The contagion versus interdependence controversy between hedge funds and equity markets

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Abstract

This study considers the ‘contagion versus interdependence’ controversy between hedge funds and equity markets. We find that contagion effects break down the established interdependence between hedge funds and equity markets and that conditional return smoothing (the tendency of hedge funds to underreport losses than gains) is a driving factor of these contagion effects during crisis. These findings are obtained by linking the single equation error correction model to the factor model and then by carrying out quantile regression and the Wald–Wolfowitz runs test.

Keywords: *Hedge funds; Contagion; Interdependence; Conditional return smoothing, Single equation error correction model; Factor model*

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1. Introduction

In a simple mean-variance framework, because hedge funds are not strongly correlated with equity markets, investors have used such funds to minimize risk in a diversified portfolio. However, in the wake of the global financial crisis that substantially affected the markets between 2007 and 2009, investors, regulators, and the financial press began to express concerns about particular hedge fund bankruptcies and criticize the hedge fund industry in general. Subsequently, researchers started to explore whether hedge funds had experienced contagion from representative markets and within hedge fund styles during the crisis. Unsurprisingly, these studies generated different results from those presented by pre-crisis research. For example, whereas Boyson *et al*. (2006) and Li and Kazemi (2007) provide no evidence of contagion between equity markets and hedge funds (i.e., before the global financial crisis), Viebig and Poddig (2010) produce empirical evidence that a strong contagion effect exists from equity markets to several hedge funds during periods of extreme stress in financial markets. These conflicting results on hedge funds and equity markets have led us to investigate the so-called 'contagion versus interdependence' controversy. This controversy is in fact closely related to the controversy introduced by Forbes and Rigobon (2002) for international equity markets. Forbes and Rigobon (2002) defined contagion as conditional correlation on crisis while defined interdependence as unconditional correlation formed between international equity markets. In a similar spirit, for contagion between equity markets and hedge funds, Boyson *et al.* (2010) defined contagion as correlation over and above that expected from economic fundamentals and measure it by clustering the bottom 10% of hedge fund returns across all hedge fund styles. Note that by clustering the bottom 10% of hedge fund returns Boyson *et al.* (2010) explicitly focused conditional correlation on crisis for contagion, while implicitly referred interdependence to unconditional correlation in the underlying fundamentals.

Essentially, the contagion versus interdependence controversy for international equity markets imposes two empirically intriguing questions regarding excessive correlations across markets during crisis periods: Does excessive correlation exceed that in the underlying fundamentals across markets (or is the contagion effect identified by a breakdown of the established interdependence between the two markets)? and Is this excessive correlation driven by strategic complementarities between markets? In this study, we consider similar questions regarding contagion between hedge funds and equity markets. More precisely, we consider two specific questions during periods of both economic crisis and economic prosperity: Is the contagion effect identified by a breakdown of the established interdependence between hedge funds and equity markets? and Is this breakdown driven by strategic complementarities in hedge fund markets?

Our investigations into these questions lead to the major findings of this paper: the established interdependence between hedge funds and equity markets suffers from breakdowns or contagions during crisis as well as prosperity periods and the breakdowns or the contagions during crisis are primarily driven by conditional return smoothing (i.e., the tendency of hedge funds to underreport losses than gains). Conditional return smoothing is a well-known and widespread strategic complementarity among hedge funds (Bollen and Pool, 2008).

To investigate the two questions set above, we propose linking the single equation error correction model (SEECM) with latent factor model, and then implementing quantile regression and the Wald–Wolfowitz runs test, which not only significantly simplifies the technical issues of the problem, but also makes it possible to handle various crisis scenarios. The SEECM is used to handle contagion dynamics as well as interdependence simultaneously. Instead of intuitively defining interdependence as correlation in the underlying fundamentals as done by Boyson *et al.* (2010), the SEECM defines it econometrically as the correlation adjusted by the corresponding market volatilities. Recall that the usual correlation calculation is subject to the bias due to increased volatility and is to be adjusted particularly during crisis periods (see Forbes and Rigobon, 2002; Corsetti *et al.*, 2005 for related discussions). Methodologically, the coefficients in the SEECM estimate the short-term and long-term correlations between markets as well as their interdependence separately and simultaneously. The latent factor model is linked to the SEECM because it handles various crisis scenarios effectively by presuming the existence of an underlying common factor between two markets. The quantile regression and the Wald-Wolfowitz runs test is carried out to find the significant correlation changes due to heteroscedasticity. In short, our model is constructed by linking SEECM and factor model and then estimated and tested by quantile regression and the Wald-Wolfowitz runs test. By running our model during periods of economic crisis as well as economic prosperity, we find sufficient support for our major findings.

We organize this paper into the following sections. Section 2 discusses our methodology and its technically advanced features. This discussion contains econometric definitions of interdependence and contagion and describes our procedures for testing for contagion. Section 3 discusses data and summary statistics and reports the results of empirical tests. Section 4 offers concluding remarks and suggestions for future research.

2. Methodology

2.1 *Contagion Modeling*

To explicitly describe the dynamics of contagion effects from the equity markets to hedge funds and handle various contagion scenarios, we link SEECM to factor model. Let Y_t represent the return series of hedge fund index and X_t represent the return series of equity market index. We use the SEECM as follows:

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

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

where $\gamma = -\frac{\beta_2}{\beta_1}$, $\Delta Y_t \equiv Y_t - Y_{t-1}$, and $\Delta X_t \equiv X_t - X_{t-1}$ and ε_t is a stationary error. It is assumed here that Y_t and X_t are stationary. The part of the equation in parentheses in SEECM (1) is the error correction mechanism, where $(Y_{t-1} - \gamma X_{t-1}) = 0$ when X and Y are in equilibrium. The coefficient β_0 specifies the short-term effects of an increase in X on an increase in Y, while β_1 specifies the speed at which X and Y return to equilibrium from a state of disequilibrium. The coefficient γ specifies the long-term effects of a one-unit increase in X on Y. These long-term effects are distributed over future periods according to the error correction rate β_1. Note that when $\beta_1 < 0$ $(\beta_1 > 0)$, the system converges to equilibrium (diverges from equilibrium). This model allows us to indicate whether market Y is affected by market X during a given period by testing the changes in β_0 (short-term effects), β_1 (speed), and γ (long-term effects). Because β_1 represents the speed of return to equilibrium (and is therefore the scaled inverse of volatility) and $\beta_2 = -\gamma\beta_1$, one can treat β_2 as the long-term relationship adjusted by the volatility of markets X (or Y). In this study, because we define interdependence econometrically as the correlation adjusted by the corresponding market volatilities, we treat β_2 as the interdependence between markets X and Y.

