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Abstract

This paper investigates the short-run relationship between closed-end fund prices and their net asset values. In particular, we document three systematic differences between the short-run pricing behaviors for stock and bonds funds. For equity funds, we show that returns processes for both prices and asset values have characteristics of a random walk, while bond funds returns are more predictable. Similarly, multivariate GARCH analysis establishes the existence of stronger news and volatility spillover effects between the fund price and the net asset value for bond funds than for stock funds. Finally, we find significantly weaker dynamic conditional correlations between the fund price and its fundamental value for bond funds after the Lehman Brothers failure, whereas no such evidence is found for stock funds. To explain these findings, we propose a mechanism based on bond market illiquidity.

Keywords: Closed-End Funds; Market Efficiency; Market Illiquidity; Common Factors; Dynamic Conditional Correlation

JEL Classification: C32; G01; G12

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I. Introduction

According to the efficient market hypothesis (EMH), asset prices fully reflect all information relevant to their fundamental values (Fama, 1970). For example, stock prices should equal the present values of rationally expected future cash flows.

The case of Closed-End Investment Funds (CEFs) is historically important in the price-fundamentals debate. CEFs are in essence merely repackaged financial assets. The "fundamental value" of a share in a CEF can be identified with the net asset value (NAV) of the underlying portfolio. NAVs are in principle calculated every trading day based on the current market value (or liquidation value) of the fund's portfolio. Thus, if transaction costs for trading fund shares are negligible and roughly deterministic, the CEF price should approximate its NAV. Furthermore, fund price deviations from NAV should be short-lived.

Yet CEF pricing has been puzzling economists for decades. As documented by Lee, Schleifer, and Thaler (1990, 1991), Berk and Stanton (2007), and many others[1], the persistence of discounts in fund share prices relative to their underlying NAVs presents a challenge to conventional models of asset pricing. A variety of explanations for the discount have been put forward, with varying levels of acceptance. Investor sentiment (Lee *et al.*, 1991; Chopra *et al.*, 1993), the structure of manager compensation contracts (Berk and Stanton, 2007), management fees (Ross, 2002), accumulated tax liabilities (Malkiel, 1995), and costly arbitrage (Pontiff, 1996) have all been proposed as sources of mispricing. Most of these explanations are plausible and have at least some empirical support.[2]

[1] For a summary of earlier studies on this subject, see Anderson *et al.* (2010).
[2] Discounts, however, are not completely ubiquitous: funds sometimes trade at a premium. As well, the process of "open ending" a closed-end fund results in a rapid adjustment of prices to NAVs. In another vein, CEFs are ordinarily issued *at a premium* to NAV, and this premium usually quickly disappears (Lee *et al.*, 1990). Thus, one can say there are many "puzzles" attached to CEFs, of which the discount is only the most well-known.

Regardless of the theory being propounded, most analyses of CEF discounts have utilized a common framework: fund (log) prices p_t and (log) net asset values NAV_t are assumed to be cointegrated series with the known cointegrating vector $[1,-1]'$. This assumption is indeed a natural one in view of the ordinary interpretation of the "efficient markets" hypothesis.[3] The validity of this approach, though, will clearly be dependent on the *time scale* over which the analysis is undertaken: cointegration relationships reflect *long-run equilibrium* conditions, and such relationships may not be expected to hold in the short run. An operative definition of the "short run", however, is likely to be dependent on the nature of the financial assets under study, and it is this idea which motivates this paper.

Our interest is in understanding the discount dynamics of CEFs in the "short run." However, previous research has shown some differences in the behavior of bond versus equity CEFs. For reasons discussed at length below, it is quite likely that equity and bond CEFs need to be treated separately, and providing such an analysis is a part of our purpose. The differences we find are, we believe, important for the understanding of the discount anomaly itself. In particular, we will show that, while the price and asset value series for equity CEFs behave essentially like random walks, the bond series do not. Further, the divergence in bond and equity CEF discount behavior grows after the Lehman Brothers bankruptcy on Sept. 15, 2008. This finding sheds light on the possible source of the large difference in equity and bond CEF discount behavior. A variety of additional types of evidence, derived from the estimation of Dynamic Conditional Correlations and Granger Causality testing, lends further support to the hypothesis that persistent mispricing in bond funds arises at least partially for reasons inapplicable to equity funds, and we conjecture that portfolio liquidity effects may be the source of this difference.

[3] That is, the fund discount measured by $(p_t - NAV_t)$ is assumed to be stationary, while the log price (p_t) and the net asset value (NAV) are individually integrated processes.

The paper proceeds as follows. After a short literature review, we introduce our econometric strategy in Section III. Section IV presents our empirical results. Section V provides some expansion and interpretation, while Section VI concludes.

II. Relevant Literature

Several strands in the literature on asset pricing and market efficiency are relevant to the analysis presented here. Briefly, these include: (i) the analysis of asset mispricing and the EMH; (ii) the comparative analysis of returns and discounts for bond versus stock CEFs; (iii) the econometric analysis of connectedness and systemic risk in financial markets; (iv) possible connections between illiquidity of assets and their prices. We review each in turn.

The Efficient Markets Hypothesis (EMH) is a compelling theoretical idea, and a vast literature addresses the problem of testing its validity. Unfortunately, such tests are neither easy nor straightforward in almost all cases. First, it is often difficult to construct or obtain reliable measures of the relevant fundamental value variables. For instance, as Miller and Modigliani (1961) pointed out, interpreting the stock price as the present value of expected earnings per share is misleading when some earnings are retained.[4,5] Furthermore, the correct method for modeling the expectation formation mechanisms of traders is unclear (at least to us). Second, given a reasonable proxy variable for the fundamental value of a security, numerous researchers have shown that there often exist large and persistent deviations of asset prices from the fundamentals (Boswijk *et al*., 2007; Campbell and Shiller, 2001; Shiller, 1981), and these

[4] Miller and Modigliani (1961) and LeRoy and Porter (1981) propose correction methods to avoid potential double counting problems.

[5] One related research question is which fundamental variables help predict excess stock returns? For example, Fama and French (1989) use an array of interest rate variables, while Lamont (1998) employs the earnings/dividend ratio. Other macro variables such as the consumption-wealth ratio (Lettau and Ludvigson, 2001) and the investment-capital ratio (Cochrane, 1991) have also been examined.

deviations may be due to irrational behavior by market participants (Barberis and Thaler, 2003; Daniel *et al*., 1998; Summers, 1986; Shiller, 1981).

Although CEFs are relatively unimportant financially, their unique financial structure has led many researchers to study them extensively. In particular, since CEFs have shares which trade as ordinary equities on financial markets and CEFs are little more than portfolios of other traded financial assets, deviations between observed share prices and the net values of the underlying portfolios provide immediate and direct evidence of apparent mispricing. Theoretical explanations for these anomalous findings include risks introduced by uninformed noise traders (Lee *et al.* 1991, Chopra 1993), arbitrage costs (Pontiff, 1996), the structure of management fees (Ross 2006), tax liability effects (Malkiel, 1995), CEFs as vehicles enabling investors to efficiently buy illiquid assets (Cherkes, Sagi and Stanton, 2009) and so on. All of these explanations are reasonable and have some support in the literature. Few would argue, though, that a final resolution to the underpricing phenomenon is at hand.

A number of authors have examined equity and bond CEFs separately, including Abraham, Elan, and Marcus (1993) and Gasborro, Johnson, and Zumwalt (2003). Results on the significance of differences between the discount behavior of stock and bond funds is mixed, however: while Abraham *et al.* (1993) find that bond CEF discounts behave similarly to equity fund discounts, Gasborro *et al.* (2003) use cointegration procedures and find some differences in the mean reversion processes for the two fund types.

The market meltdown of 2007-2008, symbolized most vividly by the collapse of Lehman Brothers on Sept. 15, 2008, has triggered widespread research on systemic risk in financial (and other) networks. Underlying the concept of systemic risk is the notion that returns, liquidity, or other measures of financial health are interconnected between firms and sectors such that an untoward shock to one sector might “spill over” to others, a form of contagion previously associated with bank runs. Because the connections between firms are complex, varied, and largely immeasurable, researchers have proposed analyzing such linkages using principal components analysis and Granger causality tests. For example, Billio, Getmansky, Lo, and Pelizzon (2012) utilize this approach to highlight the critical role of banks in transmitting shocks between sectors, and thereby contributing to financial crises. We use a very simple form of this analysis in what follows.

There have been a number of studies that have tried to determine whether investors demand higher returns for less liquid assets (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan, *et al.*, 1998; Jones, 2002; Amihud, 2002). These studies found mixed evidence of a positive relationship between illiquidity and asset returns, but a primary issue and a subject of disagreement has always been what measures/proxies of illiquidity should be used. Several definitions of liquidity, both for specific assets and for markets themselves, have been proposed and tested in the literature. Chordia *et al.* (2009) propose a novel approach utilizing two different theory-based measures of an asset’s illiquidity. In contrast to previously existing research, the proxies they used were quite primitive drivers, such as trading volume and information asymmetry (informed vs. uninformed traders). By finding empirical evidence of a positive relationship between this theory-based illiquidity and assets’ returns, Chordia *et al.* (2009) provided stronger economic underpinnings for the estimation of assets’ illiquidity and its possible impact on assets’ returns than previous studies.

An important and recent development in asset liquidity analysis relevant to the present paper is offered by Bao, Pan, and Wang (2011), who examine the effects of illiquidity in corporate bonds on market pricing. They demonstrate the presence of a significant price effect arising from illiquidity, and show that, in aggregate, the average level of the bond illiquidity premium commoves with market riskiness, e.g., with VIX. These findings strongly suggest that bond prices reflect an illiquidity premium that depends on market statistics such as overall asset price volatility. As will be explained later, however, phenomena of this sort do not easily explain variations in CEF fund discounts.

