Auburn University
Department of Economics
Working Paper Series

Fear and Closed-End Fund Discounts: Investor Sentiment Revisited

Seth C. Anderson[†], T. Randolph Beard[*],

Hyeongwoo Kim[*], and Liliana V. Stern[*]

[†]*Tuskegee University and* [*]*Auburn University*

AUWP 2011-11

Fear and Closed-End Fund Discounts: Investor Sentiment Revisited

Seth C. Anderson[†], T. Randolph Beard[*], Hyeongwoo Kim[*], and Liliana V. Stern[*]

[†]*Tuskegee University and* [*]*Auburn University*

August 2011

Abstract: The disparity between closed-end funds' net asset values and prices has been the focus of numerous research papers over the past half century. Various explanations for this discrepancy have been investigated, with mixed findings. A relatively recent topic is that of the role of investor sentiment in the pricing of these funds' shares. Lee, Schleifer, and Thaler (1990, 1991) propose a theory that explains the divergence in fund share prices and underlying values through the behavior of noise traders whose activities create an additional source of risk for which rational traders need to be compensated. Other researchers have questioned this view. In this article, we provide a new analysis of the potential role of investor sentiment by utilizing a latent factor structure to estimate the dynamic conditional correlations between fund discounts and VIX, which is a measure of the implied volatility of S&P 500 index options, often referred to as the *fear index*. Using a sample of funds over the 2004-2011 period (thus incorporating the market meltdown of 2007-2009), we find results strongly consistent with the sentiment theory.

Keywords: Closed-end fund, discount, investor sentiment, dynamic conditional correlation, multivariate GARCH

JEL Classification: C32; G01; G12

I. Introduction

In contrast to open-end mutual fund shares which can be redeemed from the fund at net asset value (NAV), closed-end fund shares trade in the secondary market. Closed-end fund (CEF) shares typically trade at discounts to NAV, although, occasionally, at premiums. This disparity between NAV and price has been the subject of numerous research papers over the past half century.

Some earlier research exemplified by Close (1952), Edwards (1968), and Malkiel (1977) primarily addresses the impact of various market frictions, including commissions, fees, taxes, and portfolio characteristics, on the pricing of CEF shares. The findings of these studies are that, to some degree, discounts are a function of these frictions, but that the magnitude and variability of discounts are not fully explained by frictions. Also, other works, including Boudreaux (1973), Zweig (1973), Richards, Fraser, and Groth (1980), Anderson (1986), and Brauer (1988), in the spirit of Sharpe and Sosin (1975), find support for the discounts of CEF shares to be mean-reverting over time.[1]

One of the underlying themes discussed, but not directly examined, in several early works, such as Pratt (1966), Simon (1969), Zweig (1973), and Boudreaux (1973), is that of discounts being a function of investor perceptions, which is akin to the construct of investor sentiment. However, beginning in the early 1990s, there appeared a number of studies that investigated how discounts might be related to investor sentiment.

[1] We implemented a panel unit root test (Bai and Ng, 2004) that allows cross-section dependence in our data. We obtain strong evidence that favors stationarity for the first common factor and for the idiosyncratic components at any conventional significance level. All results are available from authors upon requests.

Building on the work of DeLong, Shleifer, Summers, and Waldman (1990), these works posit that investors are of one of two possible types: (1) informed, rational economic agents, or (2) under-informed, irrational, "noise traders."