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 fact, SEECMs and autoregressive distributive lag (ADL) models are equivalent since we can derive an SEECM from a general ADL model that is appropriate for stationary data[1]. In other words, an SEECM is applicable for long- and short-term effects of independent variables on a dependent variable even when the data are stationary. 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 technique for stationary data than alternative approaches. (see Durr, 1992 for details).

In the next step, we link the SEECM (1) with typical contagion models based on factor models. According to Dungey *et al.* (2005), most contagion models can be described by using the following factor models. For simplicity, we assume that two returns of assets are modeled as

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[1] From a general ADL model $Y_t = \alpha + \beta_0 Y_{t-1} + \beta_1 X_t + \beta_2 X_{t-1} + \varepsilon_t$, we derive the SEECM as follows: $\Delta Y_t = \alpha + (\beta_0 - 1)Y_{t-1} + \beta_1 \Delta X_t + (\beta_1 + \beta_2)X_{t-1} + \varepsilon_t$, $\Delta Y_t = \alpha + \beta_1 \Delta X_t + \pi_0 Y_{t-1} + \pi_1 X_{t-1} + \varepsilon_t$, $\Delta Y_t = \alpha + \beta_1 \Delta X_t + \pi_0 (Y_{t-1} + \frac{\pi_1}{\pi_0} X_{t-1}) + \varepsilon_t$, where $\pi_0 = \beta_0 - 1, \pi_1 = \beta_1 + \beta_2$.

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

where W_t represents a common shock that affects all asset returns with the loadings θ_x and θ_y. For simplicity, W_t is assumed to be a latent stochastic process with zero mean and unit variance; that is,

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

In equation (2), $u_{x,t}$ and $u_{y,t}$ 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 common factor 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:

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

Note that the common factor W_t in latent factor model (2) can be assumed to be traders participating in two independent risky assets or financial institutions subject to regulatory solvency constraints that mark their assets to market.

Now, we connect the factor model (2) with the SEECM (1). One may easily derive the following from model (2):[2]

$$\Delta Y_t = \frac{\theta_y}{\theta_x}\Delta X_t - \left(Y_{t-1} - \frac{\theta_y}{\theta_x}X_{t-1}\right) - \frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y u_{y,t}. \tag{7}$$

If we employ an AR(1) model for idiosyncratic shocks that occur in hedge funds as

$$u_{y,t} = \rho u_{y,t-1} + a_{u,t}, \tag{8}$$

where $\mathrm{E}\left(a_{u,t}W_t\right) = 0$, $\mathrm{E}\left(a_{u,t}u_{y,t}\right) = 0$, and $a_{u,t} \sim iid(0,1)$, we have an SEECM derived from the common latent factor model (2),

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

where $\varepsilon_t = -\frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y a_{u,t} - \rho\theta_y W_{t-1}$.[3] Since ε_t in SEECM (9) includes the lagged common factor W_{t-1}, it is an innovation correlated with the explanatory variables unless $\rho = 0$. Noting that

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

$\mathrm{Var}(\varepsilon_t)$ depends on volatility of X and Y via δ_x and δ_y and dynamics of idiosyncratic factors of hedge funds via ρ. Dependence structure imposed by (8) is necessary because hedge fund return certainly progresses dynamically over time.

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[2] Appendix A.1 shows the derivation of equation (7).
[3] Appendix A.2 shows the derivation of equation (9).

By comparing this SEECM (9) with the SEECM (1), it is straightforward to observe that $\beta_0 = \frac{\theta_y}{\theta_x}$, $\beta_1 = \rho - 1$, $\gamma = \frac{\theta_y}{\theta_x(1-\rho)}$, and $\alpha = 0$.[4] Further, if $\rho = 0$, then $\beta_1 = -1$ and, in this case, there is no difference between the underlying interdependence $\beta_2 = -\gamma\beta_1$ and long-term coefficient γ (i.e. $\beta_2 = \gamma$). The fact of $\beta_1 = -1$ implies no significant volatility effects on the underlying interdependence or no interdependence break (no contagion) between markets X and Y. Moreover, $\rho = 0$ produces an iid error $\varepsilon_t = -\frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y a_{u,t}$ with $E(\varepsilon_t) = 0$ and a finite variance of $\mathrm{Var}(\varepsilon_t) = (\frac{\theta_y}{\theta_x}\delta_x)^2 + \delta_y^2$. This discussion implies that $\rho = 0$ produces an iid ε_t as well as no contagion, and hence an iid error check for SEECM (1) or SEECM (9) with $\rho = 0$ would be sufficient for testing no contagion (no interdependence break) between X and Y. In addition, $\mathrm{Var}(\varepsilon_t) = (\frac{\theta_y}{\theta_x}\delta_x)^2 + \delta_y^2$ is subject to heteroscedasticity because it depends on θ_x and θ_y which are likely to be context-dependent.

A major strength of the SEECM (9) linked to factor model lies in its ability to contain more general market contagion episodes through ε_t. This strength primarily results from the fact that SEECM (9) can address various dynamic errors that may cause heteroscedasticity. Because we are predominantly concerned with testing contagion effects due to volatility changes depending on the market conditions, SEECM (9) is well equipped to address any inherent heteroscedasticity. For instance, spillovers often referred as lagged effects from hedge funds to stocks and vice versa might be also suited to SEECM (9) through imposing a proper dynamic structure on ε_t.

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

2.2 *Contagion Testing*

To test contagion and interdependence defined in terms of SEECM, we first apply quantile regression to the SEECM (1) by using Y to represent hedge fund index returns and X to represent equity index returns in order to obtain N quantile slope estimates. The next step is to test the contagion and interdependence effects on the quantile regression parameters across the entire range of quantiles. Quantile regression is applied here primarily because it is an effective tool for testing regression coefficient change due to the heteroscedasticity of the error term in SEECM (1). Refer to Baur (2013) for more detailed discussions about advantages of using quantile regression. Our test is based on the idea that a random fluctuation of the slope estimates around a constant value (with only the intercept parameters systematically increasing as a function of quantile ϑ) provides evidence for the iid error hypothesis of the classical linear regression and hence for SEECM (1). 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. The simplest example of this kind of heteroscedasticity is intrinsic to what we call the linear location-scale model,

$$y_i = x'\beta + (x'\gamma)u_i \tag{10}$$

with $\{u_i\}$ iid from the distribution *F*. In this case, the coefficient associated with the ϑth quantile regression, $\hat{\beta}(\vartheta)$, converges to $\beta + \gamma F^{-1}(\vartheta)$. Therefore, all parameters would be governed by the quantile function of the errors $F^{-1}(\vartheta)$ and share the same monotone behavior in ϑ (Koenker 2005, p. 17). Equations (9) and (10) share some similarities because ε_t in (9) contains various terms related to the explanatory variables, particularly when $\rho \neq 0$. The above discussions lead to the following hypotheses:

H_0: The errors in SEECM (1) are iid (i.e., there are no contagion effects between hedge funds and equity markets).