III. The Econometric Model

Our empirical analysis is guided by several assumptions. First, we are interested in the "short-run" dynamics of fund discounts, and whether these processes differ between bond and equity CEFs. Second, we suspect that the natures of the processes generating fund returns and mispricing were potentially materially affected by the profound market events of fall, 2008. In particular, Sept. 15 2008 saw Lehman Brothers file the largest-ever corporate bankruptcy, with over 600 billion dollars in assets, triggering the greatest one-day NYSE price slide since September 11, 2001. Lehman Brothers was the largest New York bond dealer prior to its demise.[6] We wish to know if the relationship between prices and underlying asset values was affected by these events. These considerations lead us to adopt our approach.

Most previous research on CEFs pricing studies the fund price discount, defined as the natural logarithm of price (p_t) minus the log of NAV (NAV_t), by assuming that there exists a *known* cointegrating vector $[1, -1]'$ between these two nonstationary variables. This assumption

[6] "There is close to universal agreement that the demise of Lehman Brothers was the watershed event of the entire financial crisis and that the decision to allow it to fail was the watershed decision", Alan S. Blinder, an economics professor at Princeton and former vice chairman of the Fed, wrote in his history of the financial crisis, "After the Music Stopped", from Revisiting the Lehman Brothers Bailout that Never Was", by James Stewart and Peter Eavis, *The New York Times*, A1, Sept. 30, 2014.

implies that any deviation in price from "fundamental value" must be short-lived. Additionally, it is customary to use the discounts (premia) observed for *individual* funds, or in some hypothetical portfolio of funds, as the basis for estimation. We attempt to investigate important differences between the stochastic processes generating fund prices and NAVs for different sorts of funds by introducing two innovations.

First, rather than using fund prices and NAVs directly, we posit the existence of relatively general factor structures for the price and NAV processes. In other words, we allow (but do not require) the analysis to suggest that the processes generating fund prices, and those generating NAVs, are separately identified. Further, by positing the existence of underlying latent factors which (combined with idiosyncratic effects) generate fund prices and NAVs, we hope to obtain conclusions of greater generality. We then investigate the connection between estimated *latent common factors* of the prices and NAVs rather than analyzing individual fund prices and NAVs. This approach is similar to that adopted in analyses of systemic risk, such as that of Billio *et al.* (2012).

Second, we utilize the estimated common factors in a multivariate generalized autoregressive conditional heteroskedasticity specification (MGARCH) to investigate short-run pricing dynamics which incorporates the time-varying relationship between those latent common factors. This approach avoids imprecision in the analysis arising from the idiosyncratic factors which affect particular funds, and which are not relevant to any other funds. Further, this technique allows us to detect the possible occurrence of a structural break which might have taken place in the process generating NAVs during the recent market meltdown. We will show that changes in the empirical behavior of bond fund discounts after the financial crisis mostly arose because of a change in the process generating the NAVs, *not* the prices. This finding implies, in turn, that one should look at the processes generating prices and NAVs separately in some cases, and it suggests an explanation for the increasing differences between discount behavior across stock and bond funds.

A. Principal Component Analysis with Differenced Series

Let $r_{i,t}^{p}$ be the log-differenced price of fund i at time t. Similarly, $r_{i,t}^{n}$ denotes the log-differenced net asset value (NAV) of fund i at time t. That is, $r_{i,t}^{n}$ and $r_{i,t}^{p}$ are the continuously compounded *net* returns based on the NAVs and the prices of the fund, respectively.

We assume that these returns have the following factor structures:

$$r_{i,t}^{n} = \lambda_i^{n\prime} f_t^{n} + \eta_{i,t}^{n}, \tag{1}$$

$$r_{i,t}^{p} = \lambda_i^{p\prime} f_t^{p} + \eta_{i,t}^{p} \tag{2}$$

where f_t^n and f_t^p are the $k \times 1$ *common* factor components of $r_{i,t}^{n}$ and $r_{i,t}^{p}$, respectively, across all funds $i \in [1, N]$. The parameter vectors λ_i^n and λ_i^p denote the fund-specific $k \times 1$ factor loadings for the common factors f_t^n and f_t^p, respectively. That is, the degree of dependency varies across funds. Lastly, $\eta_{i,t}^{n}$ and $\eta_{i,t}^{p}$ are fund i's *idiosyncratic* components in $r_{i,t}^{n}$ and $r_{i,t}^{p}$, respectively.

Instead of investigating the dynamics of each fund, we take a practically convenient approach by focusing on the conditional correlation between the common factors f_t^n and f_t^p. Thus, our analysis should be taken as a study of the relationships between prices and fund values for "generic" equity and bond funds, with idiosyncratic factors removed.[7] We estimate the common factors and the factor loadings via the conventional principal component analysis after proper normalization.[8] Since the NAV and the price is highly likely non-stationary, we employ Bai and Ng's (2004) method, which extracts common factors from differenced variables and then restores level variables by cumulative summation.

B. The BEKK Model

We first employ the conventional BEKK (Baba-Engle-Kraft-Kroner, defined in Engle and Kroner, 1995) model to investigate time-varying relations between the NAV and the fund price through f_t^n and f_t^p allowing a *known* structural break in the data generating process.[9] For the model, we first filter out the *expected* component of $\boldsymbol{y}_t = [y_{1,t}, y_{2,t}]' = [f_t^n, f_t^p]'$ by the following vector autoregressive process:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}(L)\boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \tag{3}$$

where $\boldsymbol{\Phi}(L)$ is a lag polynomial matrix. We conventionally assume that $\boldsymbol{e}_t = [e_{1,t}, e_{2,t}]' = [e_t^n, e_t^p]'$ obeys the bivariate normal distribution,

$$\boldsymbol{e}_t|\Omega_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{H}_t), \tag{4}$$

[7] This approach follows Billio *et al.* (2012).
[8] Normalization is required because the principal component analysis is not scale-invariant.
[9] For our empirical analysis, we later use the date of the failure of Lehman Brothers (September 15, 2008).

where Ω_{t-1} denotes the adaptive information set at time t and the conditional covariance matrix $\boldsymbol{H}_t$ has the following representation:

$$\boldsymbol{H}_t = \boldsymbol{M}'\boldsymbol{M} + \boldsymbol{A}'\boldsymbol{e}_{t-1}\boldsymbol{e}'_{t-1}\boldsymbol{A} + \boldsymbol{B}'\boldsymbol{H}_{t-1}\boldsymbol{B} \tag{5}$$

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

Specifically,

$$h_{11,t} = \alpha_{11}^2 e_{1,t-1}^2 + \alpha_{21}^2 e_{2,t-1}^2 + \beta_{11}^2 h_{11,t-1} + \beta_{21}^2 h_{22,t-1} + \mathrm{X}_1,$$

$$h_{22,t} = \alpha_{12}^2 e_{1,t-1}^2 + \alpha_{22}^2 e_{2,t-1}^2 + \beta_{12}^2 h_{11,t-1} + \beta_{22}^2 h_{22,t-1} + \mathrm{X}_2,$$

where $h_{ij,t}$ denotes the $(i,j)^{\text{th}}$ component of $\boldsymbol{H}_t$, that is, the conditional variance (diagonal elements) or covariance (off-diagonal elements) and X_i is the remaining terms that include cross products.

Conventional interpretations are: the *diagonal* elements of $\boldsymbol{A}$ and $\boldsymbol{B}$ represent their *own* ARCH and the GARCH effect, respectively, while the *off-diagonal* elements provide the *cross-market effects* including the news effect and the volatility spillover effect. For example, a statistically significant estimate for α_{12} implies that there is a news effect from unexpected movements of f_t^n ($e_{1,t}$) on the conditional variance of f_t^p, and vice versa. Likewise, a statistically significant estimate for β_{21} implies that there is a significant volatility spillover effect from unexpected movements of f_t^p on the conditional variance of f_t^n.[10] Conditional correlation is measured as usual by the following:

[10] Note also the sign of these parameter estimates does not matter, because their squared values affect the conditional variances.

$$\rho_{i,j,t} = \frac{h_{i,j,t}}{\sqrt{h_{i,i,t}h_{j,j,t}}}$$

C. The Dynamic Conditional Correlation

We next employ the dynamic conditional correlation (DCC) estimator (Engle, 2002) for MGARCH models to investigate continuously time-varying relations between the NAV and the fund price. The DCC model can be viewed as a generalization of the constant conditional correlation (CCC) estimator proposed by Bollerslev (1990).

For the DCC, the conditional covariance matrix H_t from (4) is defined as:

$$\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t, \tag{6}$$

where $\boldsymbol{D}_t = diag(\sqrt{h_{i,i,t}})$ is the diagonal matrix with the conditional variances along the diagonal, and $\boldsymbol{R}_t$ is the time-varying correlation matrix. Note that the CCC is a special case of the DCC when $\boldsymbol{R}_t = \boldsymbol{R}$ for all t. (Figures for the correlations given later will exhibit both sets of correlations.)

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

$$E_{t-1}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t' = \boldsymbol{D}_t^{-1}\boldsymbol{H}_t\boldsymbol{D}_t^{-1} = \boldsymbol{R}_t = [\rho_{i,j,t}],$$

where $\boldsymbol{\varepsilon}_t = [\varepsilon_t^n, \varepsilon_t^p]' = \boldsymbol{D}_t^{-1}\boldsymbol{e}_t$ is the standardized innovation. Engle (2002) proposes the following mean-reverting GARCH(1,1) type conditional correlations:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}}\sqrt{q_{j,j,t}}}, \tag{7}$$

$$q_{i,j,t} = \bar{\rho}_{i,j}(1-\alpha-\beta) + \alpha\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta q_{i,j,t-1},$$

where $\bar{\rho}_{i,j}$ is the unconditional correlation. Or in matrix form,

$$\boldsymbol{Q}_t = \boldsymbol{S}(1-\alpha-\beta) + \alpha\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} + \beta\boldsymbol{Q}_{t-1} \tag{8}$$

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.

