European Journal of Operational Research 236 (2014) 282–291

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Decision Support

Hedge fund systemic risk signals

Roberto Savona *

Department of Economics and Management, University of Brescia, Italy

ARTICLE INFO

Article history:
Received 10 December 2012
Accepted 6 December 2013
Available online 13 December 2013

Keywords:
Hedge funds
Dynamic conditional correlations
Time-varying beta
Regression trees
Early warning system

ABSTRACT

In this paper, we realise an early warning system for hedge funds based on specific red flags that help detect the symptoms of impending extreme negative returns and the contagion effect. To do this we use regression tree analysis to identify a series of splitting rules that act as risk signals. The empirical findings presented herein prove that contagion, crowded trades, leverage commonality and liquidity concerns are the leading indicators for predicting worst returns. We not only provide a variable selection among potential predictors, but also assign specific risk thresholds for the selected key indicators at which the vulnerability of hedge funds becomes systemically relevant.

1. Introduction

In this paper we realise an early warning system (EWS) for the extreme negative returns of hedge funds based on specific red flags that help detect the symptoms of risky situations that may result in large-scale crises. The key concept of our work conceives excess correlation as the major symptom of contagion. Thus, following Boyson, Stahel, and Stulz (2010), we inspect hedge fund filtered returns (asset pricing model residuals) in order to reduce the possibility that we attribute to contagion commonality in returns due to exposure to common risk factors. We also rely on Boyson et al. (2010) to define hedge fund extreme negative returns, which are identified as the returns that fall in the bottom 10% of a hedge fund style's monthly returns, and contagion, which is defined as the number of other hedge fund styles that have a worst return in the same month.

To realise the EWS for hedge funds we rely on regression tree (RT) analysis. We develop a risk monitoring system in the spirit of the signal approach (Manasse & Roubini, 2009), which is based on specific splitting threshold values associated with the selected explanatory variables that help detect potential abnormalities in the form of worst hedge fund returns. Our paper is related to Savona (2014), since we use the three-equation system introduced in such an article to estimate the Bayesian time-varying CAPM beta model. However, while Savona (2014) explore how and why the systematic risk exposures of the major hedge fund strategies vary over time, based upon some exogenous variables that hedge fund managers are assumed to use in changing their trading strategies, here the research question is different as well as the methodological innovation. In this paper we focus on time-varying correlations, which are estimated following Alexander (2002), together with other leading indicators for predicting hedge fund worst returns. The main objective is to realise a system of rules of thumb to capture situations of extreme risk, and to do this we implement a novel regression tree algorithm introduced in Vezzoli and Stone (2007) which is well suited to inspect panel data structures. To our knowledge, this is the first study that uses RT to examine systemic risk in hedge funds.

Using data from the CSFB/Tremont indices over the period from January 1994 to September 2008, we find that contagion, crowded trades and leverage commonality are the most important leading indicators of worst hedge fund returns. Furthermore, market and funding liquidity concerns together increase the risk for hedge funds, since risky clusters are signalled when credit spread widens and funds tend to de-leverage. A clinical study of the reasons for the LTCM collapse occurred in 1998 and sub-prime crisis in terms of worst returns suffered by hedge funds suggests that, on one hand, the LTCM collapse was mainly due to extreme commonality in leverage dynamics and higher leverage level, whereas, on the other, the sub-prime crisis was caused by crowded trades together with a substantial drop in leverage commonality due to strong de-leveraging.

The remainder of this paper is organised as follows. Section 2 discusses the related literature to our work. Section 3 presents the methodology, while the dataset used in the paper is discussed in Section 4. Section 5 reports the empirical results and Section 6 concludes.

* Address: Dipartimento di Economia e Management, Università degli Studi di Brescia, c/da S. Chiara no. 50, 25122 Brescia, Italy. Tel.: +39 30 2988557/552; fax: +39 30 295814.

E-mail address: savona@eco.unibs.it

0377-2217/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ejor.2013.12.014

2. Related literature

Our work is related to several large bodies of work that focus on correlation as the major indicator of systemic risk. Firstly, our paper is complementary to Stein (2009), who emphasises the role of the comovements induced by both the crowded trade and the leverage effects, thus suggesting a way to explore systemic risk that is economically consistent with the new literature on liquidity spirals (Brunnermeier & Pedersen, 2009) and studies of leveraged arbitrageurs (Morris & Shin, 2004; Shleifer & Vishny, 1997). Following this line of reasoning, other papers that explore how hedge funds comove together, especially in times of stress, are complementary to our study. Billio, Getmansky, Lo, and Pelizzon (2012) use correlation to capture the degree of connectivity among financial institutions and its impact in terms of contagion, spillover effects and joint crashes. Boyson et al. (2010) focus on clustering worst returns and, based upon the arguments developed in Bekaert, Harvey, and Ng (2005), define hedge fund contagion as the "correlation over and above what one would expect from economic fundamentals". In their view, the clustering of worst returns is conceived as a form of excess correlation, which in turn results in contagion or interdependencies (Forbes & Rigobon, 2002).[1] Adrian (2007) relies on hedge fund return correlation to proxy for similarities in hedge fund strategies, which is assumed to be a key determinant of the risk of the entire hedge fund industry.

