Hedge Fund Styles and Their Contagion from the Equity Market

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ABSTRACT

We examine the dynamic contagion process of the equity market on 10 hedge fund styles. We investigate the contagion mechanism for each style using single equation error correction and latent factor models. We find that the contagion effects of the equity market on each style index depend specifically on the fund style strategy. We demonstrate that certain fund styles are more prone to contagion from the equity market than others. Our results help illuminate the relative effectiveness of a particular strategy under certain market conditions and provide insights into the long-standing controversy around the efficient market hypothesis.

Keywords

Hedge fund style, Contagion, Single equation error correction model, Latent factor model, Efficient market hypothesis

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1. Introduction

Investors are primarily concerned with seeking secure, steady returns during both bull and bear markets. Hedge funds are attractive options for investors since they demonstrate weak correlation to standard asset classes compared to traditional investments (e.g., standard equity investing). Hedge funds have claimed that maintaining steady returns is possible by arbitrage, forecasting, or investment diversification and that such funds are uniquely suited for risk aversion in dynamic and volatile equity markets (Brown et al.1999; Agarwal and Naik 2000, 2004; Edwards and Caglayan 2001; Boyson et al. 2006; Li and Kazemi, 2007). In a mean-variance environment, hedge funds have enjoyed growing popularity since their introduction in the 1990s. However, the role of hedge funds in financial markets has become a controversial issue in recent history because of large losses by high profile hedge funds prior to, and subsequent to, the Global Financial Crisis (GFC). The collapse of Long-Term Capital Management (LCTM), known as a fixed income arbitrage (FIA) fund, in 1998, the Soros Fund in 2000, and Amaranth in 2006 preceded the demise of the Bear Sterns funds in 2008 at the onset of the GFC, which, in turn, heralded the start of further collapses for investment banks and other hedge funds. Investors, regulators, and the financial press have expressed concerns about particular hedge fund bankruptcies and criticized the hedge fund industry in general. Hedge fund critics claim that direct contagion from the equity market exists in hedge funds, particularly in crisis periods, and therefore fund investors do not derive the expected benefits of diversification (Viebig and Poddig 2010). Here, the direct contagion from the equity market conceptually implies excessive dominance of the equity market over the hedge funds or too large an exposure of the hedge funds to the equity markets. In fact, these concerns are rooted in the long-standing controversy around whether hedge funds are capable of manipulating financial market movements and bringing large profits to their investors (e.g., Ackermann et al. 1991). Given that not all hedge fund strategies have the same exposure to the equity markets, it is critical and fair for hedge funds and their investors to investigate which fund styles are more prone to contagion than others.

In this paper, we explore a transmission mechanism of equity market crisis to each hedge fund style, which involves investigating the contagion for each hedge fund style. For this, we define the break in the short- and long-term relation between each hedge fund style and equity market. We also define interdependence as a scaled long-term relation between each hedge fund style and the equity market, and then define contagion as the break in the interdependence. In addition, we define a break point as a measure for the precise activation of short- or long-term breaks or contagion. These definitions are given precisely through a single equation error correction model (SEECM) that our methodology is based on, together with latent factor model, quantile regression and the Wald-Wolfowitz runs test. Using return data from Credit Suisse hedge fund style indices and US equity market index from January 1994 to December 2012, we analyze how financial crises spread from equity market to each hedge fund style. Our results show that the effects of the equity market on each hedge fund style index specifically depend on the strategies of each fund style. We find three groups of hedge fund index returns, each with a different relationship with equity market returns. The volatility group, based on arbitraging volatility, is found to be significantly more affected by the equity market during crisis periods. Whereas, the direction group, based on directional forecasting, appears to have chance of making consistent profits by recovering its independence from the equity market. The pool group, based on pooled or diversified strategies, shows a relatively stable relationship with equity market returns across entire periods. In addition, it is worth mentioning that our results provide some useful insights into the long-standing controversy around the efficient market hypothesis (EMH)[1].

To explore these issues in greater detail, we have organized this paper into a series of interrelated sections. In Section 2, we explain the methodology based on the SEECM. This explanation contains precise definitions for short- and long-term breaks and the interdependence break (defined as contagion). We also describe our procedure for testing for short- and long-term breaks and contagion, and identifying the break point. Next, we report the results of our empirical analysis in Section 3. Finally, we offer some useful insights as concluding remarks in Section 4.

2. Methodologies

Contagion between two markets involves a dynamic process. A crisis that occurs in a market appears to have an impact that is distributed over future periods on the other one, although some effect might also occur immediately. In principle, when a shock hits a market, we expect an immediate short-term effect of the shock on the other. If the shock effect continues, it tends to have a long-term effect and may cause deviation from the normal equilibrium. With these expectations, the SEECM is suited to dynamically model how a shock occurring in an equity market influences the error correction mechanism to reach equilibrium between the equity

[1] EMH states that it is impossible to "beat the market" as stock market efficiency causes existing share prices to always incorporate and reflect all relevant information.

market and hedge funds over the short and long term. To describe the dynamics of contagion more explicitly, we link the SEECM to latent factor model. The SEECM is based on the dynamic assumption that two or more time series exhibit an equilibrium relationship that determines both short- and long-term behavior[2].

Let Y_t represent the return series of hedge fund style index and X_t represent the return series of equity market index. We employ the SEECM expressed as:

$$\Delta Y_t = \alpha + \beta_0 \Delta X_t + \beta_1 Y_{t-1} + \beta_2 X_{t-1} + \varepsilon_t$$

$$= \alpha + \beta_0 \Delta X_t + \beta_1 (Y_{t-1} - \gamma X_{t-1}) + \varepsilon_t \quad (1)$$

where $\gamma = -\frac{\beta_2}{\beta_1}$, $\Delta Y_t \equiv Y_t - Y_{t-1}$, $\Delta X_t \equiv X_t - X_{t-1}$, and ε_t is the independent and identically distributed (iid) error. It is assumed here that Y_t and X_t are stationary. Engle and Granger's (1987) two-step error correction model relies on the cointegration of two or more time series, whereas the SEECM employed herein does not require the cointegration condition to provide the same information about the rate of error correction. In other words, an SEECM is applicable for short- and long -term effects of independent variables on a dependent variable even when the data are stationary[3]. The concepts of error correction, equilibrium, and long-term effects are not unique to cointegrated data. Furthermore, an SEECM may provide a more useful modeling

[2] The SEECM is being broadly used for describing characteristics of dynamic processes in economics and politics (Beck 1991; Durr 1992; De Boef 2001; Best 2012)

[3] From a general linear regression model $Y_t = \alpha + \beta_0 X_t + \varepsilon_t$, we derive the SEECM as follows: $\Delta Y_t = \beta_0 \Delta X_t + \varepsilon_t - \varepsilon_{t-1} = \beta_0 \Delta X_t - (Y_{t-1} - \alpha - \beta_0 X_{t-1}) + \varepsilon_t = \alpha + \beta_0 \Delta X_t - (Y_{t-1} - \beta_0 X_{t-1}) + \varepsilon_t$. Thus, the SEECM can be applied to either stationary or co-integrated case.

technique for stationary data than alternative approaches. (see Durr 1992 and De Boef and Keele 2008 for details).

The portion of the equation (1) in parentheses is the error correction mechanism and $(Y_{t-1} - \gamma X_{t-1}) = 0$ when X and Y are in a state of equilibrium. The coefficient of β_0 estimates the short-term effect of an increase in X on an increase in Y; β_1 estimates the speed at which X and Y return to equilibrium from a state of disequilibrium. The coefficient of γ estimates the long-term effect of a one-unit increase in X on Y. This long-term effect will be distributed over future time periods according to the rate of error correction β_1. The SEECM is useful for describing contagion dynamism because shocks tend to cause error deviation from the normal equilibrium and contagion can be traced via the error correction dynamism. If the contagion process begins after a shock, we expect a change in $|\beta_0|$ to result in an immediate short-term effect. If the contagion process continues, we expect a change in $|\gamma|$ as an indication of the long-term effect. When $\beta_1 < 0$ ($\beta_1 > 0$), the system converges to equilibrium (diverges from equilibrium). This explanation allows us to define a short- or long-term break due to excess and significant shock. Indeed, we define "*short-term break*" as a significant change in $|\beta_0|$ during a period of time and a "*long-term break*" as a significant change in $|\gamma|$ during a period of time. Throughout this paper, interdependence is defined econometrically as the long-term coefficient adjusted by the corresponding market volatilities using equation (1). As β_1 represents the speed of return to equilibrium (and is therefore the inverse of volatility), and $\beta_2 = -\gamma\beta_1$, we can define β_2 (the long-term relationship scaled by volatility) as the interdependence between markets X and Y (see, e.g., Forbes and Rigobon 2002 and Corsetti et al. 2005 for related definitions). Hence, we may define "*interdependence break or contagion between X and Y* " explicitly as a significant change in $|\beta_2|$ during a period of time.