H_a: The errors in SEECM (1) are not iid (i.e., there are contagion effects between hedge funds and equity markets).

To test these hypotheses, the *Z*-test and Wald–Wolfowitz runs test are performed. Let $Y_{i,N}$ be $(\hat{\varphi}_{i1}, \cdots, \hat{\varphi}_{iN})$, where $\hat{\varphi}_{ij}(i = 1,2,3,4, \ \ j = 1,..,N)$ is the *i*th slope estimate for one of the four slope estimates $(\widehat{\beta_0}, \ \widehat{\beta_1}, \ \widehat{\beta_2}, \ \hat{\gamma})$ from the ${}^{j}/_{N+1}$th quantile regression. Let $Y_{i,-1,-1}$ represent a sample constructed by excluding one element from both ends of $Y_{\mathrm{i,N}}$. The *Z*-test then calculates:

$$\frac{\hat{\varphi}_{i1} - m}{s} \quad \text{and} \quad \frac{\hat{\varphi}_{iN} - m}{s} \tag{11}$$

with sample mean m and sample standard deviation s from $\left(Y_{i,-1,-1}\right)$ and tests the following null and alternative hypotheses:

H_{0Z}: $\hat{\varphi}_{i1}$ and $\hat{\varphi}_{iN}$ originate from the same normal distribution as the others under H_0.

H_{aZ}: $\hat{\varphi}_{i1}$ and $\hat{\varphi}_{iN}$ do not originate from the same normal distribution as the others under H_a.

The Z-test is useful based on the asymptotic normality results of the slope estimates from quantile regression (see Koenker, 2005).

Because the quantile regression slope estimates behave randomly around their mean under a simple linear regression model hypothesis of iid error, the Wald–Wolfowitz runs test can also be used to test contagion through the randomness of the estimated residuals of the interdependence effects ($\widehat{\beta_2}$) across N quantiles. Here, the residuals are expressed as

$$(\hat{\varphi}_{i1} - \overline{\varphi_i}, \cdots, \hat{\varphi}_{iN} - \overline{\varphi_i}), \tag{12}$$

where $\overline{\varphi_i}$ is the sample average of the corresponding coefficients. Note that under the null and alternative hypothesis

$\mathrm{H_{0W}}$: The residuals given by (12) are iid under $\mathrm{H_0}$.

$\mathrm{H_{aW}}$: The residuals given by (12) are not iid 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 –. Given $\mathrm{H_{0W}}$, the number of runs in a sequence of N elements that contains + or - 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 $\mathrm{N} = N_+ + N_-$. By rejecting the null hypothesis $\mathrm{H_{0Z}}$ or $\mathrm{H_{0W}}$ that incorporates the slope estimate $\widehat{\beta_2}$, we can conclude that the errors in SEECM (1) and hence SEECM (9) are heteroscedastic and that contagion effects exist between hedge funds and equity markets due to the volatility changes depending on the market conditions. On the contrary, if we cannot reject the null hypothesis $\mathrm{H_{0Z}}$ or $\mathrm{H_{0W}}$ that incorporates the slope estimate $\widehat{\beta_2}$, we conclude that there is no contagion, only interdependence, between hedge funds and equity markets because we cannot detect excessive correlation adjusted by the corresponding market volatilities of hedge funds or equity markets.

To examine the heteroscedasticity and error dynamism involved, we employ the SEECM (1) connected with the factor model and hence SEECM (9), quantile regression, and Wald–Wolfowitz runs test to evaluate contagion effects precisely. Given the lack of a universally accepted definition of contagion, our approach provides one tool to focus on correlation and volatilities simultaneously in extreme and various states.

3. Empirical results

This section reports the results of our empirical tests that aim to resolve the contagion versus interdependence controversy and notes whether conditional return smoothing is the cause of the break down in interdependence between the two markets.

3.1 *Data*

There are several data sources for the information related to the hedge fund indices. In the present study, we use data from the Credit Suisse hedge fund index for January 1994 to December 2012,[5] because this index uses asset-weighted returns across funds belonging to a given hedge fund index. Other 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

[5] Index data are available from http://www.hedgeindex.com/hedgeindex.

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 (or interdependence).

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. The returns data for the Credit Suisse hedge fund index include 228 monthly observations during the sample period, which are incorporated as a response variable. We incorporate the same set of 228 monthly Russell 3000 index returns as a predictor. In fact, we calculate the monthly return of the Russell 3000 index to proxy for the returns of the U.S. equity market from January 1994 to December 2012.

Table 1 reports the summary statistics of the monthly returns and asset values of the Credit Suisse hedge fund and Russell 3000 indices. Table 1 indicates that the monthly average return for the Credit Suisse hedge fund index is higher than that of the Russell 3000 index and that equity market returns are more volatile than the returns of the Credit Suisse hedge fund index. Table 1 also shows that the standard deviation of the Russell 3000 Cap is more than twice the standard deviation of the Credit Suisse hedge fund NAV (net asset value). Note that both the returns and the NAV of the Credit Suisse hedge fund index are positively correlated with equity market value. Thus, in a mean-variance framework, investors are likely to invest in hedge funds to benefit from diversification regardless of the conditions in the equity market. Investors' apparent beliefs that the benefits of diversification are best secured by investing in hedge funds appears to be warranted because the equity market produces less substantial returns and is more volatile than the hedge fund market.

[Table 1 around here]

3.2 *Unit root tests*

We must assess whether the time series of equity and hedge fund 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 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.