Shleifer, and Thaler (1990, 1991) present evidence that both changes in the level of discounts, and changes in the offerings of new closed-end funds, are functions of investor sentiment. They report that changes in discount levels are significantly related to two proxies for irrational investors' sentiment: small-firm returns and mutual fund redemptions. Variable support for this position is offered by Noronha and Rubin (1995), Brown (1999), and others.[2] In contrast, Chen, Kan, and Miller (1993), Swaminathan (1996), and Abraham, Elan, and Marcus (1998) present findings that do not support the irrational investor hypothesis.[3]

In this paper, we investigate the relationship between CEF discounts and investor sentiment, as manifested in particular in investor "fear". To do so, we employ daily data over the period 2004 to 2011 for 32 CEFs (see Table I) and for the VIX Index, which serves as a measure of investor fear (Whaley, 2000). Unlike much of the existing literature, which assumes that the relationship between CEF discounts and investor sentiment is time-invariant and, therefore, can be described by a standard regression with constant coefficients, we estimate time-varying conditional correlations between the discounts and the sentiment index. Our sample period includes the recent financial crisis, and we are interested in estimating whether the nature of the relationship between the

---

[2] See also Nofsinger and Sias (1999), Baker and Wurgler (2006), and Kumar and Lee (2006).
[3] This entire debate highlights some of the most basic assumptions, and controversies, surrounding behavioral finance. Baker and Wurgley (2006) point out that the notion that "sentiment" can affect asset prices is the "irrefutable assumption" of behavioral finance research.

CEF discounts and investor sentiment differs during turbulent times (i.e., the financial crisis) and during more tranquil periods.

To analyze a potentially time-dependent relationship between the CEF discounts and investor sentiment, we begin by estimating the common factor of the level of discount/premium (log price minus log NAV) employing principal component analysis for possibly nonstationary variables (Bai and Ng, 2004). We proceed with estimating the dynamic conditional correlation (DCC) between this common factor and an investor sentiment variable (VIX) within a multivariate GARCH framework (Engle, 2002). We find that the DCC decreases substantially around the financial crisis. That is, when consumer fear is elevated, discounts rapidly rise. This implies that during turbulent periods, fund prices fall more rapidly than the NAV does.

The paper is organized as follows: Section II describes our baseline multivariate GARCH model with the common factor and a sentiment variable; Section III presents our main findings and interpretations; and Section IV concludes.

II. The Econometric Model

Let $d_{i,t}$ denote the log price minus the log net asset value of a closed-end mutual fund $i \in [1, N]$ at time $t \in [1, T]$. When $d_{i,t}$ is negative (positive), the fund trades at a discount (premium).

We assume that $d_{i,t}$ has the following single factor structure:

$$d_{i,t} = \lambda_i f_t + \zeta_{i,t} \tag{1}$$

where f_t is the *common* factor component of $d_{i,t}$ across all mutual funds $i \in [1, N]$ at time t. The parameter λ_i denotes the fund-specific factor loading to the common factor, f_t. That is, we allow the degree of dependency on the factor to vary across funds. Lastly, $\zeta_{i,t}$ is the fund i's *idiosyncratic* component.

Instead of investigating the dynamics of each fund, we focus on the movement of the common factor, f_t. For this purpose, we first estimate the common factor and the factor loadings via the principal component analysis after proper normalization.[4] Since $d_{i,t}$ is potentially nonstationary, we employ Bai and Ng's (2004) method to obtain the estimate for Δf_t from the following:

$$\Delta d_{i,t} = \lambda_i \Delta f_t + \Delta \zeta_{i,t} \tag{2}$$

Then, we recover the estimates for the common component and the idiosyncratic component by:

$$\hat{f}_t = \sum_{s=2}^{t} \Delta \hat{f}_s \,, \quad \hat{\zeta}_t = \sum_{s=2}^{t} \Delta \hat{\zeta}_s \tag{3}$$

Once the common factor is identified, we investigate its dynamic conditional correlations with the investor sentiment variable. We are interested in how the discount (premium) varies between tranquil and turbulent periods, employing the time of the recent U.S. financial crisis as our target period.

[4] Normalization is required because the principal component analysis is not scale-invariant.

For this purpose, we employ the dynamic conditional correlation (DCC) estimator (Engle, 2002) for multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models to estimate time-varying conditional correlations between two variables of interest, f_t and s_t, where s_t is a proxy variable for investor sentiment. The DCC model can be viewed as a generalization of the constant conditional correlation (CCC) estimator proposed by Bollerslev (1990). We also employ the conventional (diagonal) GARCH-BEKK model (Engle and Kroner, 1995) as a benchmark analysis.