We link the SEECM to typical contagion models based on factor models. According to Dungey et al. (2005), most contagion models can be described using the following factor models. For simplicity, assume that there are two returns of assets modeled as

$$X_t = \theta_x W_t + \delta_x u_{x,t} \qquad Y_t = \theta_y W_t + \delta_y u_{y,t} \tag{2}$$

The variable W_t represents a common factor that affects all asset returns with loadings θ_x and θ_y. For simplicity, W_t is assumed to be a latent dependent stochastic process with zero mean and unit variance, that is,

$$W_t \sim (0,1). \tag{3}$$

The terms $u_{x,t}$ and $u_{y,t}$ in equation (2) are idiosyncratic factors unique to a specific asset return. The contribution of idiosyncratic shocks to the volatility of asset markets is determined by the loadings δ_x and δ_y. These factors are also assumed to be stochastic processes with zero mean and unit variance, that is,

$$u_{x,t} \ and \ u_{y,t} \sim (0,1) \tag{4}$$

To complete the specification of the model, all factors are assumed to be independent:

$$\mathrm{E}(u_{x,t}u_{y,t}) = 0, \quad \mathrm{E}(u_{x,t}W_t) = 0, \quad \mathrm{E}(u_{y,t}W_t) = 0. \tag{5}$$

To highlight the interrelationships between the two asset returns in (2), the variances and covariance are represented as follows:

$$\mathrm{Cov}(X_t, Y_t) = \theta_x\theta_y , \quad \mathrm{Var}(X_t) = \theta_x^2 + \delta_x^2, \quad \mathrm{Var}(Y_t) = \theta_y^2 + \delta_y^2. \tag{6}$$

Now, we can establish a connection between the SEECM (1) and the factor model (2) assuming an autoregressive error component for both X_t and Y_t.

Proposition 1. If we employ an AR(1) model for idiosyncratic factors $u_{x,t}$ and $u_{y,t}$ in model (2),

$$u_{x,t} = \rho_1 u_{x,t-1} + a_{u,t} \quad \text{and} \quad u_{y,t} = \rho_2 u_{y,t-1} + b_{u,t} \tag{7}$$

where $\mathrm{E}(a_{u,t}W_t) = 0$, $\mathrm{E}(a_{u,t}u_{x,t}) = 0$, $\mathrm{E}(b_{u,t}W_t) = 0$, $\mathrm{E}(b_{u,t}u_{y,t}) = 0$, $\mathrm{E}(a_{u,t}b_{u,t}) = 0$, $a_{u,t} \sim iid\ (0,1)$ and $b_{u,t} \sim iid\ (0,1)$, then we have an SEECM based on latent factor model as follows;

$$\Delta Y_t = \frac{\theta_y}{\theta_x}\Delta X_t - (1-\rho_2)\left(Y_{t-1} - \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}X_{t-1}\right) + \varepsilon_t \tag{8}$$

where $\varepsilon_t = \delta_y b_{u,t} - \frac{\theta_y}{\theta_x}\delta_x a_{u,t} + (\rho_1 - \rho_2)\theta_y W_{t-1}$.

Proof) The following may easily be derived from model (2)

$$\Delta Y_t = \frac{\theta_y}{\theta_x}\Delta X_t - \left(Y_{t-1} - \frac{\theta_y}{\theta_x}X_{t-1}\right) - \frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y u_{y,t}.$$

Then, it is easy to verify that

$$\begin{aligned}
\Delta Y_t &= \frac{\theta_y}{\theta_x}\Delta X_t - (1-\rho_2)\left(Y_{t-1} - \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}X_{t-1}\right) - \frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y u_{y,t} - \rho_2 Y_{t-1} + \rho_1\frac{\theta_y}{\theta_x}X_{t-1} \\
&= \frac{\theta_y}{\theta_x}\Delta X_t - (1-\rho_2)\left(Y_{t-1} - \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}X_{t-1}\right) - \frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y u_{y,t} - \rho_2(\theta_y W_{t-1} + \delta_y u_{y,t-1}) \\
&\quad + \rho_1\frac{\theta_y}{\theta_x}(\theta_x W_{t-1} + \delta_x u_{x,t-1}) \\
&= \frac{\theta_y}{\theta_x}\Delta X_t - (1-\rho_2)\left(Y_{t-1} - \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}X_{t-1}\right) - \frac{\theta_y}{\theta_x}\delta_x a_{u,t} + \delta_y b_{u,t} - \rho_2\theta_y W_{t-1} + \rho_1\theta_y W_{t-1}.
\end{aligned}$$

$$= \frac{\theta_y}{\theta_x}\Delta X_t - (1-\rho_2)\left(Y_{t-1} - \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}X_{t-1}\right) + \delta_y b_{u,t} - \frac{\theta_y}{\theta_x}\delta_x a_{u,t} + (\rho_1 - \rho_2)\theta_y W_{t-1}$$

Proof is complete. ■

Dependence structure imposed by (7) is necessary because an asset's return certainly progresses dynamically over time. Since ε_t in (8) includes the lagged common factor W_{t-1} (or lagged dependent stationary process), it is a correlated innovation, unless $\rho_1 = \rho_2 = \rho$. Noting that

$$\mathrm{E}(\varepsilon_t) = 0, \quad \mathrm{Var}(\varepsilon_t) = \delta_y^2 + \left(\frac{\theta_y}{\theta_x}\delta_x\right)^2 + ((\rho_1 - \rho_2)\theta_y)^2,$$

$\mathrm{Var}(\varepsilon_t)$ depends on volatility of X and Y via δ_x and δ_y and dynamics of idiosyncratic factors via ρ_1 and ρ_2. By comparing the equation (8) with the SEECM (1), it is straightforward to observe that $\beta_0 = \frac{\theta_y}{\theta_x}$, $\beta_1 = \rho_2 - 1$, $\gamma = \frac{\theta_y(1-\rho_1)}{\theta_x(1-\rho_2)}$ and $\alpha = 0$.[4] If $\rho_1 = \rho_2 = \rho = 0$, i.e., if idiosyncratic factors of X_t and Y_t are iid, then we have

$$\Delta Y_t = \frac{\theta_y}{\theta_x}\Delta X_t - \left(Y_{t-1} - \frac{\theta_y}{\theta_x}X_{t-1}\right) + \varepsilon_t \tag{9}$$

where $\varepsilon_t = \delta_y b_{u,t} - \frac{\theta_y}{\theta_x}\delta_x a_{u,t}$ becomes an iid innovation error uncorrelated with the explanatory variables with $\mathrm{E}(\varepsilon_t) = 0$ and finite variance of $\mathrm{Var}(\varepsilon_t) = \delta_y^2 + \left(\frac{\theta_y}{\theta_x}\delta_x\right)^2$. It is also noted that if $\rho_1 = \rho_2 = \rho = 0$, then the speed to the equilibrium, β_1, is -1. In this case, there is no discrepancy between the underlying interdependence $\beta_2 = -\gamma\beta_1$ and the long-term coefficient γ (i.e., $\beta_2 = \gamma$). This discussion implies that $\rho_1 = \rho_2 = \rho = 0$ produces iid ε_t as well as $\beta_1 = -1$ (no significant volatility effects on the underlying interdependence between

[4] $\alpha = 0$ might always be assumed after centering ΔY_t.

markets X and Y). *Thus an iid error check for model (8) would be sufficient for testing no contagion or no interdependence break between X and Y.* In addition, it is notable that $\mathrm{Var}(\varepsilon_t) = \delta_y^2 + \left(\frac{\theta_y}{\theta_x}\delta_x\right)^2$ is likely to be subject to 'heteroskedasticity' because it depends on θ_x and θ_y, and they are likely to change based on the situation. A major strength of our model (8) involves its ability to contain more general market contagion episodes through ε_t. This strength primarily results from the fact that our SEECM (8) describes the dynamic structure of contagion effectively via the error structure and that it is well capacitated in handling heteroskedastic errors due to the parameter changes of the latent factor model (2). It is also clear that our test is primarily concerned with error structures to check the contagion effects between X and Y.