3.3 *Contagion versus interdependence*

To explore the contagion effect of equity returns on overall hedge fund returns, we treat the returns reported by the Credit Suisse hedge fund index as the outcome variable and the returns reported by the Russell 3000 index as a predictor in SEECM (1) (and hence model (9))[6]. We estimate the SEECM at 5% increments from the 5th to the 95th quantiles by using quantile

[6] We conduct the Granger causality test to identify the causal relationship between the two asset classes and to distinguish the independent and dependent variables. The p-value for a test of the null hypothesis of no causality from equity returns to hedge fund returns is 0.07, while the p-value for a test of the null hypothesis of no causality from hedge fund returns to equity returns is 0.53. These results imply that hedge fund returns should be used as a dependent variable and equity returns should be used as an independent variable in the SEECM.

regression. Table 2 summarizes the coefficient estimates with the corresponding P-values in parentheses for each quantile of the Credit Suisse hedge fund index returns. The standard errors for the estimated parameters are computed by using the Markov chain marginal bootstrap resampling method, which is robust for data that are not iid. 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 across the entire range of quantiles.

Table 2 illustrates that all of the parameter or slope estimates for short-term effects ($\widehat{\beta_0}$), long-term effects ($\hat{\gamma}$), interdependence $\left(\widehat{\beta_2}\right)$, and speed of return to equilibrium ($\widehat{\beta_1}$) are significant (P < 0.01) across the entire range of quantiles except for $\widehat{\beta_1}$ at the 95$^{\text{th}}$ quantile. The plots of the four slope estimates in Figure 1 help explain the contagion effects between the two asset classes. First, as expected, equity returns have short- and long-term positive effects on hedge fund returns ($\widehat{\beta_0} > 0,\ \hat{\gamma} > 0$) and convergence to equilibrium ($\widehat{\beta_1} < 0$). The three curves that represent the short-term effects ($\widehat{\beta_0}$), long-term effects ($\hat{\gamma}$), and speed parameters ($\widehat{\beta_1}$) in Figure 1 are parabolic, indicating a slight increase in the short-term slope ($\widehat{\beta_0}$), a steep increase in the long-term slope ($\hat{\gamma}$), and a sharp decrease in the absolute values of the speed at which the system returns to equilibrium ($|\widehat{\beta_1}|$) at the upper- and lower-limit quantiles. The increased volatility of hedge fund returns (or decreased convergence speed equivalently) at the higher and lower quantiles significantly changes the short- and long-term slopes. Moreover, the parabolic shapes of these functions become steeper in the following order: short-term, long-term, and speed. This result may serve as an indicator that heteroscedasticity, if it is the source of the parabolic shapes, directly influences the order of speed, long-term slope, and short-term slope.

[Table 2 around here]
[Figure 1 around here]

When examining the dotted line of estimates for $\beta_2 = -\gamma\beta_1$in Figure 1, interdependence appears (or no contagion effect) because the slope estimates $\widehat{\beta_2}$ seem to behave randomly near their mean. To examine the contagion versus interdependence controversy, we thus perform the two-tailed *Z*-test to test $\mathrm{H_{0Z}}$ and the two-tailed Wald–Wolfowitz runs test to test $\mathrm{H_{0W}}$ on β_2 and γ as discussed in Section 2.2. Recall that β_2 represents interdependence that derives from the long-term relationship adjusted by the volatility of X (or Y). Comparing the test results on β_2 and γ helps explain the contagion versus interdependence controversy. Here, we fix $\mathrm{N} = 19$ and hence $Y_{i,19} = (\hat{\varphi}_{i1}, \cdots, \hat{\varphi}_{i19})$, where $\widehat{\varphi}_{ij}(i = 1,2 \quad j = 1,..,19)$ is the *i*th slope estimate for one of the two slope estimates ($\widehat{\beta_2}$ and $\hat{\gamma}$) from the ${}^{j}/_{20}$ th quantile regression. Table 3 reports the test results for the estimated coefficients for long-term effects ($\hat{\gamma}$) and interdependence ($\widehat{\beta_2}$).

[Table 3 around here]

As shown in Figure 1, the *Z*-test and Wald–Wolfowitz runs test reject $\mathrm{H_{0Z}}$ and $\mathrm{H_{0W}}$ for long-term effects ($\hat{\gamma}$) (P < 0.05), implying that the magnitude of long-term effects ($\hat{\gamma}$) differs significantly across the quantiles. However, the *Z*-test fails to reject $\mathrm{H_{0Z}}$ for the long-term effects adjusted by volatility ($\widehat{\beta_2}$) (P > 0.05), suggesting the existence of interdependence but not contagion between equity markets and hedge funds. This result indicates that contagion effects did not exist in the study period but that interdependence was observed between hedge funds and equity markets.

Conversely, the results of the Wald–Wolfowitz runs test presented in Table 3 suggest the presence of contagion based on $\widehat{\beta_2}$ (P < 0.05). This result indicates the possible breakdown of the established market interdependence between equity markets and hedge funds. Upon examination of the residuals produced by $\widehat{\beta_2}$, the rejection of the null hypothesis by the Wald–Wolfowitz runs test is not surprising. Indeed, a closer examination illustrates a clear positive autocorrelation among the residuals even though their magnitudes are small. As indicated in Table 2, the $\widehat{\beta_2}$ values demonstrate an explicit pattern across the entire range of quantiles. Specifically, those included in the below-median quantiles are greater than the sample average of the coefficient sequence[7] (marked + in the Wald–Wolfowitz runs test) and those included in above-median quantiles are less than the sample average (marked –). Therefore, the residuals produced by $\widehat{\beta_2}$ are not iid and this result indicates that contagion effects exist between hedge funds and equity markets. The different test results for $\widehat{\beta_2}$ between Z-test and Wald–Wolfowitz runs test show that the Wald–Wolfowitz runs test handles correlated errors effectively and detects non-randomness more accurately than the Z-test.