IV. Empirical Results

A. Data

We use daily returns for 16 bond closed-end funds for the period of March 17, 2004 through February 27, 2011 and daily returns for 16 stock closed-end funds for the period of May 6, 2004 through February 22, 2011. 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. The sample is composed of *all* funds with data available on Yahoo satisfying these criteria.[11]

[11] This data is nearly identical to the CRSP. However, the CRSP does not have the NAV data we need for our analysis.

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. dollar denominated bonds/notes, FNMA non-mortgage backed securities, FNA mortgage-backed securities, and other mortgages. We note the presence of lower quality bonds in virtually all bond funds. 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. Descriptive statistics for individual fund NAV and price daily returns are provided in Tables I and II.

Insert Tables I and II about here

When we analyzed the price and the NAV data for the stock and bond funds in our sample, we noted an obvious difference between these two types of funds. Figures 1 and 2 show the fluctuations in the discounts for a representative bond fund (ACG) and a representative stock fund (TY). As can be seen from Figure 1, the ACG bond fund was often traded at a premium, while TY stock fund traded only at a discount throughout the entire observation period (Figure 1). Other funds display similar behavior.

We first estimate the number of common factors by the information criteria suggested by Bai and Ng (2002) for each type of fund. Overall, we obtain strong evidence for a single-factor structure, and we assume that the first common factor plays a crucial role for the variations of the price and the NAV returns for each type of fund.[12] This simplifies our task substantially.

[12] All results are available from authors upon request. Interpretations of what these factors might represent is deferred until the next section.

The estimated factor loadings λ_i^p and λ_i^n are all positive and mostly similar in magnitude. Since the factor loading coefficients represent the degree of dependence of each return to the common factor, the findings imply that the common factor estimates represent overall dynamics of individual returns fairly well. Also, we note that the common factor plays an important role relative to the idiosyncratic component because the relative variance (or standard error) of the common component ($\sigma(\lambda_i^j f_t^j)/\sigma(\eta_{i,t}^j)$) is greater than one for the majority of funds as we can see in Figures 3 and 4. That is, individual fund movements are more heavily influenced by the common (global) component than fund-specific movements. It is interesting to see that the common factor explains predominantly greater share of return variations than idiosyncratic components.[13] In a nutshell, the common factor seems to represent the dynamics of returns very well both qualitatively and quantitatively. Hence, we believe these findings imply strong support the use of the common factor methodology to analyze the price/NAV relationship.

Figures 1, 2, 3, and 4 about here

Having obtained simple common factor representations for the underlying price and asset value series, we analyze the relationship between closed-end fund prices and fundamentals (NAVs) using multivariate GARCH models such as the BEKK and the DCC model for bond and stock funds separately. These relationships can be taken to represent the inter-temporal linkages *in general*, as the underlying factors are not affected by the idiosyncratic components impacting individual funds. The estimated relationships provide information about the underlying

[13] We noticed that the equity funds are more heavily influenced by the common factor than the bond funds, since the relative variance is overall greater with the equity funds.

relationships between prices and NAVs for hypothetical funds of the two types, and it is from these relationships that we make inferences.

We first use an eye-ball metric to see how the bond fund differs from the stock fund in the way the fund price is associated with its NAV. For this purpose, we provide graphs of the NAV and the price return for each type fund in Figures 5 (bond fund) and 6 (stock fund). We also provide the descriptive statistics for the estimated common factor of both types of funds, and this is presented in Table III.

We note that the NAV return and the price return of the stock fund behave quite similarly to each other, whereas those of the bond fund differ from each other. Such differences can also be seen from the descriptive statistics in Table III. For example, the bond NAV return has a more pronounced left-tail while the right-tail is more pronounced for the bond price return. In contrast, the stock NAV return and the price return have the same sign skewness. Furthermore, as we can infer from the kurtosis values, the bond price return has a fatter tail compared with that of the bond NAV return, while the stock NAV and price returns share similar kurtosis values. These findings are also consistent with our kernel density estimates in Figure 7.

Figures 5, 6, 7, and Table III about here

B. BEKK Estimation Results

We next employ the conventional BEKK model for f_t^n and f_t^p as we described in (5). We use a conventional vector autoregressive VAR(1) specification to filter out *expected* movement components of these returns, then full BEKK model estimations are carried out using the remaining *unexpected* movement components, that is, the residuals. We implement estimations for the full sample as well as two sub-samples assuming that there exists a structural break on September 15, 2008. We report our estimates in Tables IV and V for the common components from bond funds and from stock funds, respectively.

Recall that the mean equation panel provide VAR(1) coefficient estimates, which provide information on interactions between the expected components of the NAV return and the price returns. We note that the stock fund NAV and price, which are *level* variables, exhibit behavior consistent with the random walk hypothesis in the sense that most coefficient estimates in $\mathbf{\Phi}$ are insignificant, while the bond fund returns are roughly predictable. This is particularly striking because we are examining here relatively short-run price and NAV dynamics.

The variance equation panel delivers information on the ARCH and the GARCH effects. We find statistically significant ARCH (α_{11}, α_{22}) and GARCH (β_{11}, β_{22}) effects for both type funds. We also find a significant "news effect" (α_{12}, α_{21}) and "volatility spillover effect" (β_{12}, β_{21}) for the bond fund returns from the full sample and both sub-samples. However, the news effect from the stock NAV return to the stock price return (α_{12}) was insignificant and quantitatively negligible. We also find an insignificant news effect from the other direction (α_{21}) during the post-Lehman era. The estimates for β_{12} and β_{21} for the stock returns are significant in the pre-Lehman era but not in the post-Lehman era, while β_{11} and β_{22} estimates are a lot greater in the post-Lehman era. That is, we observe stronger GARCH effects but weaker volatility spillover effects, even though we cannot exclude the possibility that these results might be due to small sample size. The full sample estimates are significant but imply quantitatively small effects. These findings might have happened because the NAV and the price return become highly volatile at the same time during the turbulent periods such as the post-Lehman era. On the other hand, we observe a lot stronger volatility spillover during the post-Lehman era for the bond funds. Interestingly, we find greater spillover effects from the price return to the NAV return ($|\beta_{12}| > |\beta_{21}|$). That is, It is more likely that high volatility spreads from the price return to the NAV return. Overall, bond fund common components exhibit higher dependence between the NAV and the price returns compared with those from the stock fund.

Tables IV and V about here

C. DCC Estimation Results

We now estimate the dynamic conditional correlation (DCC, Engle, 2002), along with the constant conditional correlation (CCC, Bollerslev, 1990) between the common component of the funds' price, f_t^p, and the common component of their NAV, f_t^n ,for the multivariate GARCH models. Model estimates are reported in Tables VI and VII.

Figures 8 and 9 show the estimated dynamic conditional correlations (DCC) for a hypothetical bond closed-end fund and a stock closed-end fund, respectively.[14] In contrast to the **Φ** estimate from the previous section, the DCC provides information on the interactions between *unexpected* changes in the variables of interest. In other words, how are unexpected changes in fund prices correlated with the shocks to NAVs, and how does this relationship change over time?

We note two striking differences between bond and stock funds. First, the correlation between the price and the NAV is much lower for a bond fund than it is for a stock fund, a finding consistent throughout the estimation period. Second, the conditional correlation for a hypothetical bond fund shows a clear structural break in late 2008. While the correlation was around 0.5 prior to the break, it decreased to about 0.3 after the break (Figure 8).The Engle's

[14] We also estimated the dynamic conditional correlations using the BEKK model. The estimates are very similar to those from Engle's (2002) method so we don't report them here. The estimates are available from the authors upon request.

(2002) test of a constant conditional correlation (against a varying dynamic conditional correlation) is rejected at the 5% significance level (p-value: 0.0349) for a bond fund. We can conclude that there is a significant change in the correlation between price and NAV for a generic bond CEF, and that the correlation got far weaker in the aftermath of the events of fall 2008.

Unlike the bond funds, the generic stock fund did not exhibit any significant change in the dynamic conditional correlation between the price and the NAV over the sample interval. As can be seen from Figure 9, and also confirmed by Engle's test, the correlation between the price and the NAV for a stock fund remains constant throughout the estimation period, with a value of around 0.9-0.95. Thus, the behavior of stock and bond CEFs is quite different in these two respects. First, equity funds exhibit much higher conditional correlations between their prices and NAVs than do bond firms. Second, the relationship between price and NAV for the bond funds underwent a significant degradation immediately after events in the autumn of 2008.

Figures 8, 9, and Tables VI, VII about here

V. Interpretation and Possible Explanations

The empirical analysis above establishes several basic conclusions:

1. There is substantial evidence of a significant shift in the processes generating discounts around the time of the Lehman Brothers bankruptcy (Sept. 15, 2008), and these effects are much more pronounced for bond funds;

2. Both the price and asset value series for generic equity funds behave like random walks, but those for bond funds exhibit non-negligible predictability;
3. In response to shocks, volatility spillovers vanish for equity funds after the Lehman failure, but such linkages strengthen for bond funds;
4. Conditional correlations between prices and asset values are very high (0.9 to 0.95) and quite stable for equity funds, while bond funds have much weaker correlations and exhibit a significant structural break in fall, 2008;
5. Estimated Dynamic Conditional Correlations (DCCs) affirm the presence of the structural break around the Lehman bankruptcy.

