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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 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.

There are at least two well-known problems in empirically testing the EMH. First, it may be difficult to construct or obtain reliable measures of the relevant fundamental 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.[1,2] Furthermore, the correct method for modeling the expectation formation mechanisms of traders is unclear. Second, given a reasonable proxy variable for the fundamental value of a security, 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 deviations may be due to irrational behavior by market participants (Barberis and Thaler, 2003; Daniel *et al*., 1998; Summers, 1986; Shiller, 1981).

The case of Closed-End Investment Funds (CEFs) is historically important in the price-fundamentals debate. The "fundamental value" of a share in a CEF can be identified with the net asset value (NAV) of the underlying portfolio. NAVs are 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.

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

[2] One related research is what 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.

In connection with the second problem in EMH evaluation, we note that CEF pricing has been puzzling economists for decades. As documented by Lee, Schleifer, and Thaler (1990, 1991), Berk and Stanton (2007), and many others[3], 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 various 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.[4]

When analyzing the behavior and the volatility of closed-end funds' discounts, ordinarily measured by the deviation of the (log) trading price (p_t), from the (log) net asset value (NAV_t), most analyses to date have implicitly assumed that prices and net asset values are cointegrated with a known cointegrating vector [1 -1]', and this assumption is indeed a natural one in view of the ordinary interpretation of the "efficient markets" hypothesis.[5] 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.

Although some previous studies have analyzed bond and stock fund discounts separately (e.g., Abraham, Elan, and Marcus, 1993; Gasbarro, Johnson and Zumwalt, 2003), and have

[3] For a summary of earlier studies on this subject, see Anderson *et al.* (2010).
[4] 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.
[5] 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.

found some differences between them, we depart here from earlier work in several respects. First, analyses based on cointegration are, by necessity, long-run in nature. Our interest, though, will focus on the short-run price dynamics, and we utilize statistical models appropriate to that task. Second, we believe that the processes generating the short-run excess return behaviors for bond and equity funds differ substantially in ways relevant to the theoretical understanding of the entire closed-end fund anomaly. In particular, our approach allows us to show that both price and NAV series for equity funds essentially behave like random walks, but bond fund series are more predictable.[6] Shocks to bond and stock fund series also exhibit quite different behavior: volatility spillovers vanished for stock funds after the Lehman bankruptcy, but persisted and even strengthened for bond funds.

We also find significant differences in the conditional correlations between the price and the NAVs for bond versus equity CEFs for the period of 2004 through 2011. First, the correlation is much higher (around 0.90 to 0.95) for the stock closed-end funds than it is for the bond funds (0.5 before a structural break in the fall of 2008 and around 0.3 after the break). This appears to be a persistent difference in the observed behaviors.

More strikingly, we also show that the estimated dynamic conditional correlation between the price and the NAV for the bond closed-end funds shows a clear structural break (or level shift) in the fall of 2008. Our hypothesis is that this decrease in the conditional correlation for the bond funds was caused, at least partially, by the bankruptcy of Lehman Brothers on September 15, 2008, and the subsequent significant downgrading or bankruptcies of several bond insurers, such as Ambac and MBIA. These events led to a well-documented catastrophic fall in the liquidity of various bond markets in the US and elsewhere. This lack of liquidity, in turn, led

[6] Cochrane (2005, p.390) notes similar patterns in the behavior of bond and stock returns.

to a change in the evolution of the NAVs of bond CEFs, altering the discount behavior of these securities.

We provide some evidence on this development by further demonstrating that NAVs of bond funds after the Lehman bankruptcy were in fact Granger-caused by earlier fund share prices but not the other way around. In other words, after market liquidity dried up in the fall of 2008, the prices of bond funds became a sort of "leading indicator" of the funds' NAVs, due to the lack of current market prices for many classes of bonds. We do not find such evidence for equity funds during this recent financial crisis, implying this type of fund does not suffer from mispricing as much as bond funds.

We draw two conclusions based on our analysis of bond and stock funds. First, we suggest that researchers should consider the possibility that funds' prices and NAVs, while closely related, are by no means uniformly related over shorter time scales, as most research strategies might imply. Second, dramatically different results for bond and stock closed-end funds provide a cautionary tale for a "one-size-fits all" theories of fund mispricing.

The rest of the paper is organized as follows. Section I presents the econometric methodology used to extract common factors from many fund prices and net asset values. Then, we provide a short explanation of the dynamic conditional correlation between the price and the NAV for closed-end funds. Section II describes the data and discusses the main empirical findings. Section III concludes.