For the DCC, consider the following vector autoregressive process for $y_t = [f_t, s_t]'$:

$$y_t = \Gamma(L) y_{t-1} + e_t, \tag{4}$$

where $\Gamma(L)$ is a lag polynomial matrix. We assume that $e_t = [e_{f,t}, e_{s,t}]'$ obeys the bivariate normal distribution,

$$e_t \,|\, \Omega_{t-1} \sim N(\mathbf{0}, H_t), \tag{5}$$

where Ω_{t-1} denotes the adaptive information set at time t. The conditional covariance matrix H_t is defined as,

$$H_t = D_t R_t D_t, \tag{6}$$

where $D_t = diag(\sqrt{h_{i,i,t}})$ is the diagonal matrix with the conditional variances along the diagonal and R_t is the time-varying correlation matrix. Note that the CCC is a special case of the DCC when $R_t = R$ for all t.

The equation (6) can be re-parameterized as follows,

$$E_{t-1}\varepsilon_t\varepsilon_t' = D_t^{-1}H_tD_t^{-1} = R_t = [\rho_{i,j,t}], \tag{7}$$

where $\varepsilon_t = [\varepsilon_{f,t}, \varepsilon_{s,t}]' = D_t^{-1}e_t$ is the standardized innovation vector. Engle (2002) proposes the following mean-reverting GARCH(1,1) type conditional correlations:

$$\rho_{f,s,t} = \frac{q_{f,s,t}}{\sqrt{q_{f,f,t}}\sqrt{q_{s,s,t}}}, \tag{8}$$
$$q_{f,s,t} = \bar{\rho}_{f,s}(1 - \alpha - \beta) + \alpha\varepsilon_{f,t-1}\varepsilon_{s,t-1} + \beta q_{f,s,t-1},$$

where $\bar{\rho}_{f,s}$ is the unconditional correlation between $\varepsilon_{f,t-1}$ and $\varepsilon_{s,t-1}$. In a matrix form,

$$Q_t = S(1 - \alpha - \beta) + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta Q_{t-1} \tag{9}$$

Stationarity is assumed with $\alpha + \beta < 1$ where α and β are non-negative scalars. Engle (2002) proposes a two-step maximum likelihood procedure for parameter estimations.

III. Data and Empirical Results

3.1. Data

We use daily returns for 32 closed-end funds for the period May 7, 2004 through February 17, 2011. Our sample includes 16 bond and 16 stock closed-end funds. The list of funds, as well as their total net assets as of February 28, 2011, is presented in Table 1.

Our sample was selected from funds with complete daily price and NAV series available on Yahoo for the period 2004 to 2011 satisfying the following additional criteria: (1) bond funds are selected from the Closed-End Fund Association's "General Bond" and "Corporate Debt BBB Rated Funds" categories, while stock funds are selected from the "Core Funds" category; (2) only funds with managed assets exceeding $50 million (US) at the conception of the sample period are selected.

As can be seen from Table 1, we use only relatively large funds, with total net assets over $100 million for the majority. Bond funds' portfolios comprise the following: Treasury bonds, corporate bonds, foreign long-term debt, foreign U.S. $-denominated bonds/notes, FNMA not-mortgage backed securities, FNA mortgage-backed securities, and other mortgages. Stock funds have portfolios allocated primarily to the following sectors: technology, industrials, health care, financials, consumer services, consumer goods, oil and gas, utilities, communications, and basic materials.

3.2. Empirical Results

We begin by estimating the common factor component, f_t, of the closed-end funds' discounts, $d_{i,t}$, as described by equation (1). To highlight its potential association with the VIX, our preferred daily investor sentiment variable, we changed the sign of the estimates, so that a positive sign on f_t means that the fund is traded at a discount. Figure 1 shows the evolution of the common factor component, f_t, and the VIX. Casual observation indicates that these two variables exhibit similar movements during the recent crisis. Next, we employ multivariate GARCH for a more rigorous analysis.