These findings strongly suggest that the processes generating prices and asset values (and hence discounts) are quite different between bond and equity funds. Further, apparent violations of efficient pricing became more pronounced for bond funds, but not stock funds, after the failure of Lehman Brothers and other events occurring in September-October 2008. Although financial markets generally were in turmoil during this period, there was no material change in the behavior of the equity fund discounts – only bond funds were affected. Yet the prices of bond CEFs are themselves determined by open trading in the equity markets. What is the explanation for this curious finding? We believe at least a partial explanation can be found in the natures of the bond markets themselves

Consider, for example, the striking divergence in DCC exhibited by the generic bond fund. Bonds are highly specific, compared to most equities, and as a result, the role of bond traders is of far greater significance to the functioning of some bond markets than might be realized. The markets for many bonds are much thinner than most equities, and the ratings of bonds therefore partially “substitute” for active, deep trading in these assets. As was widely documented in the *Wall Street Journal* and other business periodicals of the time, the Lehman bankruptcy (and associated market disorder) greatly reduced the liquidity of many bonds. Previously, the specificity of various bond issues was partially mitigated by the acceptance of bond ratings, and Lehman Brothers served as the largest bond trader in New York. Soon after the Lehman bankruptcy, however, bond insurers Ambac and MBIA faced ratings downgrades. Independent bond ratings, which had previously been accorded serious attention by many investors, suddenly appeared unreliable and perhaps even intentionally misleading. This failure disproportionately affected bond markets in certain lower quality categories. Equity markets, along with extremely deep bond markets for U.S. treasuries and the like, though affected by the downturn, continued trading virtually uninterruptedly.

This asymmetry had a logical consequence for the process that generated NAVs for bond funds: when lower grade bonds in CEF portfolios become more illiquid, some ambiguity arises is the calculation of net asset values. This ambiguity is likely to be at least partially resolved in a manner less hostile to the observed performance of the fund. While bond fund share prices are equity prices, the *asset values* of the bonds in fund portfolios had to be calculated in an environment in which immediate sale implied steep losses. If this description is valid, one would expect to observe an increase in the *persistence* of NAVs for bond (but not stock) funds.[15] Share prices, on the other hand, would presumably adjust rapidly to whatever levels the assessments of investors might support. Thus, a change in the relative liquidities of fund share prices and the fund’s underlying asset portfolio would lead to changes in the behaviors of the price and asset values series we, in fact, observe in the case of bond funds. Equity funds experienced far less

[15] Since Lehman Brothers was one of the largest bond dealers, the failure of it might have increased this illiquidity problem for the bond funds.

change in the liquidities of their share prices relative to their underlying assets. This notion is, in an approximate sense at least, testable using estimated latent factors and pairwise Granger causality tests in much the same way such analysis is used to quantify linkages between financial sectors in systemic risk studies. In this framework, we should expect to observe the share prices of bond CEFs *at time t* causing NAVs *at later times* in the Granger-causality sense, while NAVs should not Granger-cause fund prices. In other words, if the NAV series becomes sufficiently persistent, yet the prices of bond fund shares (which are equity prices) continue to adjust rapidly to investor assessments of value, then these prices should allow us to forecast future NAVs for the simple reason that, as time passes, NAVs will adjust to market reality, *but with a lag.* Although this offers us an informal test only, we implement the conventional Granger causality test to investigate this possibility (Table VIII).

Choosing September 15, 2008, as a structural break date, we implement the test for the pre- and the post-crisis periods. The test cannot reject the null of no Granger-causality (29.8% p-value) from the NAV to the price factor for the bond funds in the post-crisis period, while the null was rejected at any significance level for all other cases. On the other hand, the null of no Granger causality from the price at time *t* to the NAV at *later times* is rejected for bond funds. Therefore, we conclude that in the post-crisis period, bond fund share prices “cause” NAVs of bond funds, but the converse is not true. As for the stock funds, the NAV and the price factor seem to Granger-cause each other, i.e., they are mutually determined. This analysis is consistent with our conjecture stated above and implies that bond funds, unlike equity funds, suffer from the differential illiquidity problem during market turmoil and the process used to determine bond funds’ current NAVs generates persistence.

The results of Bao et al (2014) establish the existence of a relatively large and financially significant illiquidity premium in bond prices. This result alone, though, does not explain the differential behaviors of the generic bond CEF price and NAV series. The existence of a (negative) illiquidity premium in corporate bond prices is entirely logical. Yet, the evidence suggests that a jump in these premia, for example, is not translated into fund share prices as one would ordinarily expect. On the contrary, the price of a bond fund share, which is an ordinary equity, is informative for the future evolution of fund NAVs.

Tables VIII about here

IV. Summary and conclusions

CEFs present a unique opportunity for testing theories of market efficiency and asset pricing. In an efficient market, the relationship between any fund’s share prices and the underlying value of the fund’s assets should be very strict. That this is often not the case has stimulated the interests of academic researchers.

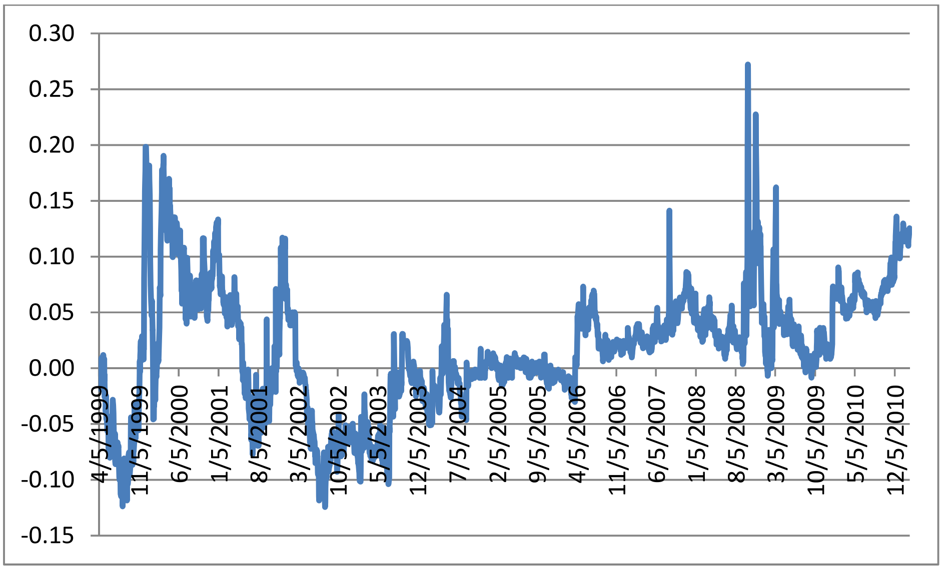
Many theories of fund share mispricing have been advanced, and a variety of explanations have at least some empirical support. Noise (irrational) traders as a source of risk, arbitrage costs, tax effects and so on are all capable, to one degree or another, of explaining the *existence* of some degree of mispricing. The mispricing issue is, however, only the best known CEF “anomaly”, and research on these financial vehicles shows no sign of abating.

In this article, we make two primary points, both potentially relevant to the mispricing research agenda. First, we show that CEFs are by no means a homogenous group: there are fundamental differences between equity and bond funds that are manifested in the correlations between their prices and NAVs. Although such differences are commonly recognized, and are in fact exploited in many empirical tests of mispricing theories, the fact that equity CEFs have price and asset series which act as random walks, while those of bond CEFs do not, is more a difference in kind than of degree. This finding is facilitated by looking not at individual funds, or groups of funds, but by attempting to “extract” the latent common factors behind the prices and asset valuations.

Second, our approach illustrates that the processes generating prices, and those generating NAVs, can undergo shifts “independently”, thereby radically altering the observed relationship between share price and share value. By focusing on the period 2004-2011, we incorporate the market disruptions of fall, 2008. This period saw unprecedented disruption of financial markets, especially in some market segments such as bonds. By including these events within our sample, we are able to look at the NAV process with sufficient focus to detect a change in its behavior. We report some evidence that 2008 saw a structural break in the process generating NAVs for bond CEFs, and we offer a possible mechanism to explain what happened. Indirect tests, based on Granger-causal relationships between fund prices and values, support our explanation.

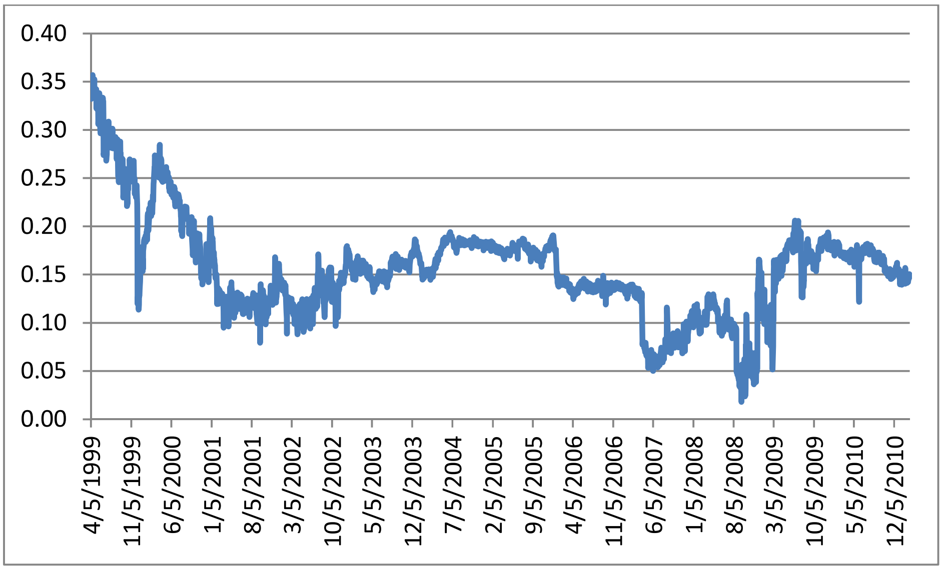
CEFs are historically and academically important because they provide a highly transparent example of a form of “double pricing”: fund assets (for example corporate bonds) are priced in a market, and simultaneously the fund portfolio itself is priced in the equity market. In the case of equity CEFs, this process, whatever its imperfections, did not materially change in response to the financial catastrophe of 2008. In stark contrast, the process generating bond CEF discounts was profoundly affected by the events of 2008, and the channel by which this occurred was the NAV process, not the price series. This is an anomaly inviting further analysis.