II. The Econometric Model

Most research on the pricing issue for CEFS studies the dynamics of 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, which implies the deviation in price from "fundamental value" must be short-lived. Additionally, it is customary to use the discounts (premia) observed in *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 in the empirical analysis.

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.

Second, we utilize the estimated common factors for a multivariate generalized autoregressive conditional heteroskedasticity specification (MGARCH) to investigate short-run pricing dynamics including 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 for bond funds (but not stock funds) during the recent market meltdown. We see 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.

A. Principal Component Analysis with Differenced Series

Let $r_{i,t}^{p}$ be the log-differenced price of mutual fund i at time t. Similarly, $r_{i,t}^{n}$ denotes the log-differenced net asset value (NAV) of mutual 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 mutual 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. We estimate the common factors and the factor loadings via the conventional principal component analysis after proper normalization.[7] 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.[8] 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,

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

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

[7] Normalization is required because the principal component analysis is not scale-invariant.
[8] For our empirical analysis, we later use the date of the failure of Lehman Brothers (September 15, 2008).

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

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

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.[9] Conditional correlation is measured as usual by the following:

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

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

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:

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

where $\boldsymbol{\varepsilon}_t = \left[\varepsilon_t^n, \varepsilon_t^p\right]' = \boldsymbol{D}_t^{-1}\boldsymbol{e}_t$ 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.

III. 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.

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 1 and 2 about here

When we analyzed the price and the NAV data for the stock and bond funds in our sample, we noted a significant 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, ACG bond fund was often traded at a premium, while TY stock fund traded only at a discount throughout the entire observation period (Figure 2). 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 funds. 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.[10] This simplifies our task substantially.

The estimated factor loadings λ_i^p and λ_i^n are all positive and mostly similar in magnitude. 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. These findings support the use of the common factor methodology to analyze the price/NAV relationship.

[10] All results are available from authors upon request.

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 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. Again, the NAV return and the price return of the stock fund are quite similar to each other, but this is not true for the generic bond fund. 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 the significant "news effect" (α_{12}, α_{21}) and the "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 on 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. The full sample estimates are significant but imply quantitatively small effects. 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.[11] In contrast to the $\mathbf{\Phi}$ 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 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

[11] 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 authors upon request.

finding consistent throughout the estimation period. Second, the conditional correlation for a 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 (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 companies 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

The striking divergence in DCC exhibited by the generic bond fund is an empirical result that calls for some sort of explanation. One plausible explanation is suggested by the Lehman Brothers' bankruptcy on September 15, 2008, and the subsequent significant downgrading of Ambac and several other bond insurers. The markets for many bonds are far 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 bond markets. Independent bond ratings, which had previously been accorded serious attention by many investors, suddenly appeared unreliable and perhaps even intentionally misleading. As many analysts noted, these ratings were assigned by the same agencies which gave investment grade status to what came to be called "toxic assets". This failure disproportionately affected bond markets, particularly, in certain lower quality categories. Equity markets, though hammered by the downturn, continued trading virtually uninterruptedly.

This asymmetry had a logical consequence for the process that generated NAVs for bond funds: absence of liquidity in the markets for some categories of bonds implied that NAV could *not* be determined in the same manner as that used prior to the market seizure. Rather, the values of bonds in fund portfolios had to be calculated using historical, rather than more contemporary, prices. If this description is valid, one would expect to observe an increase in the *persistence* of NAVs for bond (but not stock) funds. Share prices, on the other hand, would presumably adjust rapidly to whatever levels the assessments of investors might support.

In this scenario, we should 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 accepts 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 illiquidity problem during market turmoil and "older" prices are used to determine bond funds' current NAVs.

Tables VIII about here

We can obtain further evidence on bond funds' illiquidity by estimating the dynamic conditional correlation between their NAVs, prices, and the VIX index, which is used as a measure of investors' fear.

As can be seen from graphs presented in Figure 10, the NAVs of bond closed-end funds are virtually uncorrelated with the VIX index (estimates of the dynamic conditional correlation are centered at zero), while prices exhibit a slight negative correlation (around -0.25 prior to fall of 2008) which increased (in absolute terms) following the financial crisis (-0.4-0.45, post-September, 2008). This finding is additional evidence on mispricing of bond funds, especially during market turmoil.

As for equity funds, we do not observe the same phenomenon. As can be seen from Figure 11, both NAVs and prices of stock closed-end funds are highly correlated with a measure of investors' fear, the VIX index. Also, the correlation between the VIX index and the NAVs stays constant throughout the estimation period (at around -0.8 between NAVs and VIX, and -0.75 between prices and VIX). This finding is again consistent with our prior hypothesis that equity funds are not subject to mispricing (resulting from market illiquidity), as are bond funds.

