Pacific-Basin Finance Journal 29 (2014) 146–162

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

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

Stock returns, mutual fund flows and spillover shocks

Paresh Kumar Narayan [a,*], Seema Narayan [b], Prabheesh K.P [c]

[a] Financial Econometrics Group, School of Accounting, Economics and Finance, Faculty of Business and Law, Deakin University, 221 Burwood Highway, Burwood, Victoria 3125, Australia
[b] School of Economics, Finance, and Marketing, RMIT University, Australia
[c] Department of Liberal Arts, Indian Institute of Technology, Hyderabad, India

ARTICLE INFO

Article history:
Received 15 July 2013
Accepted 30 March 2014
Available online 12 April 2014

Jel Classification codes:
G12
G17

Keywords:
Stock returns
Mutual fund flows
Spillover
Financial crisis
VAR model

ABSTRACT

In this paper we examine the dynamic relationship between stock returns and mutual fund flows in India by using a generalised VAR model. We find that spillover shocks—that is, stock return shocks and mutual fund flow shocks together explain as much as 20% of the total forecast error variance of stock returns and mutual fund flows. We create a spillover index of shocks emanating from stock returns and mutual fund flows and tests whether it can actually predict stock returns and mutual fund flows. We find it does. Using the spillover index, we forecast stock returns and mutual fund flows, devise trading strategies for a mean–variance investor, and demonstrate the economic significance of the spillover index.

1. Introduction

India's mutual fund industry and stock market have grown at phenomenal rates over the last decade; yet, nothing is known about the dynamic relationship between the two markets. During the period 2000–2011, the National Stock Exchange (NSE) stock index, CNX-Nifty, grew at an annual average rate of 9%. Market capitalization as a percentage of GDP of NSE also increased, from 35% in 2001 to 85% in 2011. Similarly, the number of companies listed on the NSE more than doubled over the corresponding period, from 720 to 1552. Likewise, the turnover on the Indian stock market increased from US $621 billion in 2001 to US $1056 billion in 2011. During the same period, the total assets under management (AUM) of the mutual fund industry also increased substantially as a result of private sector participation; almost

* Corresponding author. Tel.: +61 3 9244 6180; fax: +61 3 9244 6034.
E-mail address: paresh.narayan@deakin.edu.au (P.K. Narayan).

http://dx.doi.org/10.1016/j.pacfin.2014.03.007
0927-538X/

six-fold, from Rs. 1080 billion in 2000 to Rs. 5922 billion in 2011. The trend suggests that both markets have tracked each other fairly closely over the last decade. This motivates us to undertake a dynamic analysis of the relationship between stock returns and mutual fund flows in India.

We use daily data covering the period from August 2000 to December 2011. Specifically, we investigate the relative importance of shocks (stock return and mutual fund flow shocks) in explaining the forecast error variance of stock returns and mutual fund flows. We also estimate shock spillovers—that is the effect of mutual fund shocks on the forecast error variance of stock returns, and stock return shocks on the forecast error variance of mutual fund flows. From this relationship, we construct a time-varying spillover index. Our approach, consistent with the proposal of Diebold and Yilmaz (2009, 2012), is based on a generalised vector autoregressive (VAR model); see Section 2 for details. We go a step further though. We make greater use of the time-varying spillover index by asking whether the spillover index can actually predict stock returns and mutual fund flows for India. To answer this question, we use a bi-variate time-series predictive regression model proposed by Westerlund and Narayan (WN: 2014). Using the WN estimator, we find strong evidence that the spillover index predicts both stock returns and mutual fund flows for India. We go beyond this statistical evidence of predictability by testing the economic significance of the stock returns and mutual fund shocks (as represented by the time-varying spillover index). To do this, we assume a mean–variance utility function, both for an investor who forecasts stock returns using the spillover index, and one who forecasts mutual fund flows using the spillover index. Within this framework, we compute utility gains (or certainty equivalent returns—that is, the amount of portfolio management fee that an investor is willing to pay to use a spillover index-based predictive regression model over a constant-based predictive regression model), and profits (assuming no short-selling and a 0.1% transaction cost). We find that, on the whole, investors are better-off by using a spillover index-based predictive regression model. While utility gains are stronger when investors use the spillover index to forecast stock returns than when using mutual fund flows, profits for investors in both markets are statistically different from zero and over the full-sample period are maximised at around 3.25% per annum for investors in the equity market and at 1.15% per annum for investors in the mutual fund industry.

The balance of the paper is organised as follows. The next section contains a discussion on the estimation technique. Section 3 discusses the data and analyses the empirical findings. The final section concludes the paper.

2. Estimation technique: forecast error variance and spillover effects

The forecast error variance and spillover effects, based on the VAR model, can be estimated using the approach proposed by Diebold and Yilmaz (2009, 2012). We have on hand a two-variable VAR model. Let us denote by Z_t the vector of our variables: $Z_t = [R_t, MF_t]$, where R_t is stock returns, measured by the S&P Nifty Index, which is made up of 50 stocks listed on the National Stock Exchange.[1] Mutual fund flows are denoted by MF_t. The first-order VAR model for Z_t is: $Z_t = AZ_{t-1} + \kappa_t$, where A is a 2×2 parameter matrix. The moving average representation of Z_t is: $Z_t = B(L)\eta_t$, where $B(L) = A(L)H_t^{-1}$, $\eta_t = H_t\kappa_t$, $E(\eta_t\eta_t') = I$, and H_t^{-1} is a unique lower triangular Cholesky factor of the covariance matrix of κ_t.

Two issues are crucial in extracting variance decompositions: (a) orthogonal innovations are needed; (b) variance decompositions should not be dependent on the manner in which they are ordered. To achieve orthogonal innovation one can simply use Cholesky factorisation. If done, this will attract criticism because then the variance decompositions will be variable order dependent. A criticism-free solution, which ensures that variance decompositions are invariant to the ordering of variables, has been proposed by Koop et al. (1996) and Pesaran and Shin (1998). Essentially, their idea is to utilise a generalised VAR (GVAR) framework. A key feature of the GVAR model is that it entertains correlated shocks by appropriately using the historically observed distribution of the errors. It follows that a GVAR framework does not orthogonalise shocks. The result is that the sum of the contributions to the variance of the forecast error is not necessarily equal to one (see Diebold and Yilmaz, 2012).

[1] Given that there is already a large literature that motivates the relationship between stock returns and mutual fund flows, here it is just suffice to be clear that we follow this literature and adopt the empirical framework from here; see Warther (1995), Edelen and Warner (2001), Goetzmann and Massa (2002), and Alexakis et al. (2005).