Figure 1. Log Discount: ACG (Bond Fund)



Note: The log discount denotes $\ln(NAV) - \ln(p)$, where we use the close price of each day.

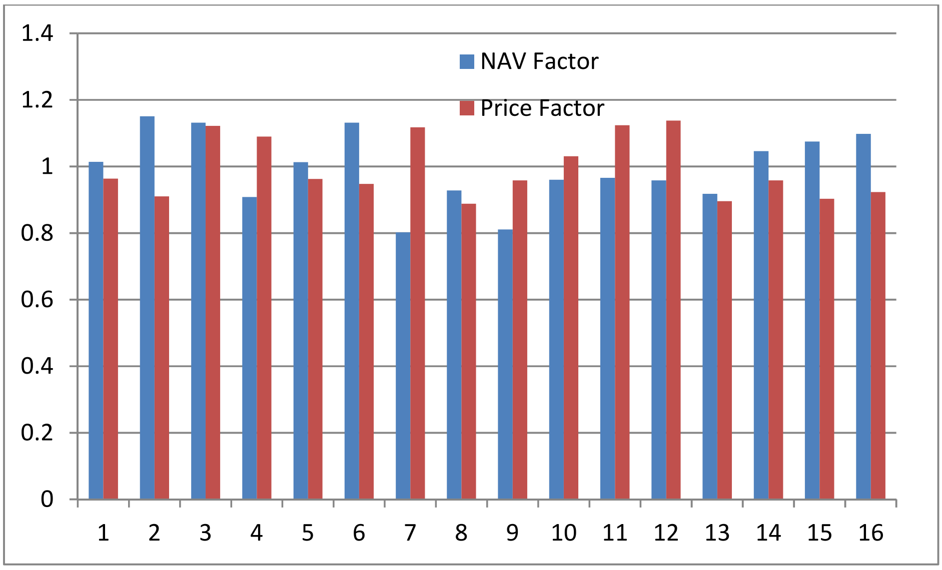
Figure 2. Log Discount: TY (Stock Fund)



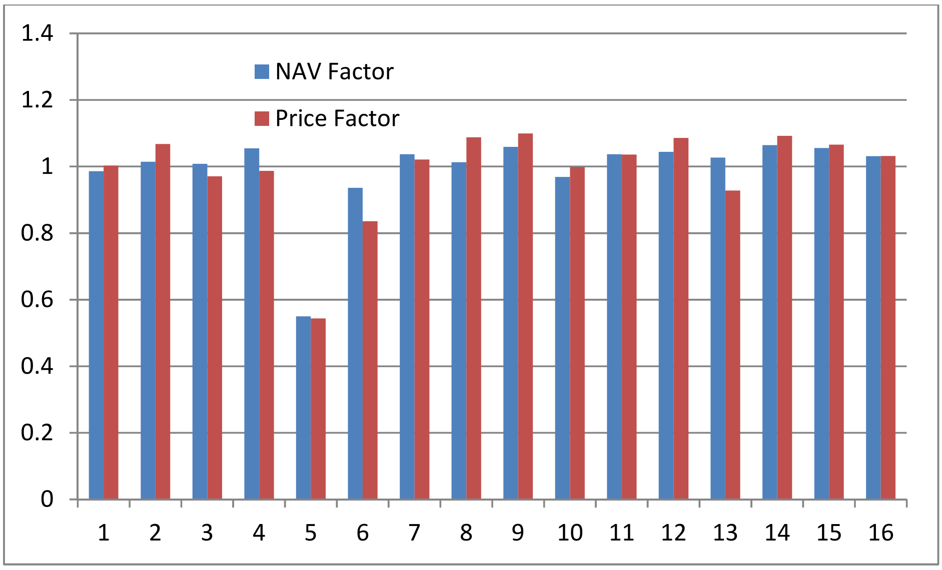
Note: The log discount denotes $\ln(NAV) - \ln(p)$, where we use the close price of each day.

Figure 3. Factor Loadings

(a) Bond Funds



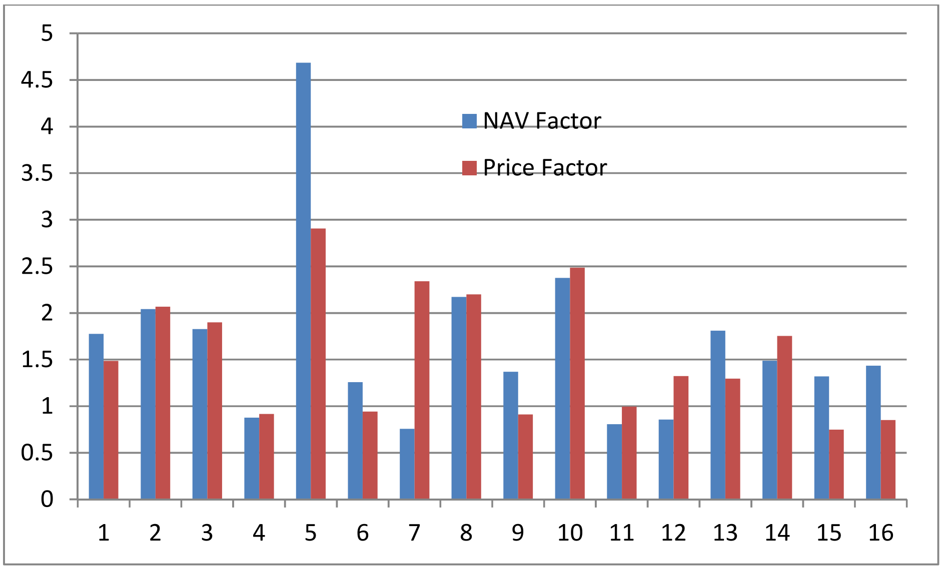
(b) Stock Funds



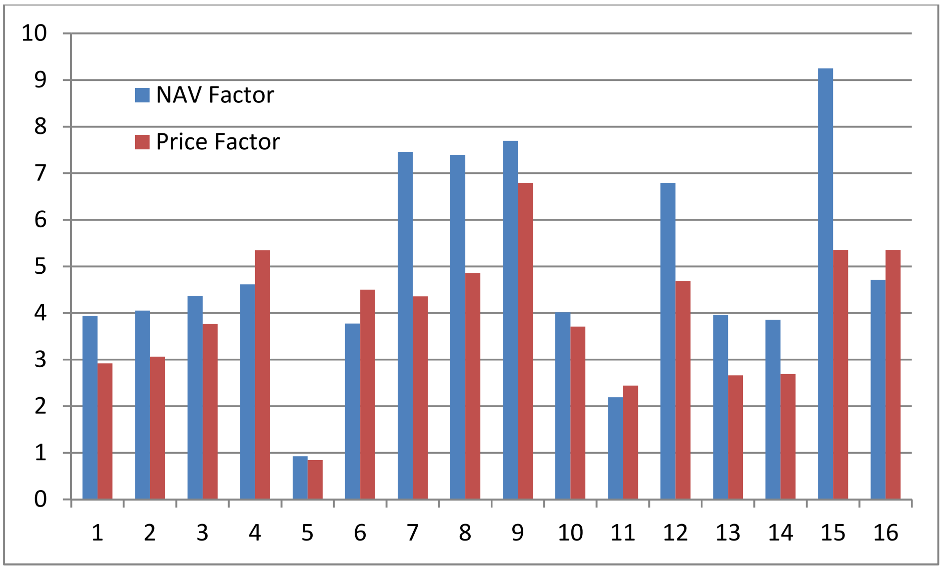
Note: Estimated factor loadings are λ_i^p and λ_i^n in equations (1) and (2). We choose 1 factor for each set of funds, that is, $k = 1$. Therefore, λ_i^p and λ_i^n are scalars. The horizontal axis is a fund's ID.

Figure 4. Relative Variations

(a) Bond Funds



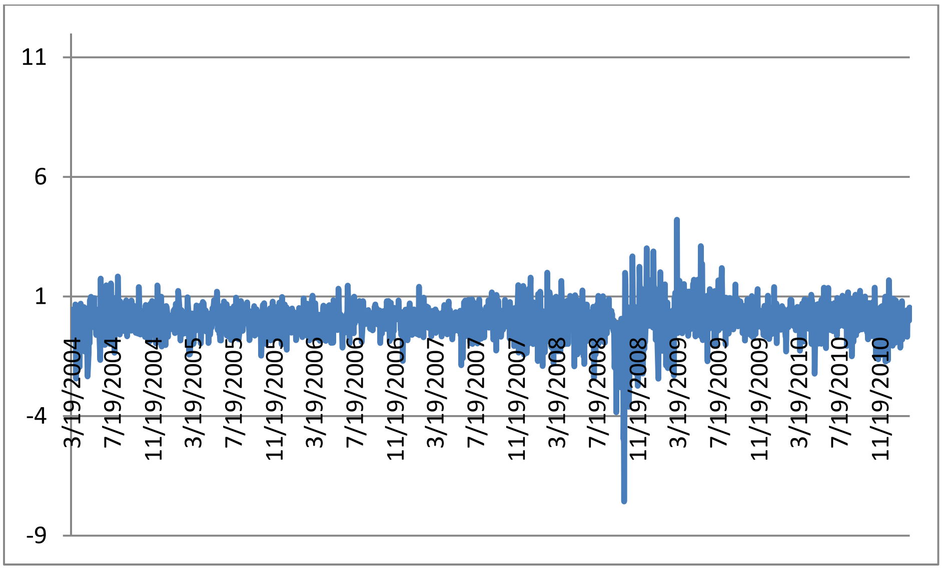
(b) Stock Funds



Note: The relative variation is defined by $\sigma(\lambda_i^j f_t^j)/\sigma(\eta_{i,t}^j)$, where σ is the estimate standard deviation and $j = n, p$. Because the common factor and the idiosyncratic component are orthogonal each other, the total variation is the sum of $\sigma(\lambda_i^j f_t^j)$ and $\sigma(\eta_{i,t}^j)$. Therefore, when this ratio is greater than one, common factor explains more variation of the variable than the idiosyncratic component. The horizontal axis is a fund's ID.