Figures 10 and 11 about here

IV. Summary and conclusions

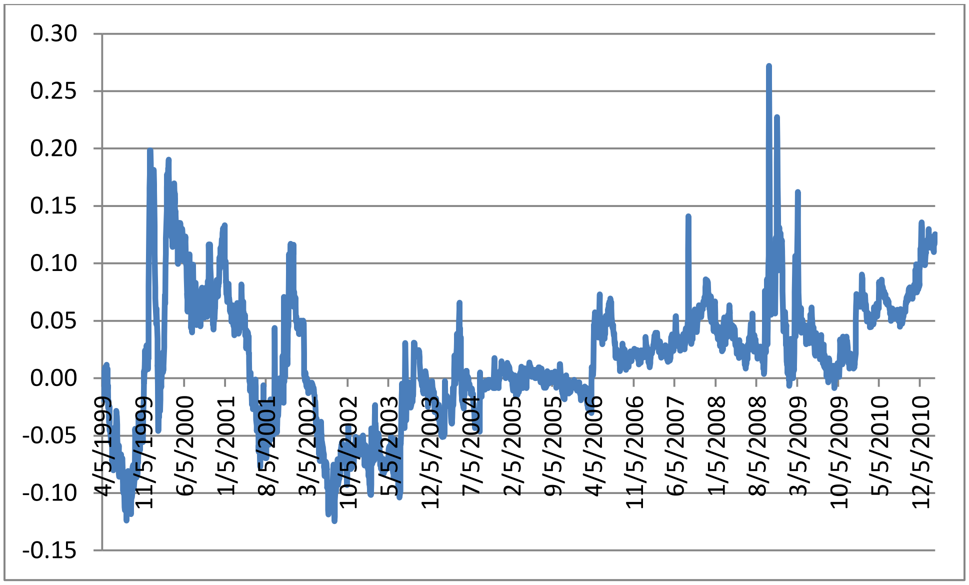
CEFs present a unique opportunity for testing theories of market efficiency and asset pricing. In an efficient market, the relationship between any fund's share prices and the underlying value of the fund's assets should be very strict. That this is often not the case has stimulated the interests of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

Many theories of fund share short-run 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. 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.

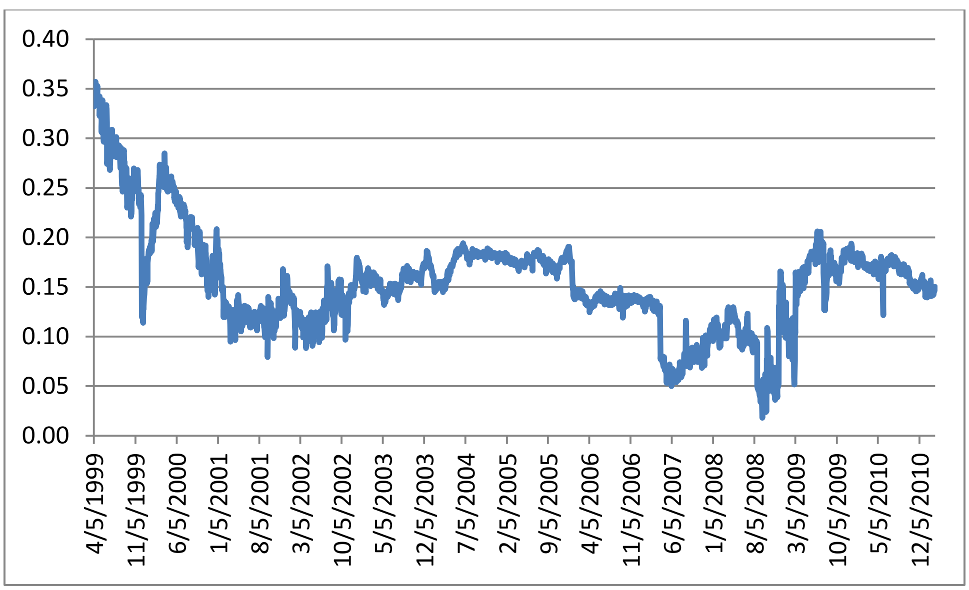
Second, our approach illustrates that the processes generating prices, and those generating NAVs, can undergo shifts "independently", thereby radically altering the observed relationship between share price and share value. By focusing on the period 2004-2011, we incorporate the market disruptions of fall, 2008. This period saw unprecedented erosion of market liquidity, 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.

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.