3.4 *Conditional return smoothing*

Bollen and Pool (2008) argue that "the structure of hedge fund incentive contracts and the competitive nature of the hedge fund industry provide more of an incentive to underreport losses

[7] The sample average of the coefficient sequence of $\widehat{\beta_2}$ is 0.3151.

than gains" (p. 269). So-called conditional return smoothing indicates that the proportion of the decrease in the return volatility of hedge funds in low quantiles is likely to exceed that in high quantiles. In other words, hedge fund managers tend to underreport losses more frequently than gains and this behavior results in a greater decrease in return volatility when they have losses (in low quantiles) than when they have gains (in high quantiles)[8]. Thus it is not surprising to note that the magnitudes of the estimated coefficients of long-term effects without adjustment ($\hat{\gamma}$) in the 95th quantile ($\widehat{\gamma_{0.95}}$ =0.6742) is greater than that in the 5th quantile ($\widehat{\gamma_{0.05}}$ =0.4952), as shown in Table 2. In other words, without adjusting the corresponding volatility suitably, the sensitivity of hedge funds to equity markets in the 5th quantile may be lower than that in the 95th quantile because hedge fund managers tend to underreport losses more frequently than gains. On the other hand, if the long-term coefficients are adjusted or scaled by the corresponding volatility, the estimated interdependence coefficients in low quantiles (when they have losses) tend to be greater than those in high quantiles (when they have gains) due to the greater decrease in return volatility in low quantiles than in high quantiles. Our results for the estimated interdependence coefficients ($\widehat{\beta_2}$) in Table 2 show this propensity. The magnitude of the estimated interdependence coefficients ($\widehat{\beta_2}$) in the 5th quantile ($\widehat{\beta_{2,0.05}}$ =0.3786) is greater than in the 95th quantile ($\widehat{\beta_{2,0.95}}$ =0.2620). The explicit patterns of $\widehat{\beta_2}$ and $\hat{\gamma}$ captured by the Wald–Wolfowitz runs test thus implies a breakdown of the established interdependence between hedge funds and equity markets.

[8] When one examines Figure 1, one may notice that the two curves that represent the long-term effects ($\hat{\gamma}$) and speed parameters ($\widehat{\beta_1}$) are parabolic but not symmetric, a steeper increase in the higher-limit quantiles than lower limit-quantiles. This is related to conditional return smoothing because, as a result of conditional return smoothing, hedge funds are less influenced by equity markets during crisis periods than prosperity periods.

In addition, the estimates provided in Table 2 show that a large deviation between the estimated interdependence coefficients ($\widehat{\beta_2}$) and long-term coefficients (γ) is observable for the 5th quantile (crisis period) and for the 95th quantile (prosperity period). According to the derivation of the SEECM (9), in the case of no autocorrelation in equation (8), i.e., $\rho = 0$, there is no difference between the underlying interdependence and the long-term coefficient, i.e., $\beta_2 = \gamma$. In this regard, our results show more or less deviation between these two coefficients, but surprisingly a large deviation between them in crisis (5th quantile) and prosperity (95th quantile) periods. These results imply that the established interdependence between hedge funds and equity markets breaks down severely in times of both crisis and prosperity. The large deviation between them in the 5th and 95th quantiles also strongly suggests return smoothing behavior in the most severe condition. Indeed, the magnitude of the deviation between the two slopes for the 95th quantile is much larger than that for the 5th quantile, which might be caused by conditional return smoothing, which makes the deviation between $\hat{\gamma}$ and $\widehat{\beta_2}$ relatively small in the 5th quantile than those in the 95th quantile

To check more precisely whether conditional return smoothing plays such a role, we conduct the same analysis as that shown in Figure 1, Table 2, and Table 3 but using unsmoothed hedge fund returns. We use the de-smoothing algorithm proposed by Brooks and Kat (2002) to gain unsmoothed hedge fund returns and the results are presented in Appendix B. The result of the Wald–Wolfowitz runs test for $\widehat{\beta_2}$ in Table B2 is interesting. It does not reject $\mathrm{H_{0W}}$ for $\widehat{\beta_2}$ (P = 0.1803), implying no breakdown in the established interdependence with unsmoothed hedge fund returns. Indeed, we find contagion effects between smoothed hedge funds and equity returns, while no contagion (i.e., just interdependence) between unsmoothed hedge funds and equity returns. This result implies that return smoothing might be indeed a major factor that drives the excessive correlation in the underlying fundamentals between equity markets and hedge funds.

4. Concluding remarks

In this study, we first found contagion effects through a breakdown of the econometrically established interdependence between hedge funds and equity markets. Second, we observed that conditional return smoothing, a well-known and widespread strategic complementarity among hedge funds, is the primary cause of this breakdown. It is also revealed that interdependence between hedge funds and equity markets suffers from unexpected breakdowns because hedge funds experience greater sensitivity to equity markets during periods of economic prosperity (high quantiles) than during periods of economic crisis (low quantiles). This unanticipated sensitivity of hedge funds to equity markets is caused by conditional return smoothing. To address these issues econometrically, we propose using the SEECM, latent factor model, quantile regression, and the Wald-Wolfowitz runs test. It turns out that our methodology not only allows for dynamic analysis of various heteroscedastic errors but also encompasses various contagion scenarios in the existing research.

Given that not all hedge fund strategies have the same exposure to equity markets, an interesting extension to this study might be to apply the proposed approach at the strategy level and then check if contagion effects are more pronounced for hedge fund strategies with a high exposure to equity markets. Additionally, this research could be extended by conducting an empirical analysis based on individual hedge fund returns, especially if the objective was to link contagion with an individual fund manager's behavior. We leave these interesting topics for future research.

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Appendix A

A.1 Derivation of the equation (7)

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

$$\Delta X_t = X_t - X_{t-1} = \theta_x (W_t - W_{t-1}) + \delta_x (u_{x,t} - u_{x,t-1})$$

$$(W_t - W_{t-1}) = \frac{1}{\theta_x} \Delta X_t - \frac{\delta_x}{\theta_x} (u_{x,t} - u_{x,t-1})$$

$$X_{t-1} = \theta_x W_{t-1} + \delta_x u_{x,t-1}$$

$$W_{t-1} = \frac{1}{\theta_x} \mathrm{X}_{t-1} - \frac{\delta_x}{\theta_x} u_{x,t-1}$$

$$Y_{t-1} = \theta_y W_{t-1} + \delta_y u_{y,t-1}$$

$$Y_{t-1} = \frac{\theta_y}{\theta_x} X_{t-1} - \frac{\theta_y}{\theta_x} \delta_x u_{\mathrm{x},t-1} + \delta_y u_{y,t-1}$$

$$Y_{t-1} - \frac{\theta_y}{\theta_x} X_{t-1} = - \frac{\theta_y}{\theta_x} \delta_x u_{\mathrm{x},t-1} + \delta_y u_{y,t-1}$$

$$\Delta Y_t = Y_t - Y_{t-1} = \theta_y (W_t - W_{t-1}) + \delta_y \left(u_{y,t} - u_{y,t-1}\right)$$

$$= \frac{\theta_y}{\theta_x} \Delta X_t - \frac{\theta_y}{\theta_x} \delta_x (u_{x,t} - u_{x,t-1}) + \delta_y (u_{y,t} - u_{y,t-1})$$

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

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

A.2 Derivation of the equation (9)

From model (7) and (8)

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

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

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

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

where $\varepsilon_t = -\frac{\theta_y}{\theta_x}\delta_x u_{x,t} + \delta_y a_{u,t} - \rho\theta_y W_{t-1}$.