Figure 5. Common Components: Bond Funds

(a) NAV return



(b) Price Return

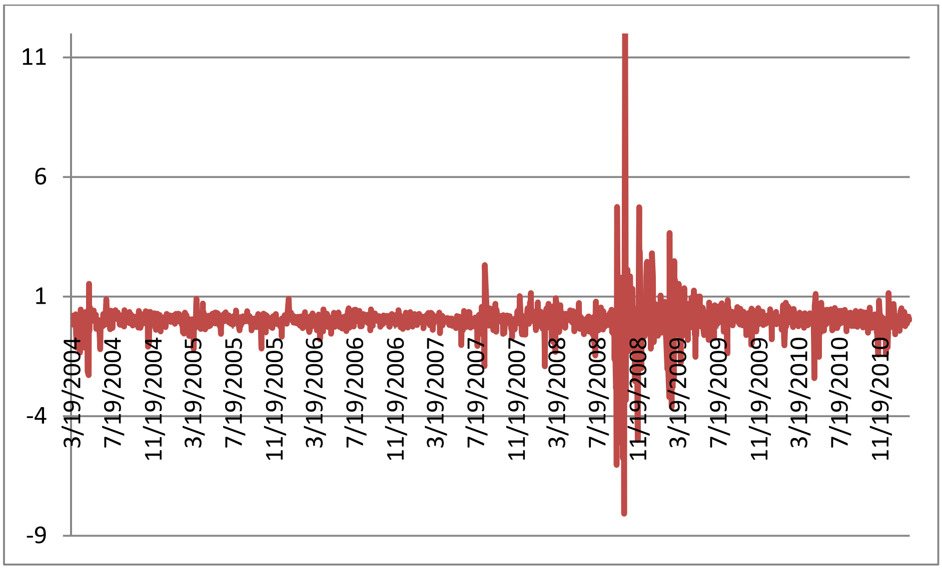
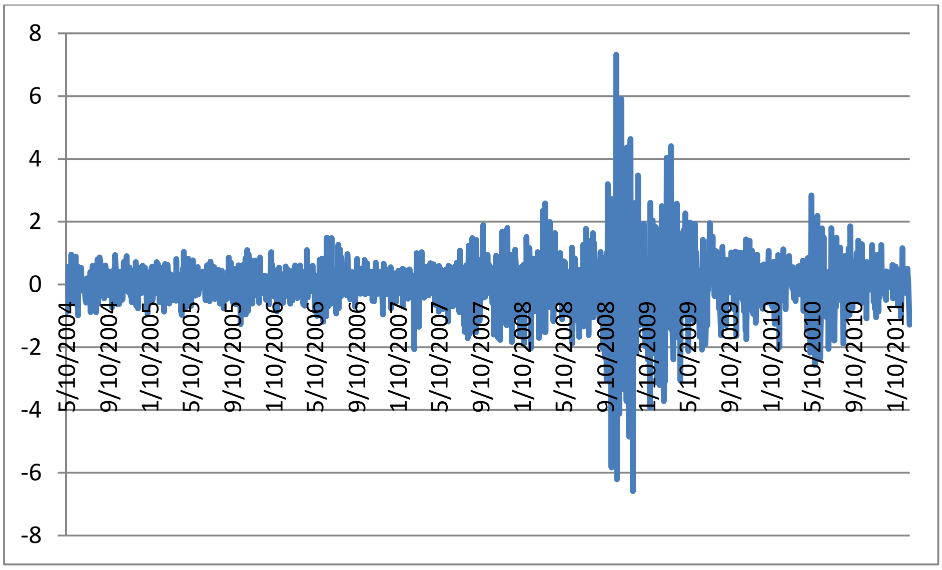


Figure 6. Common Components: Stock Funds

(a) NAV return



(b) Price Return

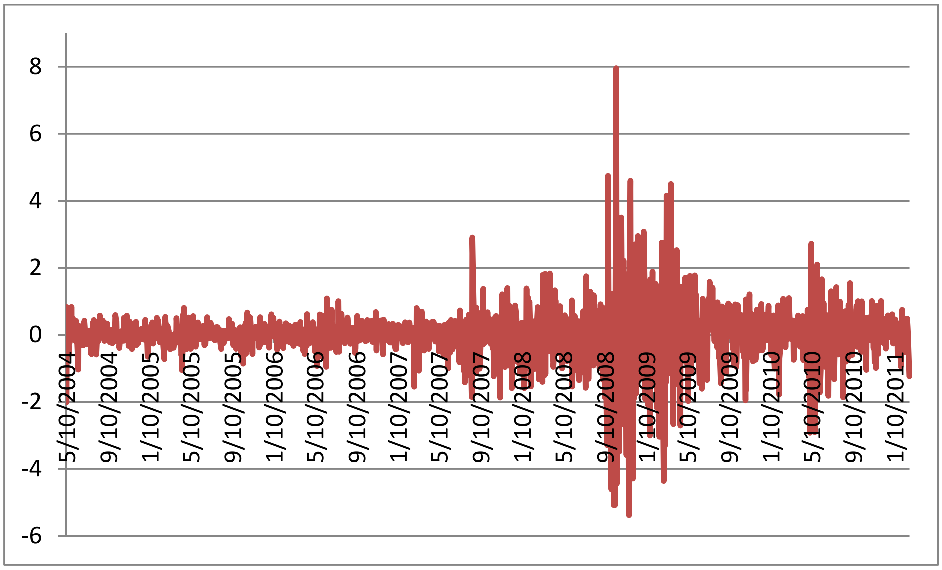
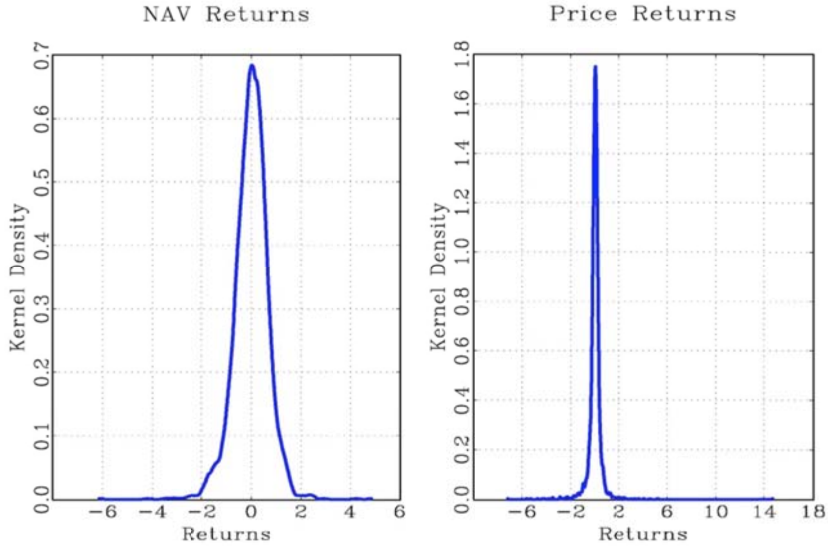
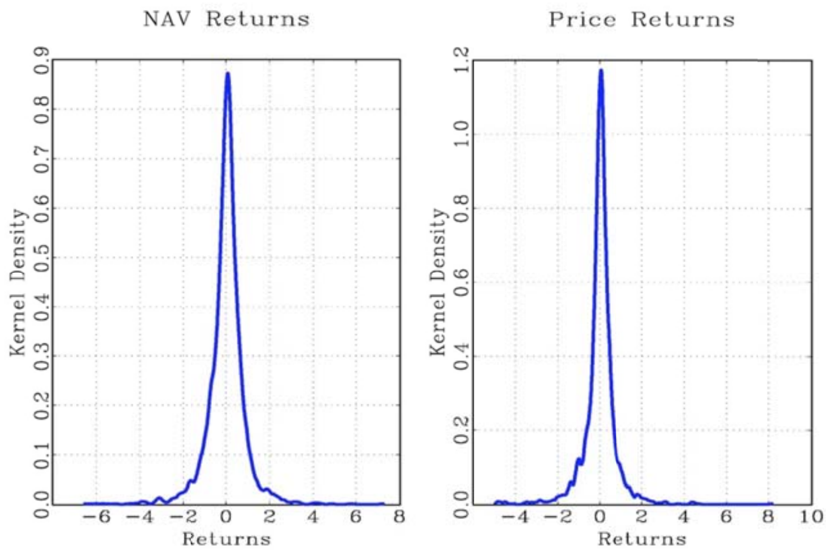


