Fear and Closed-End Fund Discounts: Investor Sentiment Revisited

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Abstract: The role of small investor sentiment in closed-end fund pricing is an active topic of research. The theory of Lee, Schleifer and Thaler (1990, 1991) 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, utilizing a latent factor structure to estimate the dynamic conditional correlations between the discounts and VIX. 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 interpretation.

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), and Anderson (1986), in the spirit of Sharpe and Sosin (1975), find support for the prices of CEF shares to be mean-reverting over time.

One of the underlying themes discussed, but not directly examined, in several earlier 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 investigate how discounts may be related to investor sentiment. Building on the work of DeLong, Shleifer, Summers, and Waldman (1990), these works posit that investors are either one of two types: (1) informed, rational economic agents, or (2) under-informed, irrational, "noise traders."

Lee, Shleifer, and Thaler (1990, 1991) present supporting evidence that both changes in the level of discounts and in the offerings of new closed-end funds are a function of investor sentiment. In this study they report that changes in discount levels are significantly related to two proxies for irrational investors' sentiment: small-firm returns and mutual fund redemptions. Varying degrees of further support of this position are offered by Brauer (1993), Noronha and Rubin (1995), Brown (1999), and others.[1] However, among yet others, Chen, Kan, and Miller (1993), Swaminathan (1996), and Abraham, Elan, and Marcus (1998) present findings that do not support the irrational investor hypothesis.[2]

In this work, we further investigate the relationship of CEF discounts and investor sentiment, as manifested 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 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 sentiment. Our sample period includes the recent financial crisis and we are interested in estimating whether the nature of the relationship between the CEF discounts and investor sentiment was different between turbulent times (i.e., the financial crisis) and more tranquil periods.

To analyze a possibly time-varying relation between the CEF discounts and investor sentiment, we begin by estimating the common factor of the level of discount/premium (log NAV minus log price) employing principal component analysis for possibly nonstationary 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

[1] See also Nofsinger and Sias (1999), Baker and Wurgler (2006), and Kumar and Lee (2006).
[2] 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.

a multivariate GARCH framework (Engle, 2002). We find that the DCC decreases substantially around the financial crisis. That is, when consumer fear is elevated, the amount of discount rapidly rises. This implies that during a turbulent period, 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. 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 is traded 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 are the *common* factor component of $d_{i,t}$ across all mutual funds $i \in [1, N]$ at time t. The parameters 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 take a practically convenient approach by focusing 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.[3] Since $d_{i,t}$ is highly likely non-stationary, 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, one can recover the estimates for the common component and the idiosyncratic component by:

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

Once the common factor is identified, we investigate its dynamic conditional correlations with an investor sentiment variable. We are especially interested in how the discount (premium) of the closed-end mutual fund changes during tranquil and turbulent periods, employing the recent U.S. financial crisis as a natural experiment.

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 $y_t = [f_t, s_t]'$:

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

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

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

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

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,

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

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 of 5/7/2004 through 2/17/2011. Our sample includes 16 bond and 16 stock closed-end funds. The list of both types of funds, as well as their total net assets as of February 28, 2011, is presented in Table 1. The sample is composed of *all* funds with data available on Yahoo satisfying the following criteria.

Our sample was selected from funds with complete daily price and NAV series available 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 fifty million dollars (US) at the conception of the sample period are selected.

As can be seen from Table 1, we use only relatively large funds, with the total net assets over \$100 million for the majority. Bond closed-end funds in our sample hold their portfolios in the following bonds/notes: 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 closed-end funds included in our sample have their portfolios allocated in 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 start with 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 relevance 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.

Using the "eyeball metric", it seems that these two variables exhibit similar movements, especially around the recent crisis. We employ multivariate GARCH to do more rigorous analysis.

Figure 2 presents estimated dynamic conditional correlations (DCC) along with the constant conditional correlation (CCC) estimates. Inspection suggests that the CCC formulation is not suitable because the DCC series seems to exhibit a structural break around late 2007, when the U.S. subprime mortgage market has 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. 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, generic evidence of the role of investor sentiment, as that nebulous magnitude is quantified by VIX, in determining the levels and changes in the levels of CEF discounts. Although this analysis will be unlikely to close the book on the entire issue, the use of the common factors methodology without the restriction that correlations be constant across the sample period, offers a strong probative case for the role of sentiment in a sense consistent with that hypothesized by Lee *et al* (1990, 1991). Because of the natures of the typical investors in CEFs, the interpretation is intuitive.

IV. Concluding Remarks

The puzzle represented by CEF discounts was occasioned extensive theorizing, and it is unlikely that any single theory is going to be adequate to explain all discounts at all times. Nevertheless, the role of investor sentiment in such discounts is perhaps the most prominent theoretical suggestion. In addition, the influence of arbitrage costs and other possible sources of these discounts are not inconsistent with the sentiment story. This article presents a new analysis of the discount issue, using tools particularly suited to this task. Rather than focusing on individual funds, we use dynamic factor analysis to extract the sources of observed discounts for a sample of funds over the 2004-2011 period. We then investigate the dynamic conditional correlation between this factor and a popular measure of investor sentiment (or perhaps “fear”), the VIX. We find a strong relationship between discounts and VIX after the initiation of the market meltdown in 2007, and this finding is consistent with the sentiment interpretation.