Appendix B. Analysis with unsmoothed hedge fund returns

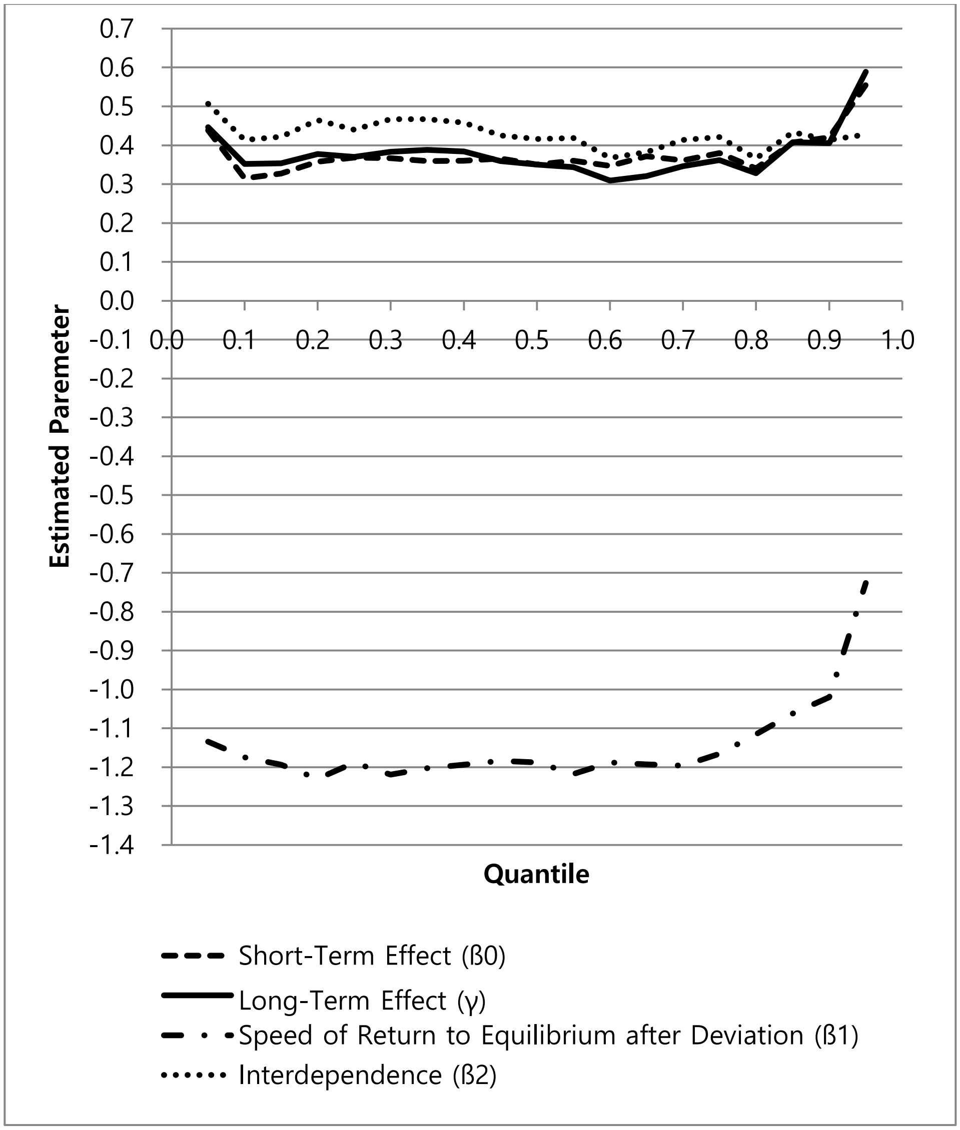

Fig. B1. Estimated parameters of the SEECM for the unsmoothed Credit Suisse hedge fund index and Russell 3000 index returns by quantile regression.

The estimated parameters of short-term effects ($\widehat{\beta_0}$), long-term effects ($\hat{\gamma}$), speed of return to equilibrium after deviation ($\widehat{\beta_1}$) and interdependence ($\widehat{\beta_2}$) in the SEECM by quantile regression are plotted across the entire range of quantiles. Unsmoothed Credit Suisse hedge fund index returns are used as a response variable and Russell 3000 index returns are used as a predictor. The SEECM is estimated at 5% increments from the 5^{th} to the 95^{th} quantiles. The unsmoothed hedge fund returns are gained by applying the de-smoothing algorithm proposed by Brooks and Kat (2002).

Table B1

The SEECM for the unsmoothed Credit Suisse hedge fund index and Russell 3000 index returns estimated by quantile regression.

This table reports the coefficient estimates with the corresponding *P*-values in parentheses for the SEECM estimated by quantile regression. Unsmoothed Credit Suisse hedge fund index returns are used as a response variable and Russell 3000 index returns are used as a predictor. The SEECM is estimated at 5% increments from the 5th to the 95th quantiles. The unsmoothed hedge fund returns are gained by applying the de-smoothing algorithm proposed by Brooks and Kat (2002).