Figure 7. Kernel Density Estimation for Common Components

(a) Bond Funds

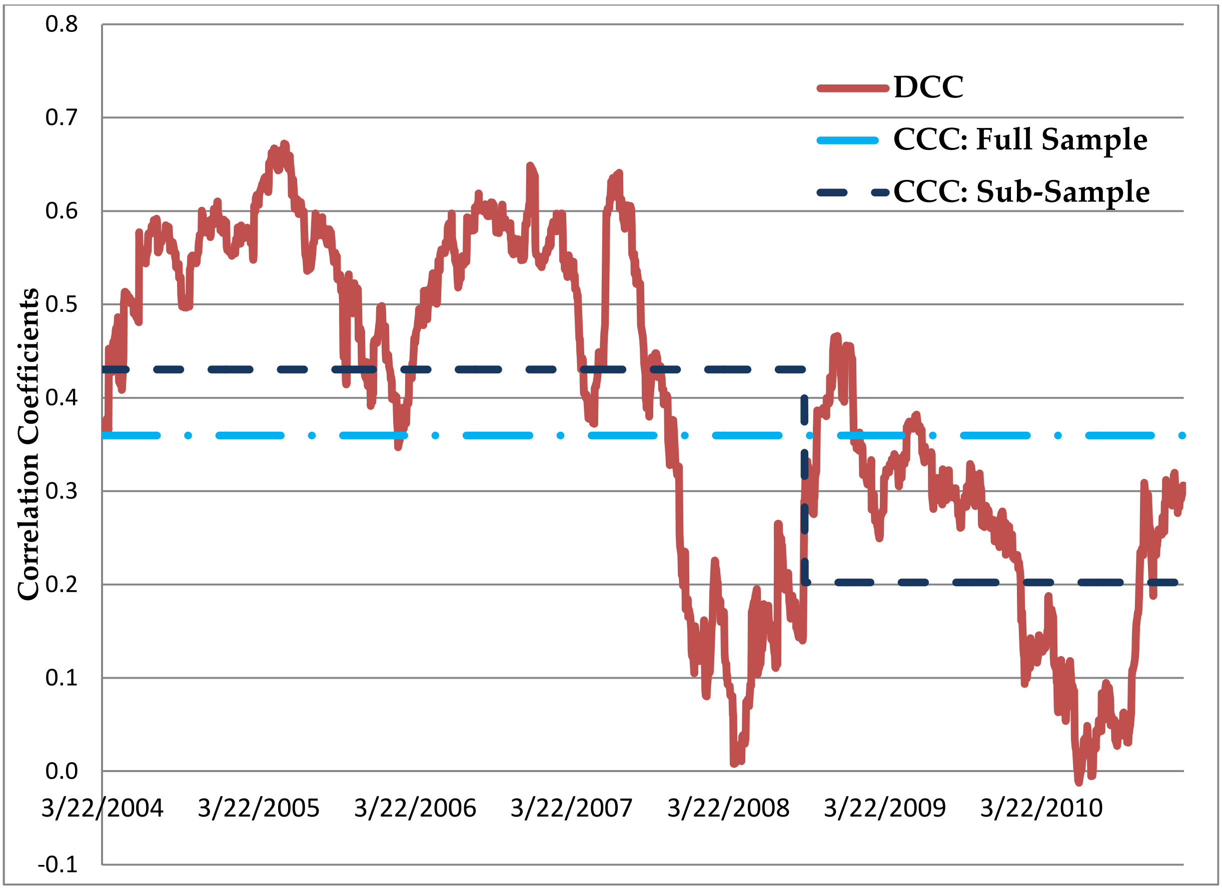


(b) Stock Funds



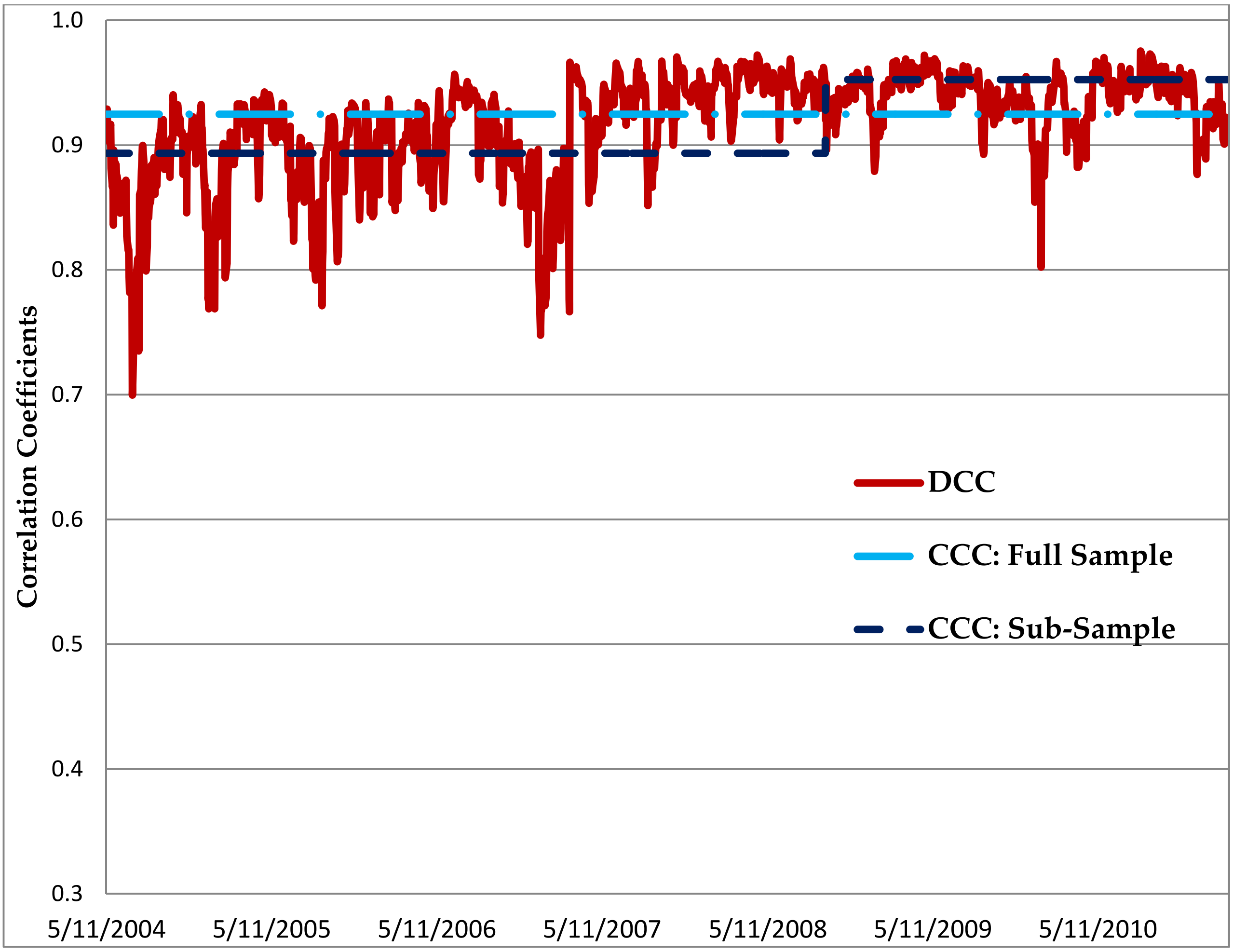
Note: We use the Gaussian kernel to estimate the kernel density functions.

Figure 8. Conditional Correlations: Bond Funds



Note: The Engle's (2002) test of the constant conditional correlation (CCC) against the dynamic conditional correlation (DCC) is rejected at the 5% significance level (p-value: 0.0349). That is, the test is in favor of the DCC. For the sub-sample CCC, we assume that there is a known structural break on September 15, 2008 when Lehman Brothers was allowed to fail.

Figure 9. Conditional Correlations: Stock Funds



Note: The Engle's (2002) test of the constant conditional correlation (CCC) against the dynamic conditional correlation (DCC) is not rejected at the 10% significance level (p-value: 0.4641). That is, the test is in favor of the CCC. For the sub-sample CCC, we assume that there is a known structural break on September 15, 2008 when Lehman Brothers was allowed to fail.

Table I. Descriptive Statistics of Individual Bond Fund Returns

Bond Fund NAV Returns

Name	Mean	Std.dev	Kurtosis	Skewness
ACG	0.0000	0.0034	3.1752	-0.6018
BHK	-0.0001	0.0051	2.7092	-0.2743
BNA	-0.0001	0.0052	2.8887	-0.3591
BPP	-0.0004	0.0080	28.2361	-2.2486
CMK	0.0000	0.0027	31.5902	-2.7786
DUC	-0.0001	0.0037	8.2647	-0.5037
EVV	-0.0001	0.0030	25.1572	-2.4733
ICB	0.0000	0.0047	124.9551	-0.6097
KST	0.0000	0.0040	27.2149	-2.9289
MMT	0.0000	0.0030	37.3105	-0.6870
PSW	-0.0005	0.0074	20.6931	-1.7336
PSY	-0.0005	0.0075	20.1723	-1.7973
TAI	-0.0001	0.0027	27.5723	-0.1078
WEA	0.0000	0.0047	10.6968	-1.2134
WIA	-0.0001	0.0047	6.0966	-0.0051
WIW	-0.0001	0.0046	7.6789	-0.1089

Bond Fund Price Returns

Name	Mean	Std.dev	Kurtosis	Skewness
ACG	-0.0001	0.0096	34.1531	-0.3648
BHK	-0.0001	0.0102	21.6532	-0.3879
BNA	-0.0001	0.0140	78.7655	1.4511
BPP	-0.0005	0.0210	32.7078	-0.4864
CMK	-0.0001	0.0117	74.5191	1.8961
DUC	-0.0002	0.0142	50.8641	1.7660
EVV	-0.0001	0.0141	46.4162	0.0275
ICB	0.0000	0.0119	40.7052	1.3753
KST	0.0000	0.0129	34.0058	-1.2990
MMT	0.0000	0.0100	45.8484	-1.4223
PSW	-0.0006	0.0211	46.0557	1.4304
PSY	-0.0005	0.0217	46.6363	0.8444
TAI	-0.0001	0.0102	38.4396	0.9204
WEA	0.0000	0.0172	37.2769	0.4233
WIA	-0.0001	0.0080	13.6484	-0.2261
WIW	-0.0001	0.0077	17.3265	-0.5268

Note: Bond fund NAV and price returns denote the log first difference of each data series.