All these studies point to correlation as a measure of connectivity among hedge funds. However, correlation by itself does not necessarily imply systemic risk, since it may reflect common membership and style affiliations, i.e. common risk factor exposure. For this reason, to inspect systemic risk among hedge funds we filter their monthly returns, namely we remove common variation in fund returns using a new asset pricing model that has recently proven to be effective to describe the time-varying risk exposure of hedge funds.

3. Methodology

Three methodological steps are used in this paper: (i) estimating an asset pricing model for hedge funds and then using filtered returns and time-varying beta estimates to (ii) compute the time-varying correlations and (iii) realise the EWS for the hedge fund industry using the RT approach. As mentioned in the introduction and discussed more deeply in the previous section, such a procedure reflects the central importance we attribute to excess correlation, assumed as the major symptom of contagion. Analytically, correlations are computed for (i) filtered returns, in order to measure *crowded trades*; (ii) time-varying betas, to measure the *leverage commonality* connected to systematic risk exposure variations; and (iii) common hedge fund risk factors, thus measuring *risk factor commonality*. We indeed conjecture that contagion could be connected to commonalities in hedge fund strategies (crowded trades), beta dynamics (leverage commonality) and cross-market comovements (risk factor commonality).

3.1. Filtered returns and time-varying betas

Until recently, research on hedge fund returns has focused on regression approaches in which returns are regressed on risk factors that proxy for different trading strategies assuming constant coefficients. However, empirical findings have proven that the risk exposures of hedge funds change significantly over time. As a result, new approaches addressing time-varying parameters have been proposed in order to handle shifts in coefficient estimates (see, for example, Bollen & Whaley, 2010; Patton & Ramodarai, 2013).

In this paper, we use the recent three-equation system implemented in Savona (2014). This is a Bayesian time-varying CAPM beta model conditional upon exogenous variables that hedge fund managers are assumed to use in changing their trading strategies. The reason we refer to this model is twofold. First, it allows the estimation of time-varying systematic risk exposure, which is needed to measure leverage commonality. Second, as documented in Savona (2014), it is a parsimonious model that has been proved to be better than simple multi-factor asset pricing models with constant coefficients, both in- and out-of-sample, thus resulting in better hedge fund filtering returns. Moreover, this also more accurately measures crowded trades.

3.1.1. Three-equation system

The model used to estimate filtered returns and time-varying betas assumes that hedge fund managers are predominantly focused on a fund-specific style benchmark expressed as a linear combination of the 7 + 1 risk factors proposed in Fung and Hsieh (2004, 2007a,b) (see Section 4.2), hereafter termed the FH risk factors. The hedge fund-specific style benchmark is simply obtained by regressing hedge fund returns onto these eight explanatory factors and then taking the corresponding expectation. As discussed in Savona (2014), this procedure is followed in order to construct single index style-matched benchmarks to be used in a CAPM context and then explore the time variability of systematic risk exposure (the CAPM beta). To this end, hedge fund managers are assumed to modify their own strategies (the style benchmark) according to some partly observable primitive risk signals (PRSs), which can be viewed as the "impulse variables" that impact on the time variability of systematic risk exposure. In a sense, these PRSs are latent factors that could affect hedge fund returns, but for which the inner mechanism of such a relationship is partly obscured by the complex nature of the dynamic trading rules followed by managers.[2]

3.1.2. The model

The econometric representation of the model used to filter hedge fund returns and estimate time-varying betas is as follows:

$$r_{p,t} = \alpha_p + \beta_{p,t} r_{b,t} + \varepsilon_{p,t} \tag{1}$$

$$\beta_{p,t} = \mu + \phi(\beta_{p,t-1} - \mu) + \Gamma' \mathbf{z}_t + \eta_{p,t} \tag{2}$$

$$r_{b,t} = \Lambda' \mathbf{z}_t + u_{b,t} \tag{3}$$

The first equation describes the excess return behaviour of the hedge fund index, where α_p is a constant, $\beta_{p,t}$ is the time-varying beta, $r_{b,t}$ is the excess benchmark return and $\varepsilon_{p,t}$ is an error term, i.e. the "filtered return". As discussed in the previous section, $r_{b,t}$ is obtained by regressing hedge fund returns onto the 7 + 1 FH risk factors and then taking the corresponding expectation expressed in terms of excess returns over the risk-free rate.

The second equation is the single beta relative to the regression-based style benchmark with ϕ to denote the persistence beta parameter, μ the unconditional mean-reverting beta term, Γ' the transposed vector of sensitivities towards $\mathbf{z}_t$, which is the vector of the PRSs, and $\eta_{p,t}$ the stochastic component. The third equation is the fund-specific style benchmark excess return, which is modelled using the same set of covariates used to describe the beta

[1] Forbes and Rigobon (2002) define significant increases in cross-market comovements as *contagion*, while continued high levels of correlations are defined as *interdependence*.

[2] The proxies for these PRSs are discussed in Section 4.3.