Quantile	$\widehat{\alpha}$	$\widehat{\beta_0}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	$\widehat{\gamma}$
0.05	-0.028 (<.0001)	0.4382 (<.0001)	-1.1343 (<.0001)	0.5064 (<.0001)	0.4464 (<.0001)
0.1	-0.0173 (<.0001)	0.3145 (<.0001)	-1.1749 (<.0001)	0.4132 (<.0001)	0.3517 (<.0001)
0.15	-0.0103 (<.0001)	0.3269 (<.0001)	-1.1933 (<.0001)	0.4220 (<.0001)	0.3536 (<.0001)
0.2	-0.0066 (<.0001)	0.3574 (<.0001)	-1.2296 (<.0001)	0.4642 (<.0001)	0.3775 (<.0001)
0.25	-0.0048 (0.0001)	0.3687 (<.0001)	-1.1887 (<.0001)	0.4396 (<.0001)	0.3698 (<.0001)
0.3	-0.0022 (0.1232)	0.3668 (<.0001)	-1.2189 (<.0001)	0.4672 (<.0001)	0.3833 (<.0001)
0.35	0.0000 (0.9917)	0.3596 (<.0001)	-1.2025 (<.0001)	0.4667 (<.0001)	0.3881 (<.0001)
0.4	0.0012 (0.3735)	0.3602 (<.0001)	-1.1933 (<.0001)	0.4577 (<.0001)	0.3836 (<.0001)
0.45	0.0039 (0.0074)	0.3658 (<.0001)	-1.1837 (<.0001)	0.4254 (<.0001)	0.3594 (<.0001)
0.5	0.0057 (0.0005)	0.3501 (<.0001)	-1.1881 (<.0001)	0.4161 (<.0001)	0.3502 (<.0001)
0.55	0.0089 (<.0001)	0.3604 (<.0001)	-1.2175 (<.0001)	0.4184 (<.0001)	0.3437 (<.0001)
0.6	0.0114 (<.0001)	0.3471 (<.0001)	-1.1879 (<.0001)	0.3676 (<.0001)	0.3095 (<.0001)
0.65	0.0131 (<.0001)	0.3716 (<.0001)	-1.1931 (<.0001)	0.3824 (<.0001)	0.3205 (<.0001)
0.7	0.0153 (<.0001)	0.3611 (<.0001)	-1.1965 (<.0001)	0.4138 (<.0001)	0.3458 (<.0001)
0.75	0.0172 (<.0001)	0.3796 (<.0001)	-1.1656 (<.0001)	0.4213 (<.0001)	0.3614 (<.0001)
0.8	0.0209 (<.0001)	0.3404 (<.0001)	-1.1157 (<.0001)	0.3660 (<.0001)	0.3280 (<.0001)
0.85	0.0264 (<.0001)	0.4067 (<.0001)	-1.0618 (<.0001)	0.4334 (<.0001)	0.4082 (<.0001)
0.9	0.0311 (<.0001)	0.4203 (<.0001)	-1.0201 (<.0001)	0.4136 (<.0001)	0.4055 (<.0001)
0.95	0.0459 (<.0001)	0.5549 (<.0001)	-0.7262 (0.0068)	0.4279 (0.0025)	0.5892 (<.0001)

Table B2

P-values for the Wald-Wolfowitz runs test and *Z*-test
for unsmoothed Credit Suisse hedge fund return.

This table reports the *P*-values for the two-tailed Wald–Wolfowitz runs test and *Z*-test for long-term effects ($\hat{\gamma}$) and interdependence ($\widehat{\beta_2}$) in unsmoothed Credit Suisse hedge fund index returns. The unsmoothed hedge fund returns are gained by applying the de-smoothing algorithm proposed by Brooks and Kat (2002).

	Wald-Wolfowitz Run Test *P*-Value	*Z*-Test *P*-Value	
		$\hat{\varphi}_{i,1}$	$\hat{\varphi}_{i,19}$
Long-Term Slope ($\hat{\gamma}$)	0.0269	0.0022	0.0000
Interdependence ($\widehat{\beta_2}$)	0.1803	0.0072	0.8712

Tables and Figures

Table 1

Summary statistics of monthly returns and asset values of the Credit Suisse hedge fund index and equity market: January 1994 to December 2012.

This table reports the summary statistics for the monthly returns and asset values of the Credit Suisse hedge fund and Russell 3000 indices. The number of observations for each index is 228. The return and asset value correlations between the Credit Suisse hedge fund and Russell 3000 indices are reported in the last column. Asset values are based on million U.S. dollar values.

	Mean	Median	SD	Min	Max	Correlation with Russell 3000 Index Return
Credit Suisse Hedge Fund Index Return (%)	0.718	0.77	2.155	-7.55	8.53	0.597
Russell 300 Index Return	0.607	1.234	4.537	-17.783	11.365	1.000
						Correlation with Russel 3000 Index Cap
Credit Suisse Hedge Fund Index NAV (MUS$)	284.058	268.360	120.624	91.910	484.780	0.709
Russell 3000 Cap	1172.715	1206.150	276.012	493.100	1649.800	1.000

Table 2

The SEECM for the Credit Suisse hedge fund index
and Russell 3000 index returns estimated by quantile regression.

This table reports the coefficient estimates with the corresponding *P*-values in parentheses for the SEECM estimated by quantile regression. Credit Suisse hedge fund index returns are used as a response variable and Russell 3000 index returns are used as a predictor. The SEECM is estimated at 5% increments from the 5th to the 95th quantiles.

Quantile	$\hat{\alpha}$	$\widehat{\beta_0}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	$\hat{\gamma}$
0.05	-0.0234 (<.0001)	0.3469 (<.0001)	-0.7645 (<.0001)	0.3786 (<.0001)	0.4952 (<.0001)
0.1	-0.0149 (<.0001)	0.2982 (<.0001)	-0.8817 (<.0001)	0.3819 (<.0001)	0.4331 (<.0001)
0.15	-0.0071 (0.0006)	0.2536 (<.0001)	-0.9695 (<.0001)	0.3448 (<.0001)	0.3556 (<.0001)
0.2	-0.0054 (0.0003)	0.2585 (<.0001)	-0.9419 (<.0001)	0.3396 (<.0001)	0.3605 (<.0001)
0.25	-0.0034 (0.0018)	0.2602 (<.0001)	-0.9062 (<.0001)	0.3349 (<.0001)	0.3696 (<.0001)
0.3	-0.0022 (0.0379)	0.2659 (<.0001)	-0.9302 (<.0001)	0.3583 (<.0001)	0.3852 (<.0001)
0.35	-0.0009 (0.4519)	0.2556 (<.0001)	-0.9386 (<.0001)	0.3448 (<.0001)	0.3674 (<.0001)
0.4	0.001 (0.3988)	0.2705 (<.0001)	-0.9451 (<.0001)	0.3366 (<.0001)	0.3562 (<.0001)
0.45	0.0026 (0.0665)	0.2807 (<.0001)	-0.8997 (<.0001)	0.3210 (<.0001)	0.3568 (<.0001)
0.5	0.0039 (0.0082)	0.2612 (<.0001)	-0.8942 (<.0001)	0.3108 (<.0001)	0.3476 (<.0001)
0.55	0.0063 (<.0001)	0.2621 (<.0001)	-0.8903 (<.0001)	0.2836 (<.0001)	0.3185 (<.0001)
0.6	0.0086 (<.0001)	0.2446 (<.0001)	-0.9267 (<.0001)	0.2784 (<.0001)	0.3004 (<.0001)
0.65	0.0098 (<.0001)	0.2475 (<.0001)	-0.9539 (<.0001)	0.2847 (<.0001)	0.2985 (<.0001)
0.7	0.0107 (<.0001)	0.2625 (<.0001)	-0.9297 (<.0001)	0.2873 (<.0001)	0.3090 (<.0001)
0.75	0.0116 (<.0001)	0.257 (<.0001)	-0.9048 (<.0001)	0.2840 (<.0001)	0.3139 (<.0001)
0.8	0.0143 (<.0001)	0.2356 (<.0001)	-0.8919 (<.0001)	0.2525 (<.0001)	0.2831 (<.0001)
0.85	0.0184 (<.0001)	0.2864 (<.0001)	-0.7633 (<.0001)	0.2989 (<.0001)	0.3916 (<.0001)
0.9	0.0231 (<.0001)	0.3116 (<.0001)	-0.8178 (<.0001)	0.3142 (<.0001)	0.3842 (<.0001)
0.95	0.0312 (<.0001)	0.3548 (<.0001)	-0.3886 (0.1208)	0.2620 (0.0090)	0.6742 (<.0001)