The above discussions lead to the following hypotheses:

H_0: The errors in model (8) or (1) are iid.

H_a: The errors in model (8) or (1) are not iid.

Under these hypothesis of H_0 and H_a, we derive null and alternative hypothesis for testing the short- and long-term breaks and contagion effects defined in terms of the SEECM (8). To investigate and test contagion, we employ quantile regression. Quantile regression is employed for handling heteroskedasticity during crisis periods or at the corresponding quantile because it is an effective tool for testing the regression coefficient change due to the heteroskedasticity of the error term in the SEECM (8) (Koenker 2005). Refer to Baur (2013) for more detailed discussions about advantages of using quantile regression. In quantile regression, it is known that:

(H0): *A random fluctuation of the slope estimates around a constant value (with only the* *intercept parameters systematically increasing as a function of the quantile* $0 \leq \vartheta \leq 1$*) provides evidence for the iid (independent and identically distributed) error hypothesis of classical linear regression (Koenker 2005, p. 17).*

Our test is based on (H0) for the SEECM (8). If some of the slope coefficients are changing as a function of quantile $0 \leq \vartheta \leq 1$, then heteroscedasticity may be inherent in the data.

Once we estimate the quantile regression parameters across the entire range of quantiles of ΔY_t, we test the short- and long-term breaks and interdependence break (contagion) between X and Y during the sample period using the Wald-Wolfowitz runs test. Suppose that we have the estimated coefficients $(\widehat{\beta_{01}}, \cdots, \widehat{\beta_{0N}})$, $(\widehat{\beta_{21}}, \cdots, \widehat{\beta_{2N}})$, and $(\widehat{\gamma_1}, \cdots, \widehat{\gamma_N})$ (i.e., we estimate the regression parameters for equation (1) at N quantiles). The Wald-Wolfowitz runs test can be used to test for the pure randomness of the estimated residuals of the short-term (β_0), long-term (γ), and interdependence (β_2) effects in the SEECM across N quantiles because the quantile regression slope estimates behave randomly around their means under the iid error process, according to (H0). Here, the residuals are expressed as:

$$(\widehat{\beta_{01}} - \overline{\beta_0}, \cdots, \widehat{\beta_{0N}} - \overline{\beta_0}), \quad (\widehat{\beta_{21}} - \overline{\beta_2}, \cdots, \widehat{\beta_{2N}} - \overline{\beta_2}), \quad (\widehat{\gamma_1} - \overline{\gamma}, \cdots, \widehat{\gamma_N} - \overline{\gamma})$$

where $\overline{\beta_0}$, $\overline{\beta_2}$, and $\overline{\gamma}$ are the sample averages of the corresponding coefficients. Under (H0), we derive the null and alternative hypotheses for testing the short- and long-term breaks and contagion between dependent and independent variables. The hypotheses are stated as follows:

H_0^{SB}: *The residuals given by* $(\widehat{\beta_{01}} - \overline{\beta_0}, \cdots, \widehat{\beta_{0N}} - \overline{\beta_0})$ *are iid (or there is no significant change in* $|\beta_0|$ *or no short-term break between X and Y under* H_0*).*

H_1^{SB}: *The residuals given by* ($\widehat{\beta_{01}} - \overline{\beta_0}, \cdots, \widehat{\beta_{0N}} - \overline{\beta_0}$) *are not iid (or there is a significant change in* $|\beta_0|$ *or short-term break between X and Y under* $\mathrm{H_a}$*).*

H_0^{LB}: *The residuals given by* ($\widehat{\gamma_1} - \overline{\gamma}, \cdots, \widehat{\gamma_N} - \overline{\gamma}$) *are iid (or there is no significant change in* $|\gamma|$ *or no long-term break between X and Y under* $\mathrm{H_0}$*).*

H_1^{LB}: *The residuals given by* ($\widehat{\gamma_1} - \overline{\gamma}, \cdots, \widehat{\gamma_N} - \overline{\gamma}$) *are not iid (or there is a significant change in* $|\gamma|$ *or long-term break between X and Y under* $\mathrm{H_a}$*).*

H_0^{IB}: *The residuals given by* ($\widehat{\beta_{21}} - \overline{\beta_2}, \cdots, \widehat{\beta_{2N}} - \overline{\beta_2}$) *are iid (or there is no significant change in* $|\beta_2|$ *or interdependence prevails between X and Y under* $\mathrm{H_0}$*).*

H_1^{IB}: *The residuals given by* ($\widehat{\beta_{21}} - \overline{\beta_2}, \cdots, \widehat{\beta_{2N}} - \overline{\beta_2}$) *are not iid (or there is a significant change in* $|\beta_2|$ *or some interdependence break or contagion between X and Y under* $\mathrm{H_a}$*).*

The Wald-Wolfowitz runs test evaluates the degree to which the residual sequence distribution is random by taking the residuals in the order provided and marking the coefficient greater than the sample average of the coefficient sequence with + and the coefficient less than the sample average with –. In this manner, the Wald-Wolfowitz runs test handles correlated errors due to crisis effectively. Given H_0^{SB}, $H_0^{LB}, or\ H_0^{IB}$, the number of runs in a sequence of N elements is a random variable whose conditional distribution, given the number of observations with + (N_+) and the number of observations with – (N_-), is approximately normal, with mean μ and variance σ^2, where $\mu = \frac{2N_+N_-}{N} + 1$, $\sigma^2 = \frac{(\mu-1)(\mu-2)}{N-1}$ and $\mathrm{N} = N_+ + N_-$, $N_+ > 10$ and $N_- > 10$. For a small N, there are tables to determine critical values that depend on values of N_+ and N_- (Mendenhall and Reinmuth, 1982). Rejecting the null hypotheses H_0^{SB}, H_0^{LB} or H_0^{IB} implies that the distribution of the residuals is not random; therefore, we can conclude that the errors in model (8) are correlated or heteroskedastic. This means that there is a significant change in $|\beta_0|$, $|\gamma|$ or $|\beta_2|$ during a period of time and that there is short-or long-term break or interdependence break between two markets or assets due to the volatility changes depending on the market conditions. On the other hand, if we cannot reject the null hypotheses H_0^{SB}, H_0^{LB} or H_0^{IB}, we conclude that there is no short- or long-term break or no contagion between the markets or assets because we cannot detect excessive correlation or that adjusted by the corresponding market volatilities of X or Y. This approach not only significantly simplifies the estimating and testing procedure for contagion but also makes it unnecessary to define the crisis and tranquil periods ex-ante to test contagion between two markets.

Next, we define a new measure, the break point, which identifies a specific percentile at which the relation with the equity market begins to break (i.e., the percentile at which short- or long-term break or contagion starts to occur) for each short- or long-term break or contagion.

Break Points: Let $Y_N = (y_1, \cdots, y_N)$ denote a given (contaminated) sample that includes elements from different data-generating processes, and let $Y_{-m_1,-m_2}$ represent a sample that excludes m_1 and m_2 elements from both ends of Y_N. Then, the low- and high-percentile break points of the sample Y_N, ε_{N1}^* and ε_{N2}^*, are respectively defined by $\varepsilon_{N1}^* = \left[\frac{m_1^*(Y_N)}{N+1} \times 100\right]$ and $\varepsilon_{N2}^* = [(1 - \frac{m_2^*(Y_N)}{N+1}) \times 100]$ where $m_1^*(Y_N)$ and $m_2^*(Y_N)$ are the lowest integers m_1 and m_2 such that the test statistic $T_N(Y_{-m_1,-m_2})$ accepts the null hypothesis that the sample is from one data-generating process.