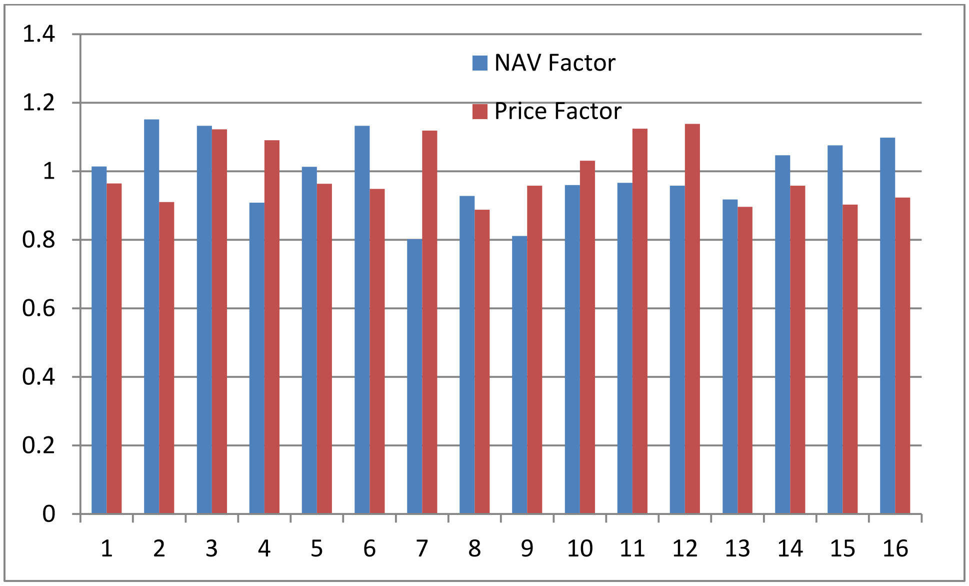
Figure 2. Log Discount: TY (Stock Fund)



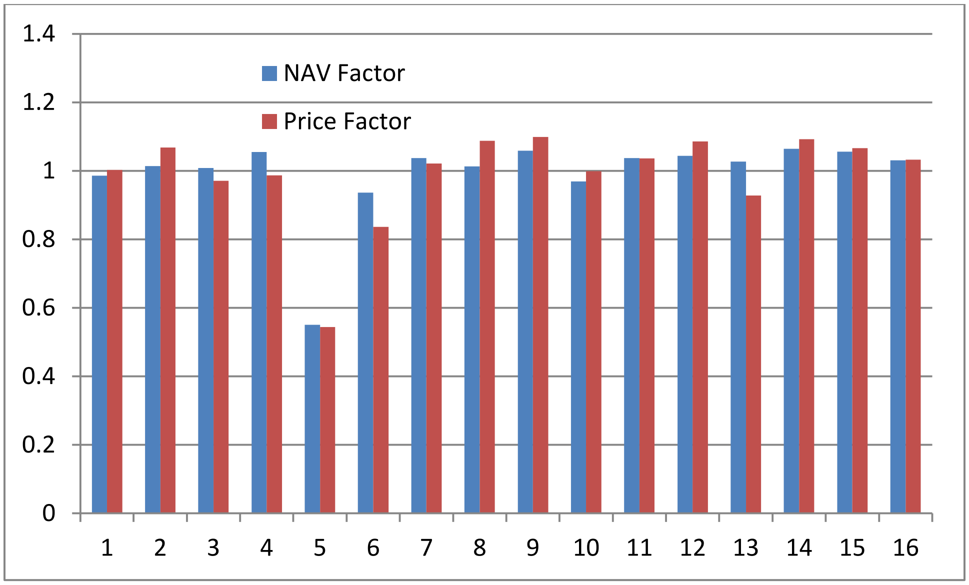
Note: The log discount denotes $\ln(NAV) - \ln(p)$, where we use the close price of each day.