Table 3

P-values for the Wald–Wolfowitz runs test and *Z*-test.

This table reports the *P*-values for the two-tailed Wald–Wolfowitz runs test and *Z*-test for long-term effects ($\hat{\gamma}$) and interdependence ($\widehat{\beta_2}$) in Credit Suisse hedge fund index returns. The estimated coefficients for $Y_{i,19}$ are used for the tests and the corresponding *P*-values are reported for each slope.

	Wald–Wolfowitz Runs Test *P*-Value	*Z*-Test *P*-Value	
		$\hat{\varphi}_{i,1}$	$\hat{\varphi}_{i,19}$
Long-Term Slope ($\hat{\gamma}$)	0.0484	0.0002	0.0000
Interdependence ($\widehat{\beta_2}$)	0.0002	0.0638	0.1214

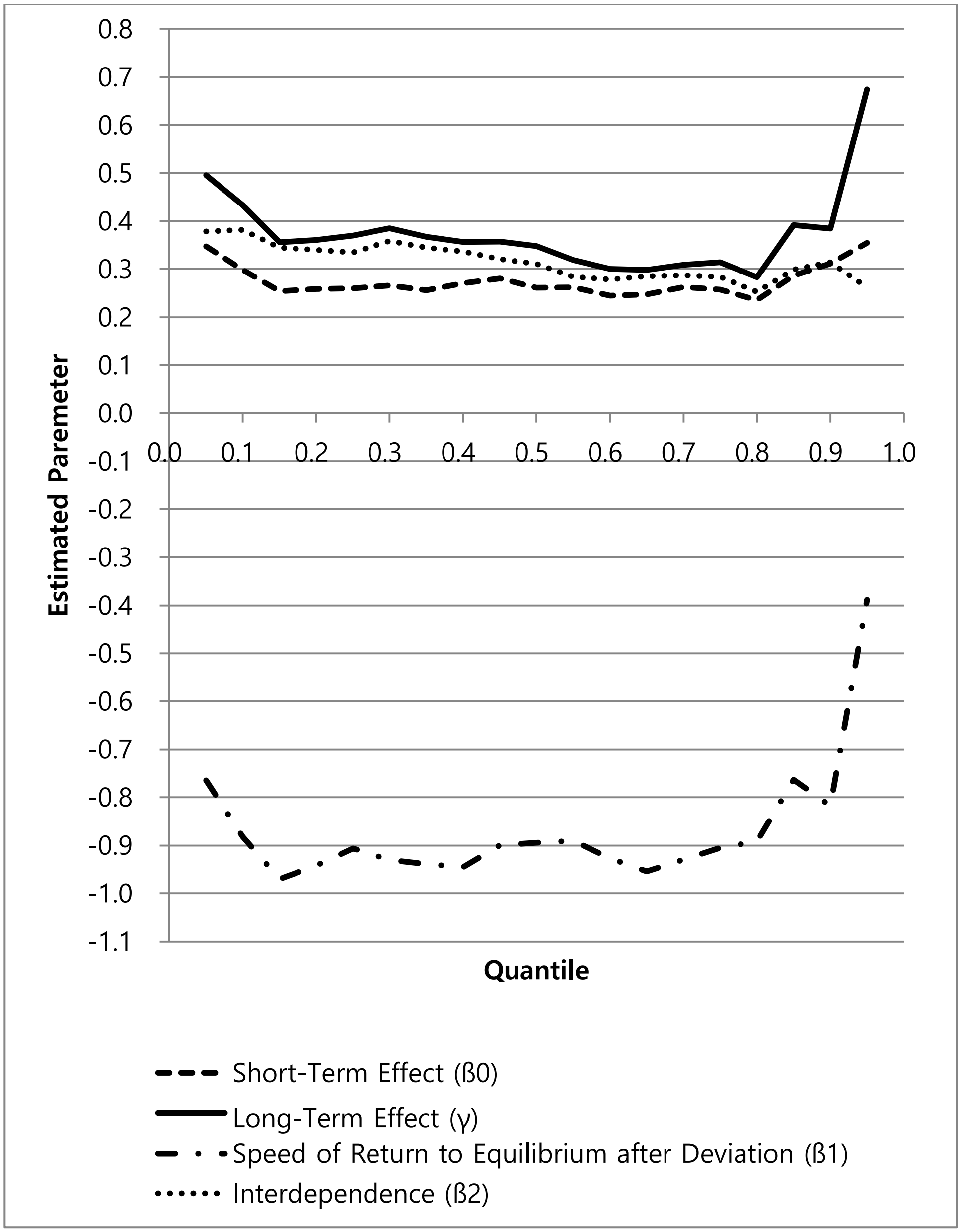

Fig. 1. Estimated parameters of the SEECM for the Credit Suisse hedge funds index and Russel 3000 index by quantile regression.

The estimated parameters of short-term effects ($\widehat{\beta_0}$), long-term effects ($\hat{\gamma}$), speed of return to equilibrium after deviation ($\widehat{\beta_1}$) and interdependence ($\widehat{\beta_2}$) in the SEECM by quantile regression are plotted across the entire range of quantiles. Credit Suisse hedge fund index returns are used as a response variable and Russell 3000 index returns are used as a predictor. The SEECM is estimated at 5% increments from the 5th to the 95th quantiles.