To identify the break points using this procedure, Y_N is $(\hat{\varphi}_{i1} - \overline{\varphi}_i, \cdots, \hat{\varphi}_{iN} - \overline{\varphi}_i)$ where $\widehat{\varphi}_{ij} (i = 1,2,3, j = 1,..,N)$ is the *i*th slope estimate for one of the slope estimates ($\widehat{\beta_0}$, $\widehat{\beta_2}$, or $\hat{\gamma}$) from the $j/(N+1)$th quantile regression, and $\overline{\varphi}_i$ is the sample average of $(\hat{\varphi}_{i1}, \cdots, \hat{\varphi}_{iN})$. Given the definition for the break point, T_N plays a key role in determining the break. Our procedure employs the Wald-Wolfowitz runs test statistics as T_N and produces the desired break point. Using the break points obtained, we can see whether a hedge fund suffers from a break in a given period. For instance, a break occurs to a hedge fund if the percentile of the hedge fund return is less than ε_{N1}^* or greater than ε_{N2}^* during a given time period.

There are two approaches employed for examining the relationship of contagion between hedge funds and broad market returns. The traditional approach focuses on various factors behind the relationship[5] while the dynamic approach pays attention to the dynamic mechanism describing the time-varying relation between the hedge funds and the market returns (Fung and Hsieh 1997; Boyson et al. 2010; Sabbaghi 2012; Viebig and Poddig 2010). Our SEECM has the advantage of combining the two approaches properly as it is linked to a latent factor model through dynamic error correction. Additionally, the SEECM is quite effective when there is endogeneity or a correlated error in a linear regression model.

[5] The seven-factor model by Fung-Hsieh (2004) known as the return generating process for hedge fund returns might be considered.

3. Empirical Analysis

3.1. Hedge fund style data

There are several data sources for information related to hedge fund indices. For the purposes of our study, we use data from the Credit Suisse hedge fund indices from January 1994 to December 2012[6]. These indices use asset-weighted returns across the funds in a given hedge fund style index[7]. Indices that use equal-weighted returns place more weight on small hedge funds compared with those that use asset-weighted returns. Since the downside risk exposure for small hedge funds is expected to be higher than that for large hedge funds (Dudley and Nimalendran 2011), a contagion test based on an index using equal-weighted returns is likely to be biased against the null hypothesis of no contagion.

The Credit Suisse hedge fund database tracks approximately 9,000 funds that (i) are valued at US$50 million (minimum), (ii) possess a 12-month track record, and (iii) have audited financial statements. Credit Suisse calculates and rebalances the index on a monthly basis and reflects performance net of all fees and expenses. We use monthly return data for each hedge fund style index and calculate the returns of the Russell 3000 index to proxy for the returns of the US equity market. The return data for each hedge fund index include 228 monthly observations during the sample period, which are incorporated as the response variable in our estimation of model in equation (1). We incorporate the same set of 228 monthly Russell 3000 index returns into the model as the predictor.

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[6] This hedge fund return database is subject to survivorship bias due to a lack of regulatory environment of hedge funds.

[7] Index data are available at http://www.hedgeindex.com/hedgeindex.

We obtained monthly hedge fund returns for 10 style indices from the Credit Suisse Hedge Index, LLC. The 10 hedge fund styles were: convertible arbitrage (CA), emerging markets (EM), event driven (ED), fixed income arbitrage (FIA), equity market neutral (EMN), long/short equity (LSE), managed futures (MF), multi-strategy (MS), dedicated short bias (DSB), and global macro (GM)[8]. Table 1 reports the summary statistics related to the monthly returns of the overall Credit Suisse hedge fund index, the 10 hedge fund style sub-indices, and the Russell 3000 index. Table 1 indicates that the monthly average return for the Credit Suisse overall hedge fund index (0.718%) is higher than that of the Russell 3000 index (0.607%) and that equity market returns are more volatile than the returns of all hedge fund styles except for DSB funds. Whereas GM hedge funds enjoy the highest average monthly return (0.966%), DSB funds generate the lowest average monthly return (-0.256%) and are characterized by the most substantial standard deviation of all fund styles. The fact that the returns of the DSB funds exhibit the highest negative correlation with equity market returns may be attributable to these funds typically holding a larger number of short than long positions and therefore earning returns by maintaining net short exposure in long and short equities.

[8] Detailed descriptions of each style index are available by clicking on the link to "Documents" at http://www.hedgeindex.com.

Table 1 Summary statistics of monthly returns of hedge fund style indices and the equity market: January 1994 to December 2012

	Mean (%)	SD (%)	Min (%)	Max (%)	Correlation with Russell 3000 Index
Credit Suisse Hedge Fund	0.718	2.155	-7.550	8.530	0.597
CA	0.625	1.972	-12.590	5.810	0.399
EM	0.694	4.238	-23.030	16.420	0.565
ED	0.758	1.808	-11.770	4.220	0.663
FIA	0.463	1.629	-14.040	4.330	0.351
EMN	0.451	2.940	-40.450	3.660	0.306
LSE	0.771	2.838	-11.430	13.010	0.711
MF	0.504	3.363	-9.350	9.950	-0.106
MS	0.654	1.535	-7.350	4.280	0.411
DSB	-0.256	4.867	-11.280	22.710	-0.798
GM	0.966	2.766	-11.550	10.600	0.240
Russell 3000 Index	0.607	4.537	-17.783	11.365	1.000

This table reports summary statistics for the monthly returns of 11 hedge fund indices and the Russell 3000 index. The hedge fund indices include the Credit Suisse hedge fund (overall hedge fund), and the sub-indices convertible arbitrage (CA), emerging markets (EM), event driven (ED), fixed income arbitrage (FIA), equity market neutral (EMN), long/short equity (LSE), managed futures (MF), multi-strategy (MS), dedicated short bias (DSB), and global macro (GM). The number of observations for each index is 228. Correlations between each hedge fund index return and the Russell 3000 index return are reported in the last column.

3.2. Group analysis of the hedge funds

To explore the contagion effect of equity returns on the returns generated by each hedge fund style, we utilize the monthly returns reported by 10 different hedge fund style indices and the Russell 3000 index. Specifically, we treat the returns reported by the Credit Suisse hedge fund style index as the outcome variable and the returns reported by the Russell 3000 index as the predictor in the equation (1). We must assess whether the time series of equity and hedge fund style returns used in this study are stationary before being able to justify adopting the SEECM. We first test for unit roots in each return series based on the augmented Dickey–Fuller test (Dickey and Fuller 1979) to identify the stationary condition of the equity and hedge fund style return series. A series that does not have unit root problems is regarded as stationary. Our result shows that neither return series has a unit root at the 1% significance level, thereby satisfying the stationarity assumption. Given the stationary condition of the two return series, we can now continue to use the SEECM with our data.[9]

We estimate the SEECM at 5% increments, from the 5th to the 95th quantile, using quantile regression. The parameters in the regression estimate the change in a specified quantile of the response variable produced by a one-unit change in the predictor variable. This approach allows us to compare whether the relationship between a predictor variable and a given quantile of the response variable is more or less pronounced than an analogous relationship involving a different quantile. Figure 1 plots the estimated coefficients in equation (1) across the entire range of quantiles of the returns of the 10 hedge fund style indices. The plots of the three slope estimates in each box of Figure 1 help us understand the short-and long-term relationships and interdependence between each fund style and the equity market returns. The heavy dashed lines indicate the short-term effect of equity returns on hedge fund returns ($\widehat{\beta_0}$), the solid black lines indicate the long-term effect ($\hat{\gamma}$), and the other dotted lines show the interdependence ($\widehat{\beta_2}$)