Figure 3. Factor Loadings

(a) Bond Funds



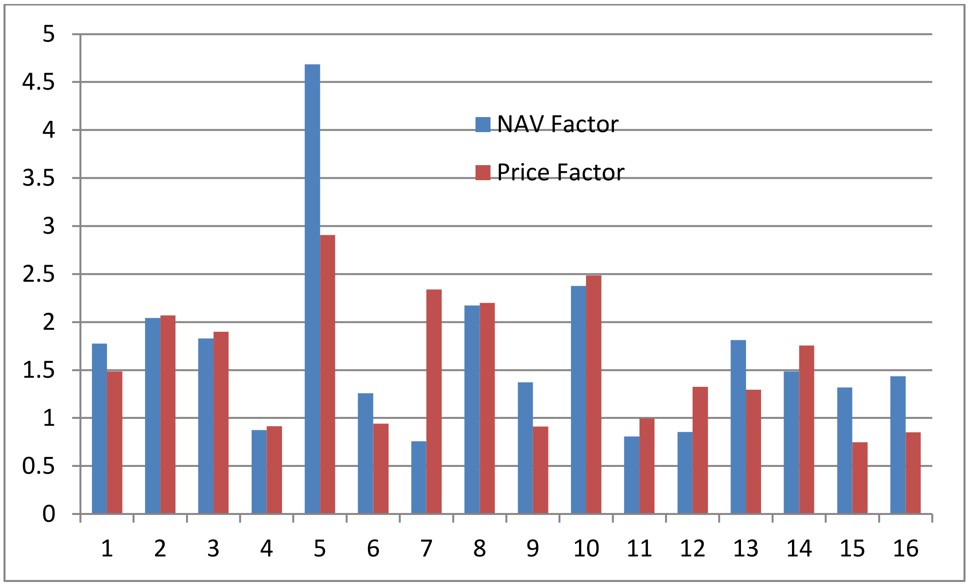
(b) Stock Funds



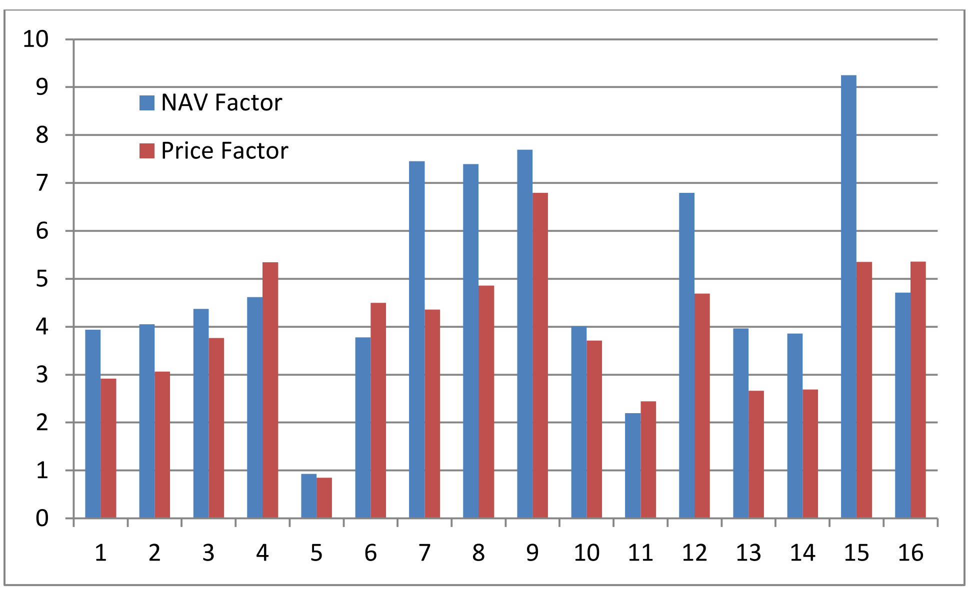
Note: Estimated factor loadings are λ_i^p and λ_i^n in equations (1) and (2). We choose 1 factor for each set of funds, that is, $k = 1$. Therefore, λ_i^p and λ_i^n are scalars. The horizontal axis is a fund's ID.