Figure 2 presents estimated dynamic conditional correlations (DCC) along with the constant conditional correlation (CCC) estimates. Visual inspection suggests that the CCC formulation is unsuitable because the DCC series appears to exhibit a structural break around late 2007, when the U.S. subprime mortgage market collapsed, triggering investor fear in most financial markets. Engle's (2002) test rejects the CCC null hypothesis against the DCC alternative at the 10%-significance level with about a 7%-value. Note also that prior to the U.S. financial crisis, the correlation was virtually 0%, while it has increased (in absolute value) dramatically in the post crisis period (reaching its peak at around -0.5 in late 2008-early 2009). This implies that the fund discount may be heavily influenced by investor sentiment, as suggested by Lee *et al.* (1990, 1991).

We also report conventional BEKK estimation results in Table 2. All parameter estimates are significant at the 1% level. The CCC and DCC parameters are provided in Table 3. Most key parameters are significant at the 1% level.

On balance, the results provide strong evidence of the role of investor sentiment, as proxied by VIX, in determining the levels and changes in the levels of CEF discounts. This lends support to the role of sentiment in discounts in a sense consistent with that hypothesized by Lee *et al.* (1990, 1991).

IV. Concluding Remarks

The puzzle represented by CEF discounts has occasioned extensive theorizing, but it is unlikely that any single theory can adequately explain their existence, magnitude, and variability over time. Regardless, the role of investor sentiment in such discounts is perhaps the most prominent recent theoretical explanation. Also, the influence of arbitrage costs and other possible forces influencing discounts is not inconsistent with the sentiment hypothesis.

This article presents a novel approach to the analysis of the discount issue by using a method particularly well-suited to this task. Rather than focusing on individual funds, we use dynamic factor analysis to abstract the sources of observed discounts. We then investigate the dynamic conditional correlation between this factor and the popular proxy for investor sentiment, VIX, which is a measure of the implied volatility of S&P 500 index options. Using a sample of funds over the period 2004-2011, we find a strong relationship between discounts and VIX after the initiation of the market meltdown in 2007. This finding is consistent with the investor sentiment theory proposed by Lee, Schleifer, and Thaler (1990, 1991).

Reference

Abraham, Abraham, Don Elan, and Alan J. Marcus. "Does Sentiment Explain Closed-End Discounts? Evidence from Bond Funds." *Financial Review* 28.4 (November 1998), 609-619.

Anderson, Seth C. "Closed-End Funds Versus Market Efficiency." *The Journal of Portfolio Management* 13.1 (Fall 1986), 63-65.

Bai, Jushan and Serena Ng, 2004, A PANIC attack on unit roots and cointegration, *Econometrica* 72(4), 1127-1177.

Baker, Malcolm and J. Wirgler, "Investor Sentiment and the Cross-Section of Stock Returns". *Journal of Finance* 61(4), August 2006, pp. 1645-80

Bollerslev, Tim. "Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model," *The Review of Economics and Statistics* 72 (1990): 498-505.

Boudreaux, Kenneth J. "Discounts and Premiums on Closed-End Mutual Funds: A Study of Valuation." *Journal of Finance* 28.2 (May 1973), 515-522.

Brauer, Greggory A. "Closed-End Fund Shares' Abnormal Returns and Information Content of Discounts and Premiums." *Journal of Finance* 43.1 (March 1988), 113-127.

Brown, Gregory W. "Volatility, Sentiment, and Noise Traders" *Financial Analysts Journal* 55:2 (March/April 1999) 82-90.

Chen, Nai Fu, Raymond Kan and Merton H. Miller. "Are the Discounts on Closed-End Funds a Sentiment Index?" *Journal of Finance* 48:2 (June 1993): 795-800.

Close, James A. "Investment Companies: Closed-End versus Open-end." *Harvard Business Review* 30 (1952), 79-88.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers and Richard J. Waldman. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98 (1990): 703-738.