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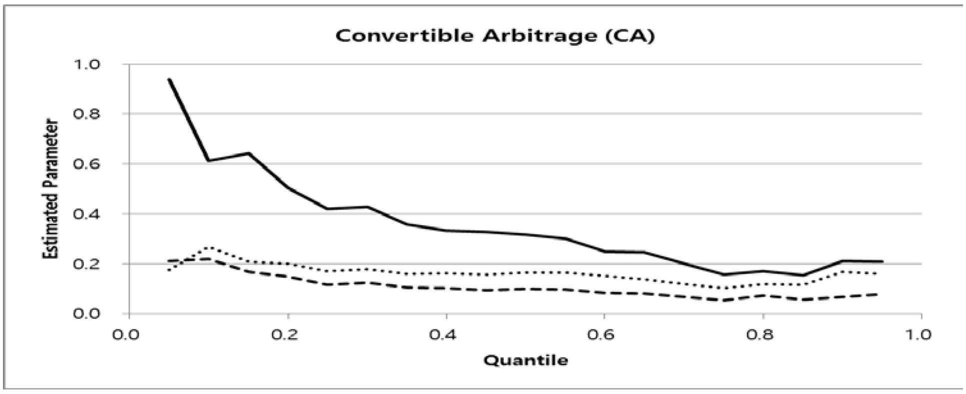
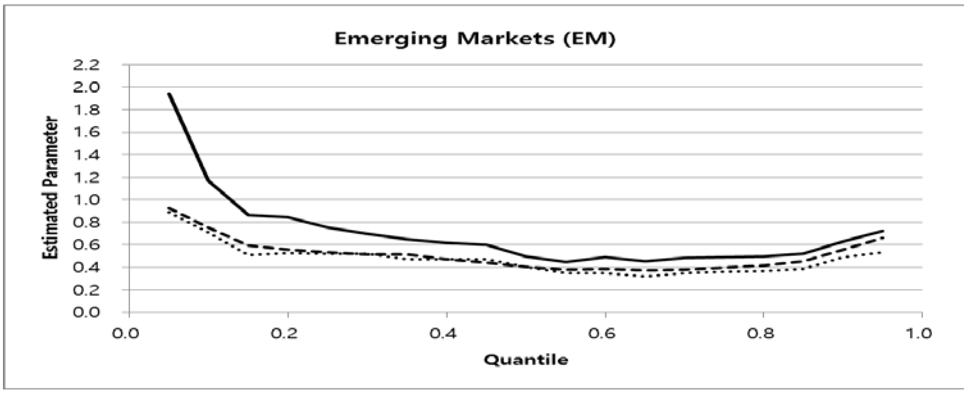
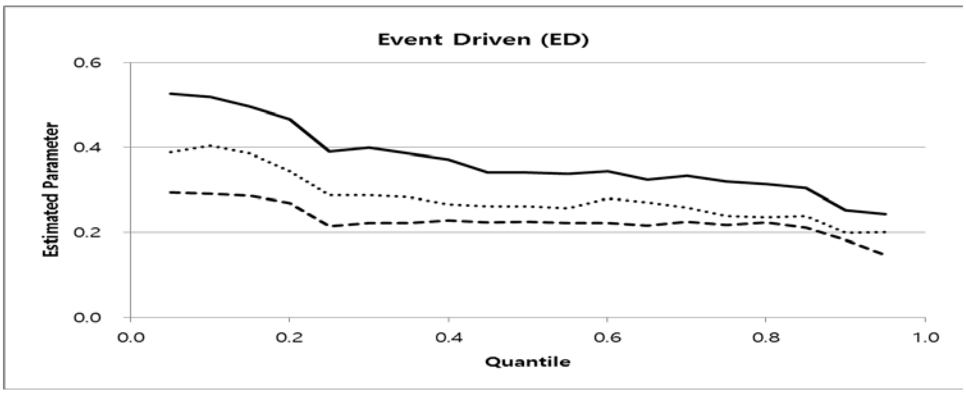
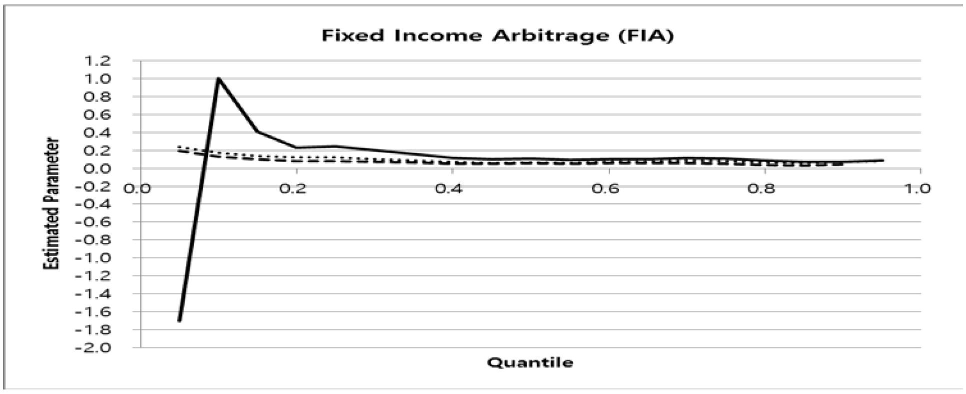
[9] We conduct the Granger causality test to identify the causal relationship between the two asset classes and to distinguish the independent and dependent variables. At the 5% significance level, the null hypothesis of no causality from equity returns to hedge fund style returns is rejected, while the null hypothesis of no causality from hedge fund style returns to equity returns cannot be rejected. These results imply that hedge fund style returns should be used as a dependent variable and equity returns should be used as an independent variable in the SEECM.

between hedge fund style and equity returns.








Fixed Income Arbitrage (FIA)
Estimated Parameter
Quantile
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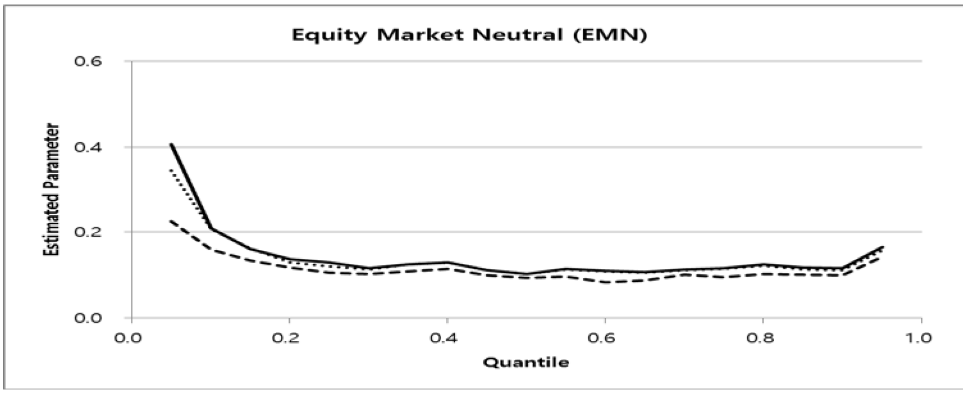
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
-1.4
-1.6
-1.8
-2.0
0.0
0.2
0.4
0.6
0.8
1.0