Figure 4. Relative Variations

(a) Bond Funds



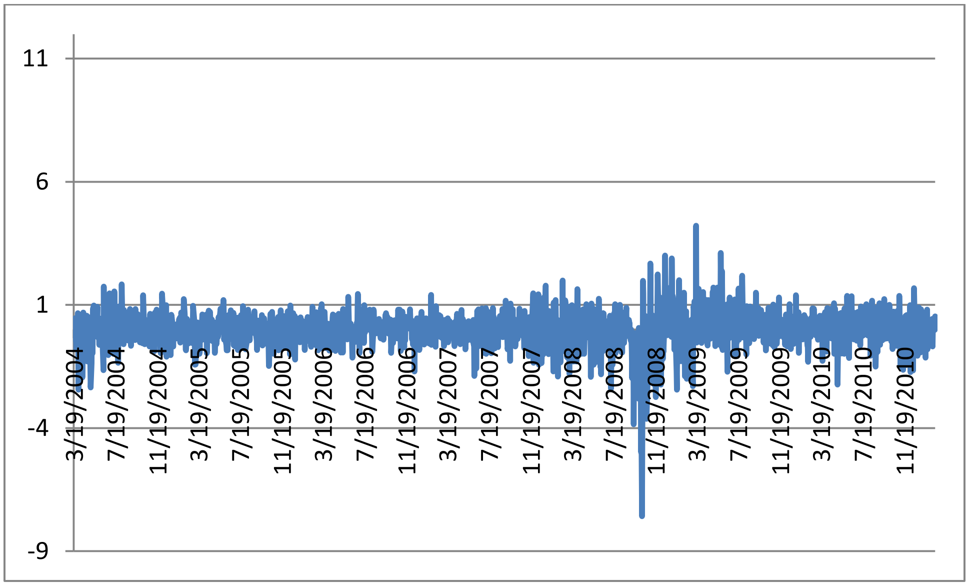
(b) Stock Funds



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

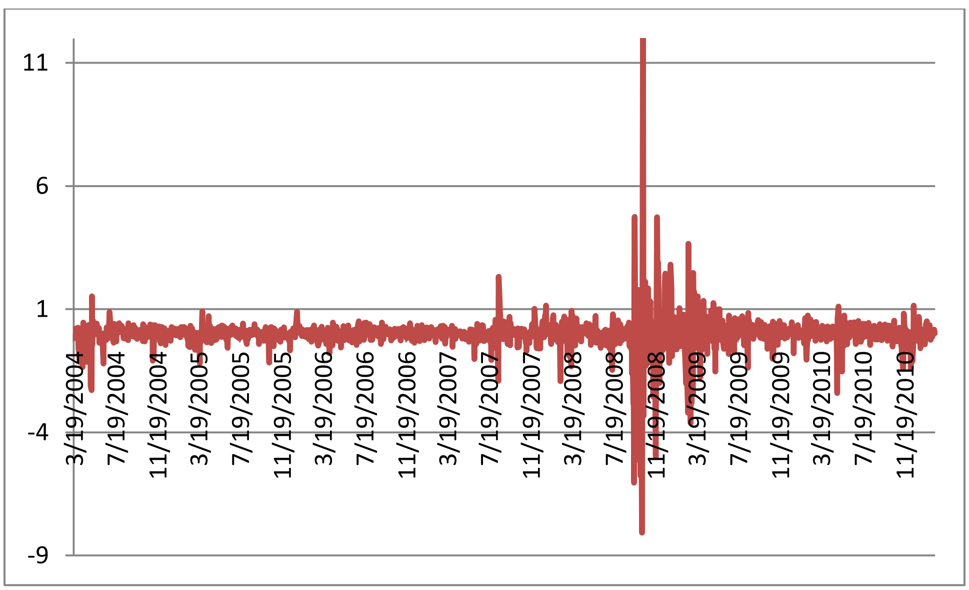
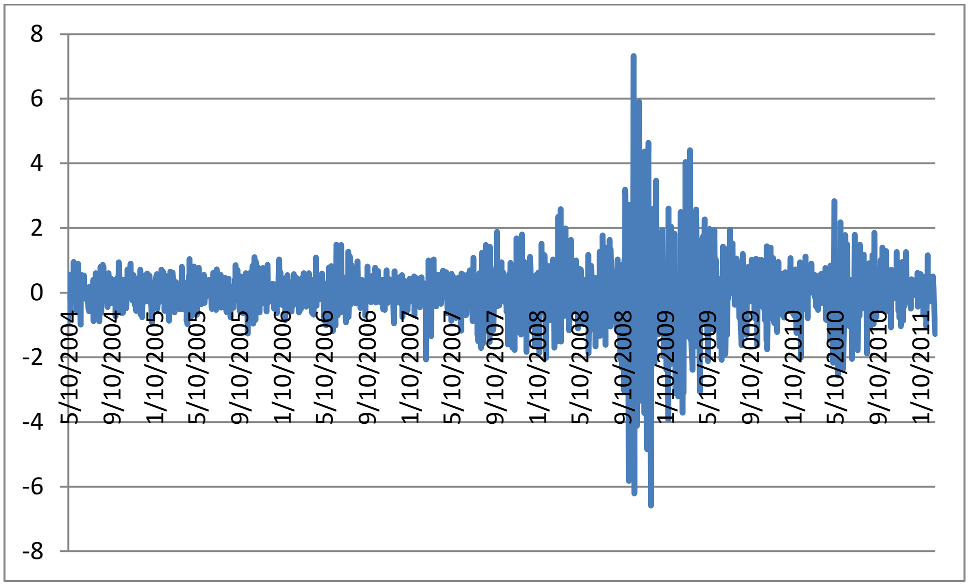