Edwards, Robert G. "Closed-End Discounts Due to Capital Gain Problems?" *The Commercial and Financial Chronicle* 207 (January 11, 1968).

Engle, Robert F. and Kroner, Kenneth F. "Multivariate Simultaneous Generalized ARCH," *Econometric Theory* 11 (1995): 122-150.

Engle, Robert. "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business & Economic Statistics* 20 (2002): 339-350.

Kumar, Alok and Charles Lee, "Retail Investor Sentiment and Return Co-movements". *Journal of Finance* 61 (5), October 2006, 2451-86

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler, "Anomalies: Closed-End Fund Mutual Funds." *Journal of Economic Perspectives* 4.4 (Fall 1990): 154-64.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler. "Investor Sentiment and the Closed-End Fund Puzzle." *Journal of Finance* 66.1 (March 1991): 75-109.

Malkiel, Burton G. "The Valuation of Closed-end Investment Company Shares." *Journal of Finance* 32.3 (June 1977), 847-859.

Nofsinger, John, and Richard Sias, "Herding and Feedback Trading by Institutional and Individual Investors". *Journal of Finance* 54 (6), December 1999, 2263-95

Noronha, Gregory M. and Bruce L. Rubin. "Closed-End Bond Fund Discounts: Agency Costs, Investor Sentiment and Portfolio Content." *Journal of Economics and Finance* 19.3 (Summer 1995): 29-44.

Pratt, Eugene J. "Myths Associated With Closed-End Investment Company Discounts". *Financial Analysts Journal* 22.4 (July-August 1966), 79-82.

Richards, R. Malcolm, Donald R. Fraser, and John C. Groth. "Premiums, Discounts, and the Volatility of Closed-End Mutual Funds." *The Financial Review* 14.3 (Fall 1979), 26-33.

Sharpe, William F. and Howard Sosin. "Closed-End Investment Companies in the United States: Risk and Return." *Proceedings, 1974 Meeting of the European Financial Association*. Ed. Betrand Jacquillat. Amsterdam: North-Holland Publishing Company, (1975): 37-63.

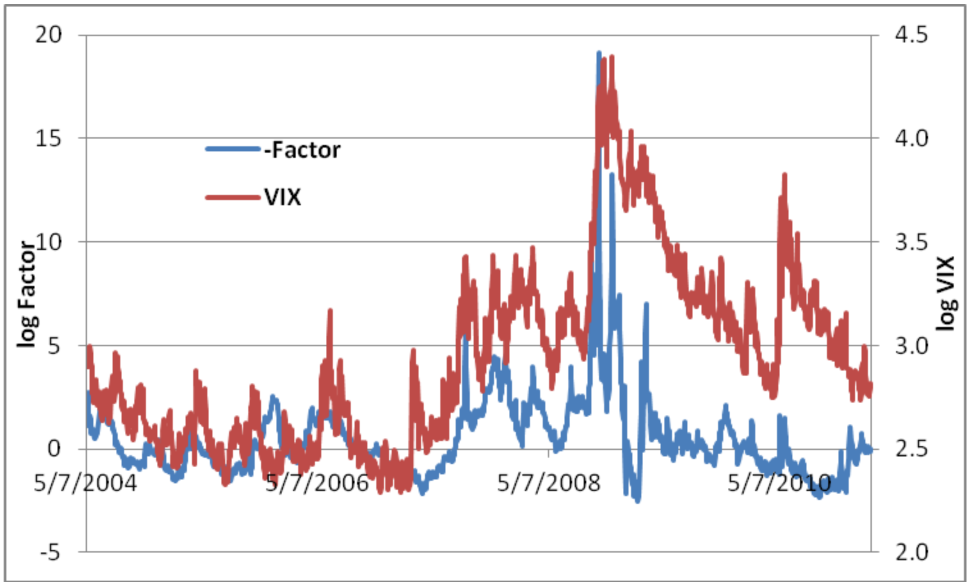
Simon, Julian L. "Does 'Good Portfolio Management' Exist?" *Management Science* 15.6. (February 1969), 308-319.