Equity Market Neutral (EMN)
Estimated Parameter
Quantile
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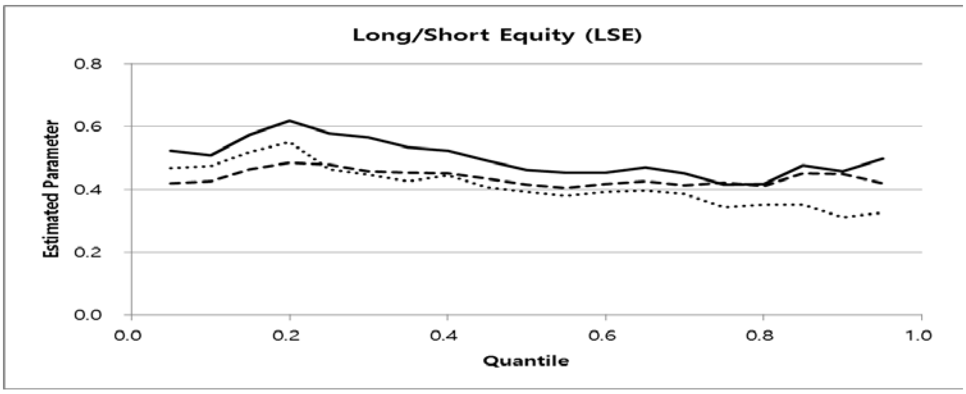
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Long/Short Equity (LSE)
Estimated Parameter
Quantile
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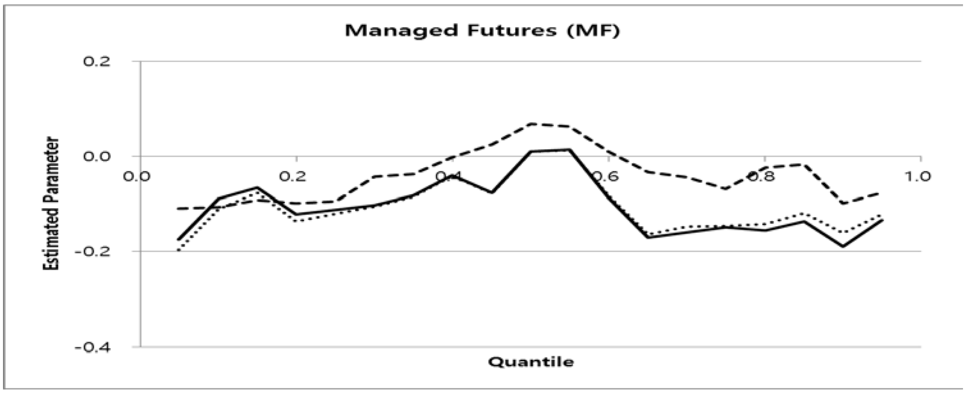
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Managed Futures (MF)
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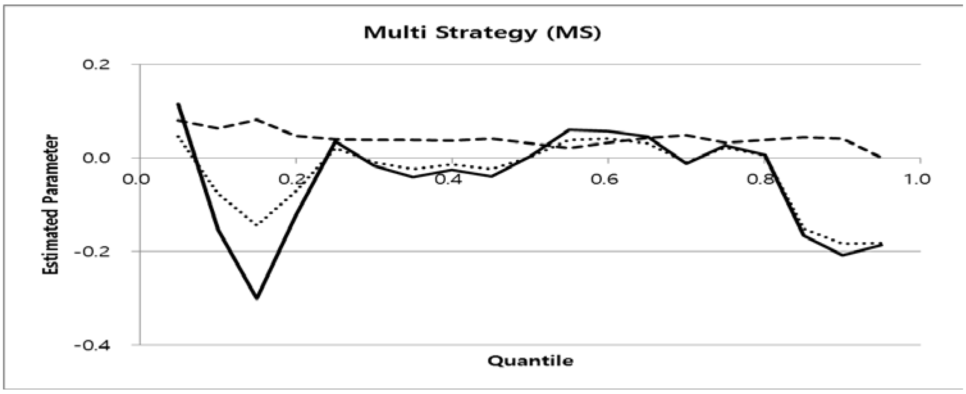
-0.4
0.0
0.2
0.4
0.6
0.8
1.0
Estimated Parameter
Quantile


Multi Strategy (MS)
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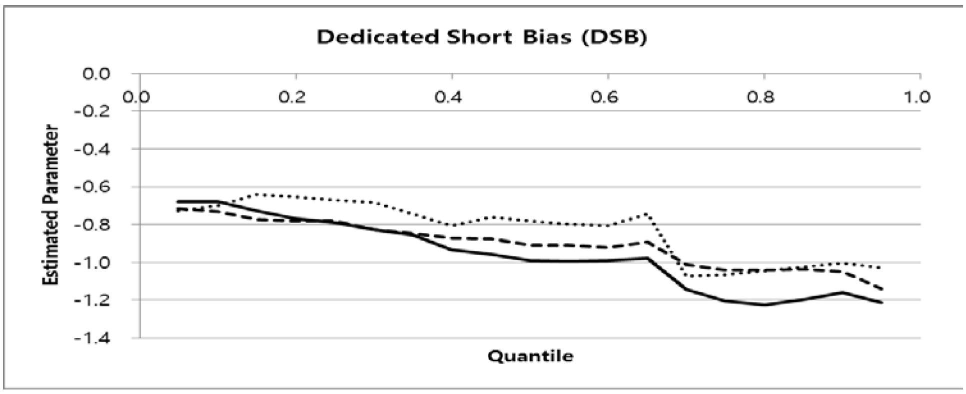
-0.4
0.0
0.2
0.4
0.6
0.8
1.0
Estimated Parameter
Quantile


Dedicated Short Bias (DSB)
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
-1.4
0.0
0.2
0.4
0.6
0.8
1.0
Estimated Parameter
Quantile

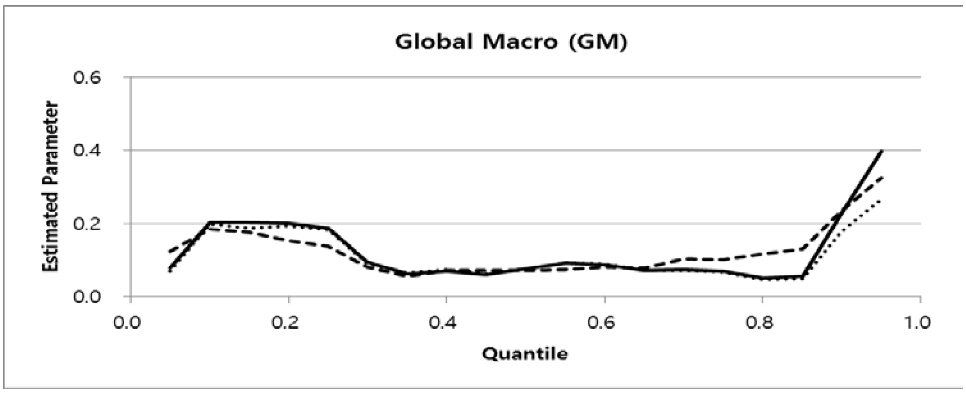


Figure 1 Estimated parameters of SEECM for 10 hedge fund style index returns by quantile.

The estimated parameters of short-term ($\widehat{\beta_0}$), long-term ($\hat{\gamma}$), and interdependence ($\widehat{\beta_2}$) in the SEECM through quantile regression are plotted across the entire range of quantiles. Each hedge fund style index return is used as the response variable and the Russell 3000 index return is used as the predictor. The SEECM is estimated at 5 % increments from the 5th to the 95th quantile. The heavy dashed line indicates the short-term effect of equity returns on hedge fund returns ($\widehat{\beta_0}$), the solid black line indicates the long-term effect ($\hat{\gamma}$), and the other dotted line shows interdependence ($\widehat{\beta_2}$) between hedge fund style and equity returns.

When examining the results for the short-term effects ($\widehat{\beta_0}$), long-term effects ($\hat{\gamma}$), and interdependence $(\widehat{\beta_2})$ for each hedge fund style in Figure 1, the effects of equity market returns on hedge fund index returns reveal three patterns. One group of hedge funds including CA, EM, ED, FIA, and EMN are found to be much more affected by the equity markets in crisis periods (low quantiles) than other periods. This pattern indicates that they are more sensitive to volatility changes in the equity market in a crisis period than in other periods. Considering that their common strategy is arbitraging market price variance, it is not surprising that they are quite sensitive to noticeable volatility increases due to crises. We call this group the "volatility group." Other hedge fund styles, including LSE, MF, and MS funds, show no particular pattern (i.e., the relationship between those funds and equity market returns fluctuate across the entire range of quantiles). This appears to be due to the fact that such funds seek diversified or pooled investment strategies including investing in future markets. We call this group the "pool group."

The final group of fund styles includes DSB and GM of which common strategy is forecasting market price direction. GM funds appear to be more sensitive to equity markets during prosperity periods (high quantiles) than in other periods. On the contrary, DSB funds are found to be more sensitive to equity markets during crisis periods (high quantiles) than in other periods[10]. We notice that the GM (DSB) funds achieve the highest (lowest) average monthly returns in Table 1. We call this group the "direction group."

Given the estimated parameters in the quantile regression, we assess whether the equity market exerts statistically significant short- and long-term breaks on hedge funds of different styles. We also test the interdependence break (contagion) between the equity market and the 10 hedge fund styles. Table 2 reports the Wald-Wolfowitz runs test statistics, with p-values in parenthesis, for short-term, long-term, and interdependence parameters by fund style. We also report the results of testing the null hypotheses H_0^{SB}, H_0^{LB}, and H_0^{IB} with a 1% significance level.

[10] High quantiles (low quantiles) for DSB is crisis (prosperity) periods for equity markets due to a negative correlation between DSB and equity market returns.