Figure 6. Common Components: Stock Funds

(a) NAV return



(b) Price Return

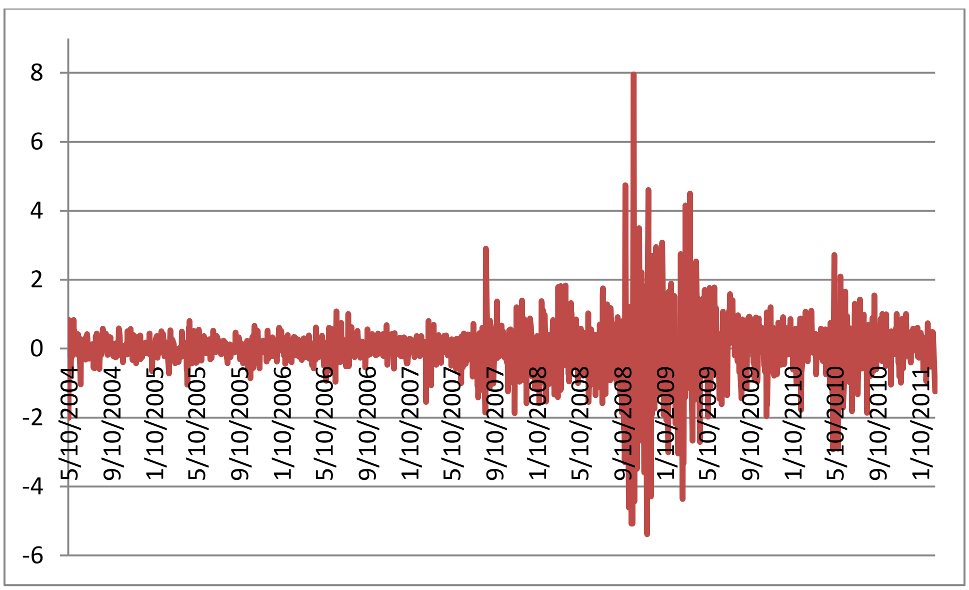
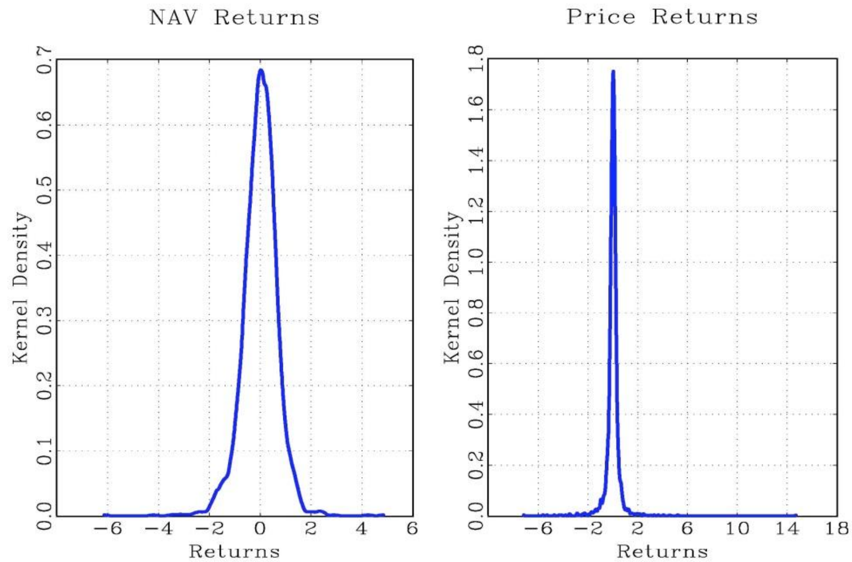
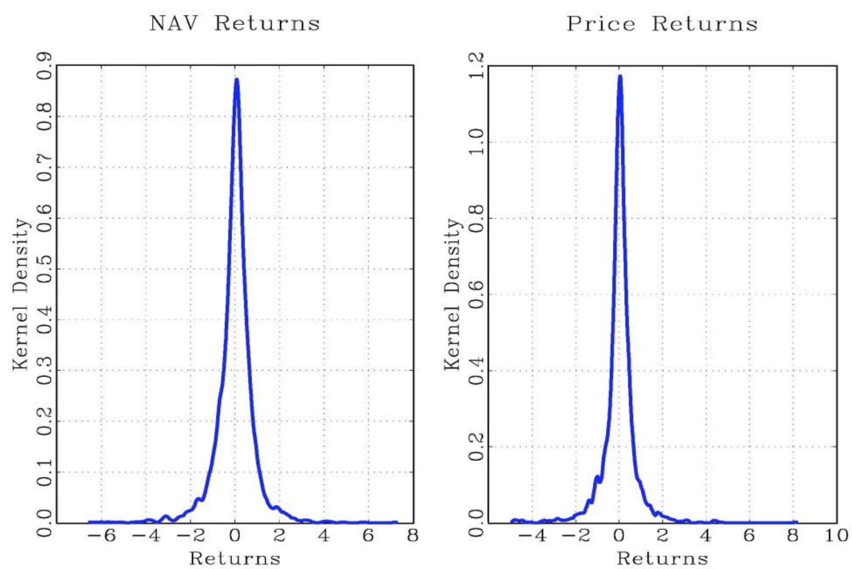


