section 3 describes data construction, and also presents the pretesting results for the US excess stock returns in relation to some preliminary evidence of potential nonlinearity and time-varying tail dependence and asymmetry between absolute returns and signs. Section 4 reports empirical results for both the statistical significance and economic value of our forecasting performances. Section 5 concludes this paper.

2. The model

The return decomposition in Eq. (1.1) can be rewritten as

$$r_t = |r_t| \left(2s_t - 1\right), \tag{2.1}$$

[1] If the excess return at time t is distributed symmetrically around zero, then the absolute returns and signs are independent and the expected sign equals zero (Randles & Wolfe, 1979, Lemma 2.4.2). If the distribution of the excess return at time t has a small degree of asymmetry, then the absolute returns and signs might be weakly dependent. In contrast, if the excess return at time t is distributed asymmetrically, then the absolute returns and signs are dependent. In the second and third cases, the expected sign is nonzero.

[2] Christoffersen, Diebold, Mariano, Tay, and Tse (2007) have documented that, even if the expected returns are zero, and regardless of whether volatility dynamics are present, sign predictability arises as long as conditional skewness dynamics are present. This property remains intact in conditionally non-Gaussian environments. See Christoffersen and Diebold's (2006) online supplement.

[3] See Manner and Reznikova (2012) for a recent survey of time-varying copulas.