Table 2 Wald-Wolfowitz runs test for short- and long-term breaks and contagion by fund style

	Short-Term		Long-Term		Interdependence	
	T_n (p-value)	Test Result	T_n (p-value)	Test Result	T_n (p-value)	Test Result
CA_v	-3.7002 (0.0002)	SB	-3.7408 (0.0002)	LB	-1.8816 (0.0599)	NIB
EM_v	-3.3022 (0.0010)	SB	-3.1488 (0.0016)	LB	-3.279693 (0.0010)	C
ED_v	-2.3959 (0.0166)	NSB	-3.7646 (0.0002)	LB	-3.7408 (0.0002)	C
FIA_v	-3.6346 (0.0003)	SB	-3.3309 (0.0009)	LB	-3.7002 (0.0002)	C
EMN_v	-2.0460 (0.0408)	NSB	-2.7940 (0.0052)	LB	-2.7940 (0.0052)	C
LSE_p	-2.3098 (0.0209)	NSB	-3.3022 (0.0010)	LB	-3.7646 (0.0002)	C
MF_p	-2.3552 (0.0185)	NSB	-2.3552 (0.0185)	NLB	-2.2123 (0.0270)	NIB
MS_p	-1.7028 (0.0886)	NSB	-2.5974 (0.0094)	LB	-2.5974 (0.0094)	C
DSB_d	-2.8287 (0.0047)	SB	-3.7757 (0.0002)	LB	-3.7002 (0.0001)	C
GM_d	-2.7218 (0.0065)	SB	-2.5974 (0.0094)	LB	-2.5974 (0.0094)	C

This table reports the Wald-Wolfowitz runs test statistics (T_N) with the corresponding p-values in parenthesis for short-term ($\widehat{\beta_0}$), long-term ($\hat{\gamma}$), and interdependence ($\widehat{\beta_2}$) parameters by fund style. The letters of test results of “SB,” “LB,” “NIB,” “NSB,” “NLB,” and “C” denote short-term break, long-term break, no interdependence break, no short-term break, no long-term break, and contagion, respectively. The significance level of these test results is at 1%. Additionally, each fund style is subscripted by one of three letters, v(volatility), p(pool), or d(direction) to denote its corresponding associated group.

As indicated in Table 2, the strength of short- and long-term effects and the contagion effect vary by fund strategy. From here on, each fund style is subscripted by their corresponding associated group letter, v (volatility), d (direction), or p (pool). We find that most strategies, except for CA_v and MF_p, exhibit interdependence breaks or long-term breaks with the US equity market. In the meantime, the corresponding p-values for the short-term parameters show that ED_v, EMN_v, LSE_p, MF_p, and MS_p maintain their short-term relation with the equity market across entire periods while the others suffer from short-term breaks. It is interesting to see that no strategies in pool group are subject to the short-term break. As shown by our analysis of the test results in the below, whether the short-term relation breaks or not provides useful information in analyzing each hedge fund strategy. It turns out that (i) no short-term break (or NSB) with the equity market returns tends to yield a good performance or a robust relation of hedge funds with the equity market, and (ii) short-term break (SB) with the equity market returns in a quite different manner could yield consistent profits by recovering its independence from the equity market.

The CA_v funds are worthy of further analysis because their short- and long-term breaks from the equity market are most pronounced in terms of p-value but are not affected by contagion. CA_v fund managers typically build long positions in convertible bonds and other equity hybrid securities and then hedge the equity component of the long bond positions by shorting the underlying stocks. As the price of convertible bonds is directly connected to the price of the underlying stock, the combined position of convertible bonds and stocks are sensitive to the equity market. In the 1987 stock market crash (not included in our sample periods) many convertible bonds declined more than their underlying stocks, apparently for liquidity reasons, with the market for the stocks being much more liquid than the relatively small market for the bonds. This liquidity problem is believed to be behind the strong long-term and short-term breaks of CA_v. On the other end of the spectrum, when a stock declines (rises), the associated convertible bond will decline (rise) less, because it is protected by its value as a fixed-income instrument; meaning, it pays interest periodically. This explains the observed robustness of CA_v funds against contagion.

The EM_v funds typically invest in stocks, bonds, currencies, and other instruments of emerging markets, and arbitrage the inefficient market mechanism. The graph for EM_v in Figure 1 indicates that the estimated values of $|\beta_0|$, $|\gamma|$, and $|\beta_2|$ are much larger than for the other fund styles. This is explained by the fact that emerging markets have essentially much larger variations than the US equity market. As is well known, the estimated coefficients are basically the ratio of response variations (EM_v) to predictor variations (the US equity market). In this context, it is not surprising that EM_v funds are found to have all types of breaks (strong short- and long-term breaks and contagion), particularly in crisis periods (low quantiles).

The ED_v funds seek to profit from securities mispricing related to corporate directional events including mergers, acquisitions, restructuring, bankruptcies, reorganizations, and revelations of bad news about a particular company. These events can result in the short-term mispricing of a company's stock. If fund managers feel positive about the event and the strength of the company, they may buy shares to sell later when the price adjusts. Test results for ED_v funds in Table 2 show that the funds experience long-term breaks and contagion effects from the equity market, but no short-term breaks. Their skillfulness in handling the short-term effect is not surprising since the impact of corporate directional events on the markets are inherently of a short-term character. Note that ED_v reports a relatively high average monthly return from Table 1.

In the graph for the FIA_v funds in Figure 1, we see a negative value of long-term effects (γ) and a positive value of interdependence (β_2) at low quantiles. This implies a positive value of speed of return to equilibrium (β_1) at low quantiles because $\beta_2 = -\gamma\beta_1$. Hence, FIA_v funds suffer from divergence or deviations from equilibrium at low quantiles. The anomaly of the FIA_v graph at low quantiles might be explained by behavioral biases of some managers during the collapse of FIA_v funds in 1998 such as LTCM. FIA_v fund managers typically invest in fixed income securities and generate profits by exploiting inefficiencies and price anomalies in those securities. To neutralize interest rate risk, FIA_v managers tend to bet on credit spread and yield curves. In 1998, the credit spread increased to a record level and caused massive dislocation in fixed-income and credit markets due to the default of the Russian government debt. FIA_v managers who purchased cheaper bonds and shorted more expensive ones could have made extraordinary profits by maintaining their spread positions to maturity. However, many FIA_v managers made the decision to unwind their spread positions for safety as the gap between the long and short side grew larger during that period and they would have been required to restore additional margin or liquidate their positions. The desire for liquidity and safety by some managers overwhelmed the other managers who attempted to arbitrage such preferences, causing those arbitrage relations and equilibrium with the equity market to break down in 1998 (low quantiles). Test results for FIA_v funds in Table 2 show that the funds experienced strong short- and long-term breaks and contagion, mainly attributable to such behavioral biases, a critical weakness of FIA_v.

Both the EMN_v and LSE_p funds adopt long and short positions in the equity markets to minimize their exposure to equity market movement, but their ultimate strategies are not the same. The EMN_v funds seek to exploit differences in stock prices by holding a long and short position in stocks within the same sector or industry, whereas LSE_p funds frequently use stocks in different sectors or industries for their long and short positions. In general, EMN_v can be considered as the limiting case of LSE_p. This difference produces different patterns of coefficient lines in Figure 1 and enables us to separate the two fund styles into two different groups, (i.e., the volatility group and the pool group). The EMN_v funds are much more affected by the equity market in crisis period, whereas the LSE_p funds are affected by the equity market across the entire range of quantiles, but not more significantly in crisis period. The two styles are not found to suffer from short-term breaks but from long-term breaks and contagion. Such robust short-term relations of the two funds respectively produce desirable aspects. After examining the p-values of all parameters for the EMN_v and LSE_p funds in Table 2, we find that on the average, p-values for EMN_v are larger than for LSE_p. This implies that the EMN_v funds' relation with the equity market is more robust than that of the LSE_p funds. It is well known that EMN_v occupies a distinct place in the hedge fund landscape by exhibiting one of the lowest correlations with other alternative strategies. For the LSE_p funds, one may note from Table 1 that LSE_p funds report relatively high average monthly return.

The MF_p funds are the only fund style that has no short- or long-term break, and no contagion from the equity market. The graph for MF_p in Figure 1 shows that the short- and long-term and interdependence parameters are negative in most of the quantiles, except for between the 40^{th} and 60^{th} quantiles. All parameters are similar across all quantiles, confirming that volatility change in the equity market (regardless of whether the market is up or down) does not significantly affect the short- and long-term relationship and interdependence between the MF_p funds and equity market returns. This result is likely attributable to the fact that MF_p fund managers typically bet on trends in global futures markets, such as bonds, equities, currencies, and commodities, and this strategy mitigates portfolio risk in a way that is not possible in direct equity investments. Additionally, Table 1 shows that MF_p has the lowest correlation in terms of magnitude with the equity market returns. The MF_p funds demonstrate that indirect investment strategy is an effective way for keeping robust relation with equity markets.