Swaminathan, Bhaskaran. "Time-Varying Expected Small Firm Returns and Closed-End Fund Discounts." *Review of Financial Studies* 9.3 (1996): 845-887.

Whaley, Robert, "The Investor Fear Gauge." *Journal of Portfolio Management* 26(3), January 2000.

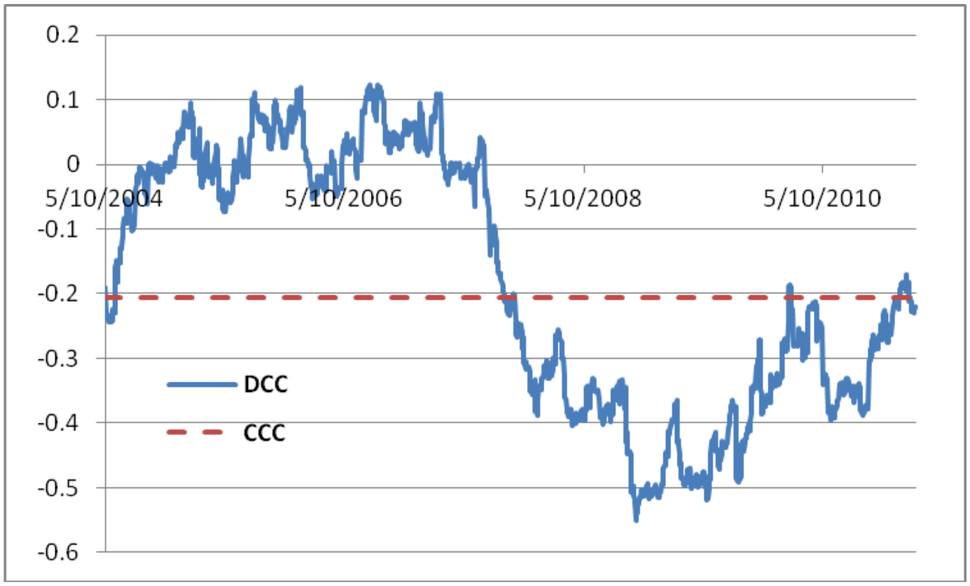
Zweig, Martin E. “An Investor Expectations Stock Price Predictive Model Using Closed-End Fund Premiums”. *Journal of Finance* 28.1 (March 1973), 67-78.

Figure 1. Common Factor Discount and the VIX



Note: The common factor is obtained by the principal component analysis for the 32 closed-end mutual fund data, the log price minus the log NAV. The common factor is multiplied by -1, which equals the log discount. Individual series also typically exhibit rapidly-rising discounts during the recent financial crisis around 2008. Observations are daily and span from May 7, 2004 to February 17, 2011.

Figure 2. Conditional Correlations between f_t and VIX



Note: The common factor is obtained by the principal component analysis for the 32 closed-end mutual fund data. Observations are daily and span from May 7, 2004 to February 17, 2011. DCC denotes the dynamic conditional correlation proposed by Engle (2002), and CCC is the constant conditional correlation by Bollerslev (1990). The estimated conditional correlation from the BEKK model (Engle and Kroner, 1995) is similar to the DCC and omitted from the graph. Engle's (2002) test for the constant conditional correlation is rejected at the 10% significance level (p -value = 0.0733).