Table II. Descriptive Statistics of Individual Stock Fund Returns

Stock Fund NAV Returns

Name	Mean	Std.dev	Kurtosis	Skewness
BDT	-0.0001	0.0151	10.0812	0.0367
BDV	-0.0002	0.0132	10.0891	-0.3351
BLU	-0.0002	0.0164	11.7972	-0.4273
DCS	0.0000	0.0471	791.2317	22.7678
FUND	0.0000	0.0182	13.4060	-1.4306
GAB	-0.0002	0.0187	11.1368	-0.2250
GAM	0.0000	0.0167	13.0022	-0.7682
RVT	0.0000	0.0176	7.3988	-0.5245
SOR	0.0001	0.0159	6.9506	-0.4774
TY	-0.0001	0.0148	11.2416	-0.5242
USA	-0.0002	0.0151	7.9583	-0.2653
ZF	-0.0002	0.0123	9.1352	-0.3958
ASG	-0.0002	0.0148	11.0872	-0.3133
GDV	0.0000	0.0170	13.9910	-0.3247
HTD	0.0000	0.0165	22.4015	-0.1856
JTA	-0.0002	0.0157	14.9840	-0.6589

Stock Fund Price Returns

Name	Mean	Std.dev	Kurtosis	Skewness
BDT	-0.0002	0.0157	10.2259	-0.4430
BDV	-0.0002	0.0152	8.5569	0.2929
BLU	-0.0003	0.0178	13.9638	-0.3466
DCS	-0.0001	0.0458	905.3593	25.3956
FUND	-0.0001	0.0218	18.2529	-0.8557
GAB	-0.0002	0.0207	15.9606	0.0134
GAM	0.0000	0.0155	16.7933	-0.8976
RVT	-0.0001	0.0185	14.0870	-1.0577
SOR	-0.0001	0.0169	17.2909	0.0732
TY	-0.0001	0.0147	10.9159	-0.5746
USA	-0.0004	0.0158	10.2311	-0.6776
ZF	-0.0002	0.0145	13.3721	-0.0942
ASG	-0.0003	0.0167	9.6895	-0.5519
GDV	0.0000	0.0170	29.3654	0.7654
HTD	-0.0001	0.0169	14.5184	-0.3284
JTA	-0.0002	0.0183	21.1061	-0.5937

Note: Stock fund NAV and price returns denote the log first difference of each data series.

Table III. Descriptive Statistics of Common Factor Returns

	Bond Funds		***Stock Funds***	
	NAV	Price	NAV	Price
Mean	0.000	0.000	0.000	0.000
Std Dev	0.736	0.720	0.916	0.820
Skewness	-0.494	3.981	-0.513	-0.056
Kurtosis	10.22	128.95	14.08	17.43
Jarque-Bera	3856.5	1156056	8816.9	14824

Note: NAV and Price denote the first common factor of the fund NAV returns and the fund price returns. The mean is zero by construction because the PANIC uses standardized series before estimating the common factor. We use VAR(1) specification to extract whitened residuals and report the skewness, kurtosis, and Jarque-Bera test statistics for the residuals.

Table IV. Full BEKK Estimations: Bond Funds

$$\boldsymbol{Y_t} = \begin{bmatrix} f_t^n & f_t^p \end{bmatrix}', \boldsymbol{Y_t} = \boldsymbol{\Phi Y_{t-1}} + \boldsymbol{e_t}, \boldsymbol{\Phi} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

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

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

			Mean Equation			
	Full Sample		*Pre-Lehman*		*Post-Lehman*	
	estimate	std. err.	estimate	std. err.	estimate	std. err.
ϕ_{11}	**0.12314**	0.02486	**0.14623**	0.02941	-0.00518	0.04617
ϕ_{12}	**0.23986**	0.02539	**0.22123**	0.02755	**0.33647**	0.07679
ϕ_{21}	**0.11067**	0.02508	**0.10830**	0.03262	**0.10304**	0.02777
ϕ_{22}	**0.11956**	0.02561	**0.12394**	0.03056	0.06561	0.04618

			Variance Equation			
	Full Sample		*Pre-Lehman*		*Post-Lehman*	
	estimate	std. err.	estimate	std. err.	estimate	std. err.
ω_{11}	**0.07881**	0.00032	**-0.06901**	0.00057	**0.01319**	0.00002
ω_{12}	**-0.00002**	0.00000	**0.00245**	0.00000	**0.00800**	0.00002
ω_{22}	**0.08825**	0.00019	**-0.08259**	0.00026	**0.00485**	0.00003
α_{11}	**0.14965**	0.00054	**0.12406**	0.00062	**0.11458**	0.00186
α_{12}	**0.09703**	0.00219	**0.11725**	0.00222	**-0.16848**	0.00607
α_{21}	**-0.01730**	0.00121	**-0.05130**	0.00134	**0.14393**	0.00092
α_{22}	**0.60228**	0.00482	**0.62656**	0.00623	**0.44797**	0.00946
β_{11}	**0.98733**	0.00002	**0.99471**	0.00004	**0.93661**	0.00035
β_{12}	**-0.05886**	0.00059	**-0.06438**	0.00061	**0.20282**	0.00258
β_{21}	**0.00985**	0.00005	**0.02071**	0.00007	**-0.04338**	0.00039
β_{22}	**0.80083**	0.00163	**0.79606**	0.00232	**0.81320**	0.00251
$-lnL$	2015.43		1415.09		1607.31	

Table V. Full BEKK Estimations: Stock Funds

$$\boldsymbol{Y_t} = \begin{bmatrix} f_t^n & f_t^p \end{bmatrix}', \boldsymbol{Y_t} = \boldsymbol{\Phi Y_{t-1}} + \boldsymbol{e_t}, \boldsymbol{\Phi} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

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

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

	Mean Equation					
	Full Sample		*Pre-Lehman*		*Post-Lehman*	
	estimate	std. err.	estimate	std. err.	estimate	std. err.
ϕ_{11}	-0.06111	0.06341	0.09971	0.06732	-0.11523	0.11320
ϕ_{12}	-0.00402	0.07082	**-0.24031**	0.08282	0.06401	0.12300
ϕ_{21}	0.02121	0.05625	**0.14350**	0.05449	-0.01162	0.10313
ϕ_{22}	0.11762	0.06282	-0.11910	0.06704	0.17533	0.11205

	Variance Equation					
	Full Sample		*Pre-Lehman*		*Post-Lehman*	
	estimate	std. err.	estimate	std. err.	estimate	std. err.
ω_{11}	**0.08169**	0.00046	**0.17933**	0.00113	**0.11937**	0.00154
ω_{12}	**0.03499**	0.00003	**0.00002**	0.00000	**0.02922**	0.00028
ω_{22}	**0.04728**	0.00031	**0.02250**	0.00026	**0.12244**	0.00188
α_{11}	**0.29185**	0.00315	**0.18013**	0.00846	**0.28734**	0.01385
α_{12}	-0.00836	0.00542	0.03013	0.01602	-0.00850	0.01764
α_{21}	**0.02079**	0.00332	**-0.10473**	0.00382	0.02311	0.01581
α_{22}	**0.32194**	0.00581	**0.44088**	0.00752	**0.31865**	0.02039
β_{11}	**0.93872**	0.00118	**0.71144**	0.01690	**0.93840**	0.00807
β_{12}	**0.01684**	0.00168	**0.28933**	0.02236	0.01385	0.01044
β_{21}	**0.00592**	0.00089	**0.09471**	0.00211	0.00122	0.00828
β_{22}	**0.92981**	0.00132	**0.83195**	0.00399	**0.92816**	0.01048
$-lnL$	1222.44		299.667		862.561	

Table VI. CCC and DCC Estimations: Bond Funds

CCC: $\boldsymbol{H_t} = \boldsymbol{D_t R D_t}, \boldsymbol{D_t} = diag\left[\sqrt{h_{i,i,t}}\right], \boldsymbol{R} = \left[\rho_{i,j}\right]$
DCC: $\boldsymbol{Q_t} = \boldsymbol{S}(\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta}) + \boldsymbol{\alpha \varepsilon_{t-1} \varepsilon'_{t-1}} + \boldsymbol{\beta Q_{t-1}}$

		Estimate	Standard Error
CCC	$\rho_{1,2}$	**0.35968**	0.00052
DCC	α	**0.01531**	0.00006
	β	**0.98468**	0.00016

Note: All parameter estimates are significant at the 1% level. DCC denotes the dynamic conditional correlation proposed by Engle (2002) and CCC is the constant conditional correlation by Bollerslev (1990).

Table VII. D-BEKK, CCC, and DCC Estimations: Stock Funds

CCC: $\boldsymbol{H_t} = \boldsymbol{D_t R D_t}, \boldsymbol{D_t} = diag\left[\sqrt{h_{i,i,t}}\right], \boldsymbol{R} = \left[\rho_{i,j}\right]$
DCC: $\boldsymbol{Q_t} = \boldsymbol{S}(\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta}) + \boldsymbol{\alpha \varepsilon_{t-1} \varepsilon'_{t-1}} + \boldsymbol{\beta Q_{t-1}}$

		Estimate	Standard Error
CCC	$\rho_{1,2}$	**0.92467**	0.00001
DCC	α	**0.08600**	0.00050
	β	**0.84806**	0.00278

Note: All parameter estimates are significant at the 1% level. DCC denotes the dynamic conditional correlation proposed by Engle (2002) and CCC is the constant conditional correlation by Bollerslev (1990).

Table VIII. Granger Causality Tests

	Bond Funds		
	Full Sample	Pre-Crisis	Post-Crisis
$f_t^n \rightarrow f_t^p$	9.508 (0.000)	19.47 (0.000)	1.228 (0.298)
$f_t^p \rightarrow f_t^n$	27.91 (0.000)	13.53 (0.000)	13.49 (0.000)

	Stock Funds		
	Full Sample	Pre-Crisis	Post-Crisis
$f_t^n \rightarrow f_t^p$	3.522 (0.007)	1.552 (0.185)	2.528 (0.040)
$f_t^p \rightarrow f_t^n$	3.328 (0.010)	1.018 (0.397)	2.923 (0.021)

Note: We report the F-test statistic from the bivariate VAR with 1-week long lagged daily returns as explanatory variables. The null hypothesis is no Granger causality. p-values are reported in parenthesis. For instance, the NAV return of the bond funds does not help predict its associated price return, while the price return helps predict the NAV return during the post-crisis period. We split the sample around September 15, 2008 when Lehman Brothers was allowed to fail.

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