MS_p managers seek diversification by simultaneously employing various hedge fund strategies intended to reduce exposure to overall market movements. By allocating capital based on perceived opportunities among several hedge fund strategies, MS_p managers attempt to generate positive returns regardless of the directional movement in the equity market. The added diversification benefits may reduce single-strategy risk and the volatility of the portfolios. The graph for MS_p in Figure 1 shows that MS_p returns maintain positive short-term coefficients across the entire range of quantiles, whereas the long-term coefficients between MS_p and the equity market returns fluctuate within a reasonable limit across the quantiles. As shown in Table 2, the MS_p funds keep 'the most robust short-term relation' with equity market returns in terms of p-value. As a result, in Table 1, we see that MS_p funds have the lowest standard deviation of monthly returns and the highest minimum monthly return.

The DSB_d returns are negatively correlated with equity market returns due to the DSB_d funds' intended directional trading strategy (refer to Table 1), which entails taking a net short position in the market. In other words, DSB_d funds typically take more short positions than long positions and earn returns when the equity market declines. Therefore, all parameters of short- and long-term effects and interdependence in equation (1) for DSB_d show negative values as indicated in the graph in Figure 1. The results in Table 2 show that the DSB_d funds suffer from strong short- and long-term breaks and contagion from the equity market. Interestingly, we find that unlike the other strategies, the estimated values of $|\beta_0|$, $|\gamma|$, and $|\beta_2|$ for DSB_d in high quantiles are higher than those in low quantiles. This is resulted from the fact that high quantiles (low quantiles) for DSB_d is assumed to be crisis (prosperity) periods for equity markets due to a negative correlation between DSB_d and equity market returns. Therefore, DSB_d funds are more likely to be affected by volatility change in periods of crisis (high quantiles). It is interesting to note from Table 1 that DSB_d funds generate the highest maximum monthly return while they also show the lowest average monthly return.

The GM_d fund managers place directional bets on the prices of the underlying assets (i.e., stocks, bonds, commodities, currencies, and derivatives) and their judgments regarding these activities are key to their investment decisions. Table 1 indicates that the GM_d funds generate the highest average monthly return and quite a low correlation with the equity market. The graph for GM_d in Figure 1 and Table 2 together indicate that it suffers from the short- and long-term breaks and contagion particularly at high quantiles (prosperity periods). It is interesting to see from Figure 1 that at low quantiles, the coefficients of GM_d funds decrease while those of other styles generally increase and result in short-or long-term breaks or contagion. In other words, the short- and long-term breaks and contagion for GM_d funds occur in a quite different manner, which appears to make them independent of the equity market. These results strongly suggest that directional forecasting strategy by GM_d funds could yield consistent profits by recovering their independence from the equity market.

3.3. Fund-wise analysis of break points

In Table 3 we report the low- and high-percentile break points for short-term, long-term, and interdependence parameters by fund style.

Table 3 Percentile break points by fund styles

	Short-Term		Long-Term		Interdependence	
	Percentile Break Point		Percentile Break Point		Percentile Break Point	
	Low	High	Low	High	Low	High
CA_v	15th	85th	30th	70th	NIB	
EM_v	10th	90th	30th	70th	35th	65th
ED_v	NSB		30th	70th	20th	80th
FIA_v	15th	85th	25th	75th	20th	80th
EMN_v	NSB		10th	90th	15th	85th
LSE_p	NSB		30th	70th	35th	65th
MF_p	NSB		NLB		NIB	
MS_p	NSB		10th	90th	15th	85th
DSB_d	15th	85th	30th	70th	30th	70th
GM_d	20th	80th	15th	85th	20th	80th

This table reports low- and high-percentile break points for short-term ($\widehat{\beta_0}$), long-term ($\hat{\gamma}$) and interdependence ($\widehat{\beta_2}$) parameters by fund style. The test results notations "NSB," "NLB," and "NIB," denote no short-term break, no long-term break, and no interdependence break, respectively. The significance level of these test results is at 1%.

The high- and low-percentile break points for each hedge fund style provide investors with a wealth of useful information. Using the data, investors can decide whether a hedge fund is prone to contagion from an equity market during a given time period (by checking its quantile). For instance, the 15^{th} and 85^{th} percentiles represent the short-term low and high break points, respectively, for a fund defined by a CA_v strategy. This implies that the equity market has a short-term break effect on a hedge fund using a CA_v strategy, if the percentile of the hedge fund return is less than the 15^{th} or greater than the 85^{th} percentile. The GM_d funds that show low- and high-percentile short-term break points in the 20^{th} and 80^{th} quantiles, respectively, are more prone to short-term breaks than other funds in the sense that the low (high) percentile break points of those funds are higher (lower) than other funds. In contrast, the EMN_v and MS_p funds that show low- and high-percentile long-term break points of the 10^{th} and 90^{th} quantiles, respectively, are less prone to long-term breaks relative to the other funds in the sense that the low (high) percentile break points of those funds are lower (higher) than in the other funds. Concerning the interdependence parameter, the EM_v and LSE_p funds show low- and high-percentile interdependence break points of the 35^{th} and 65^{th} quantiles, respectively. These results imply that they are more likely to see contagion from the equity market than the other fund styles. Again, EMN_v and MS_p funds that show low- and high-percentile interdependence break points of the 15^{th} and 85^{th} quantiles, respectively, are less prone to contagion from the equity markets than the other styles. Introducing the break point helps investors understand whether one hedge fund index is more attractive than another in their investment horizon.

In sum, the results of contagion status and degree for each fund style can help to illuminate the relative effectiveness of a particular hedge fund strategy under certain market conditions. For example, for strategic asset allocation, a risk-averse and short-term investor should select hedge funds that exhibit no break in the short-term relation with the equity market (e.g., ED_v or MS_p). In contrast, a long-term investor should select hedge funds that show no break in the long-term relation with the equity market or no contagion from the equity market (e.g., MF_p). If the investor is keenly interested in making a large profit, then he might choose one from the direction group, DSB_d or GM_d.

4. Conclusions

In this paper, we classify hedge fund styles into three groups based on the patterns of the equity market effects on hedge fund styles: the volatility group, the direction group, and the pool group. Funds classified in the same group have common strategic intent and show similar behavior. Arbitraging is the central strategy for the volatility group, forecasting is the central strategy for the direction group, and pooling diversification is the central strategy for pool group. Arbitrage is the most popular strategy among hedge funds achieving large profits, but this appears to be severely affected by the equity market during crisis periods due to a lack of liquidity (e.g., FIA_v or CA_v). These analyses are closely related to those addressed by Boyson et al. (2010) and Viebig and Poddig (2010). Boyson et al. (2010) demonstrate that a liquidity shock in equity market has a significant impact on hedge fund flows and Viebig and Poddig (2010) show significant volatility spillover effects from equity markets to hedge fund styles that adopt arbitrage strategy (e.g., convertible arbitrage, merger arbitrage, relative value arbitrage) during periods of extreme stress in equity markets. Directional forecasting appears to be a good alternative for making good profits but at the cost of unstable relation with the equity markets (e.g. DSB_d or GM_d). Pooling diversification appears to yield relatively stable and robust outputs across entire periods (e.g., MF_p.) Recall that one of useful findings of our result is the importance of the short-term behavior in analyzing various hedge fund styles.

It is interesting to see that our results might provide basic answers to the long-standing question of whether it is possible to reap consistent profits by hedging against the equity markets (or the efficient market hypothesis, EMH). If we think that a hedge fund style should be rather independent of the equity market to make consistent profits, then our study suggests that perhaps GM_d is a close answer because its correlation to the equity market is very low and it suffers from all types of breaks from the equity market to be independent. Recall that GM_d reports the highest profit. If we think a hedge fund style should maintain its intended original relation with the equity market to make steady profits, then we might see such a strategy (i.e., MF_p is subject to neither short- and long-term breaks nor contagion). Thus, our results advise that though it is hard to "beat the market", there are some possibilities for making consistent profits. i.e., trying to achieve independence or maintain a robust relation with the equity markets. Certainly more research based on our contagion approach would be desirable to resolve the controversy between believers and non-believers in the EMH. This can be done in future work.

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