Table 1. Closed-End Funds

Bond Fund Name	Total Net Assets, $ million (as of 2/28/2011)	Stock Fund Name	Total Net Assets, $ million (as of 2/28/2011)
AllianceBernstein Income (ACG)	$2,129.20	Liberty All-Star Growth (ASG)	$142.70
BlackRock Core Bond Tr (BHK)	$364.90	BlackRock Str Div Achvr (BDT)	$323.00
BlackRock Income Opp (BNA)	$362.30	BlackRock Div Achvrs (BDV)	$584.90
BlackRock Crdt All Inc 3 (BPP)	$226.50	Blue Chip Value Fund (BLU)	$114.70
MFS IntMkt Inc I (CMK)	$100.20	Claymore Div & Inc (DCS)	$91.80
Duff & Phelps Util&Corp (DUC)	$318.40	Royce Focus Trust (FUND)	$206.90
Eaton Vance Ltd Dur Inc (EVV)	$1,994.30	Gabelli Equity Trust (GAB)	$1,435.20
Morg Stan Income Sec (ICB)	$162.70	General Amer Investors (GAM)	$1,186.40
DWS Strategic Income Tr (KST)	$65.00	Gabelli Div & Inc Tr (GDV)	$2,020.90
MFS Multimkt Inc Tr (MMT)	$580.10	J Hancock Tx-Adv Div Inc (HTD)	$970.70
BlackRock Crdt All Inc 1 (PSW)	$109.70	Nuveen Tx-Adv TR Strat (JTA)	$182.00
BlackRock Crdt All Inc 2 (PSY)	$467.20	Royce Value Trust (RVT)	$1,380.60
Transam Income Shares (TAI)	$142.20	Source Capital (SOR)	$539.80
Western Asset Prem Bond (WEA)	$167.20	Tri-Continental Corp (TY)	$1,117.70
Western Asset/Cly IL S&I (WIA)	$385.10	Liberty All-Star Equity (USA)	$1,088.00
Western Asset/Cly IL O&I (WIW)	$815.80	Zweig Fund (ZF)	$357.90

Table 2. Diagonal BEKK Model Estimation

$$Y_t = \Phi Y_{t-1} + e_t, Y_t = [f_t \quad s_t]'$$

$$H_t = M + A' e'_{t-1} e_{t-1} A + B H_{t-1} B'$$

$$M = \begin{bmatrix} \omega_f & \omega_c \\ \omega_c & \omega_s \end{bmatrix}, A = \begin{bmatrix} \alpha_f & 0 \\ 0 & \alpha_s \end{bmatrix}, B = \begin{bmatrix} \beta_f & 0 \\ 0 & \beta_s \end{bmatrix}$$

	Estimate	Standard Error	t -Stat
ω_f	4.88224	0.66064	7.39074
ω_c	-0.14806	0.01324	-11.1822
ω_s	1.48862	0.03829	38.8754
α_f	0.47430	0.00193	245.691
α_s	0.27166	0.00067	450.619
β_f	0.87634	0.00048	1822.49
β_s	0.93404	0.00010	9384.31
$-lnL$	13384.2		

Note: The BEKK model is based on Engle and Kroner (1995). All parameter estimates are significant at the 1% level.

Table 3. Conditional Correlations Model Estimation

GARCH: $h_{i,i,t} = \omega_i + \alpha_i e^2_{i,t-1} + \beta_i h_{i,i,t-1}$

CCC: $H_t = D_t R D_t$, $D_t = diag\left[\sqrt{h_{i,i,t}}\right]$, $R = [\rho_{i,j}]$

DCC: $Q_t = S(1-\alpha-\beta) + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1}$

		Estimate	Standard Error	t -Stat
GARCH	ω_f	38.3049	202.408	0.18925
	α_f	0.33759	0.00316	106.859
	β_f	0.66240	0.00320	207.216
	ω_s	4.14045	1.81470	2.28162
	α_s	0.14095	0.00064	219.792
	β_s	0.76468	0.00154	498.024
CCC	$\rho_{f,s}$	-0.20670	0.00077	-267.224
DCC	α	0.01345	0.00001	944.845
	β	0.98316	0.00002	43295.6

Note: Subscripts 1 and 2 denote f_t and VIX_t, respectively. DCC denotes the dynamic conditional correlation proposed by Engle (2002), and CCC is the constant conditional correlation by Bollerslev (1990). All parameter estimates are significant at the 1% level with an exception of ω_f.