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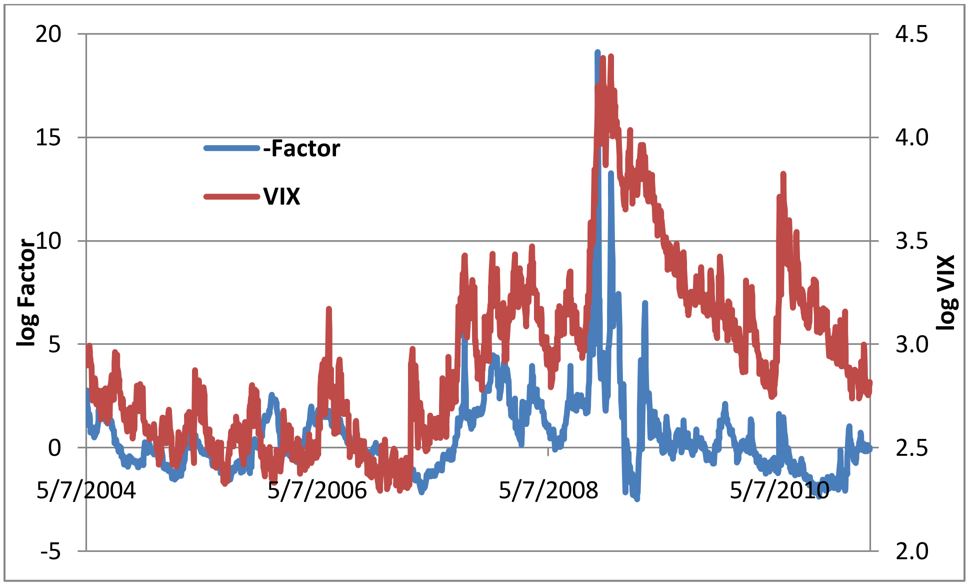
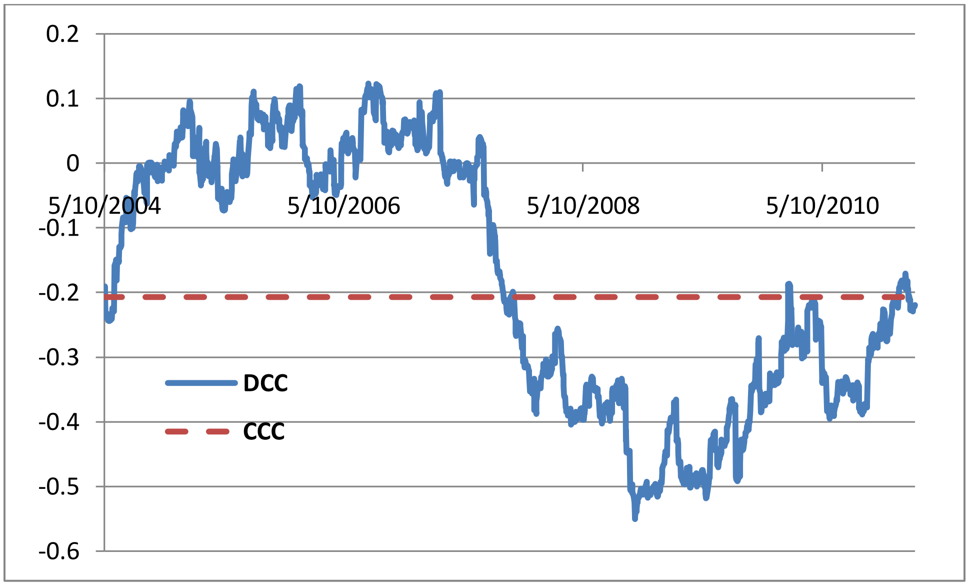
Figure 1. Common Factor Discount and the VIX



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 discount 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

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

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

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

	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

$$\text{GARCH: } \boldsymbol{h_{i,i,t} = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,i,t-1}}$$

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

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

		Estimate	Standard Error	t-Stat
GARCH	$\boldsymbol{\omega_f}$	38.3049	202.408	0.18925
	$\boldsymbol{\alpha_f}$	0.33759	0.00316	106.859
	$\boldsymbol{\beta_f}$	0.66240	0.00320	207.216
	$\boldsymbol{\omega_s}$	4.14045	1.81470	2.28162
	$\boldsymbol{\alpha_s}$	0.14095	0.00064	219.792
	$\boldsymbol{\beta_s}$	0.76468	0.00154	498.024
CCC	$\boldsymbol{\rho_{f,s}}$	-0.20670	0.00077	-267.224
DCC	$\boldsymbol{\alpha}$	0.01345	0.00001	944.845
	$\boldsymbol{\beta}$	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.