Figure 7. Kernel Density Estimation for Common Components

(a) Bond Funds

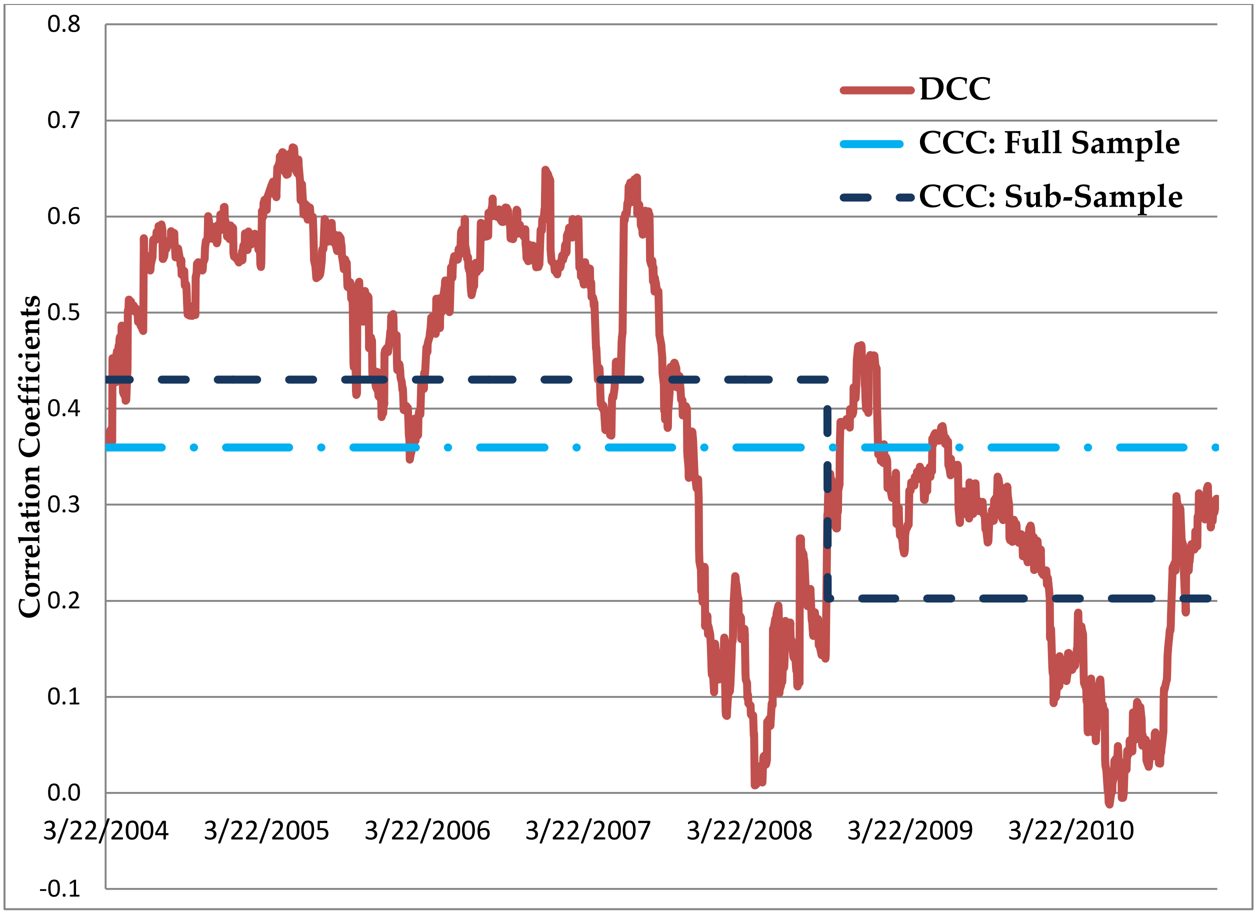


(b) Stock Funds



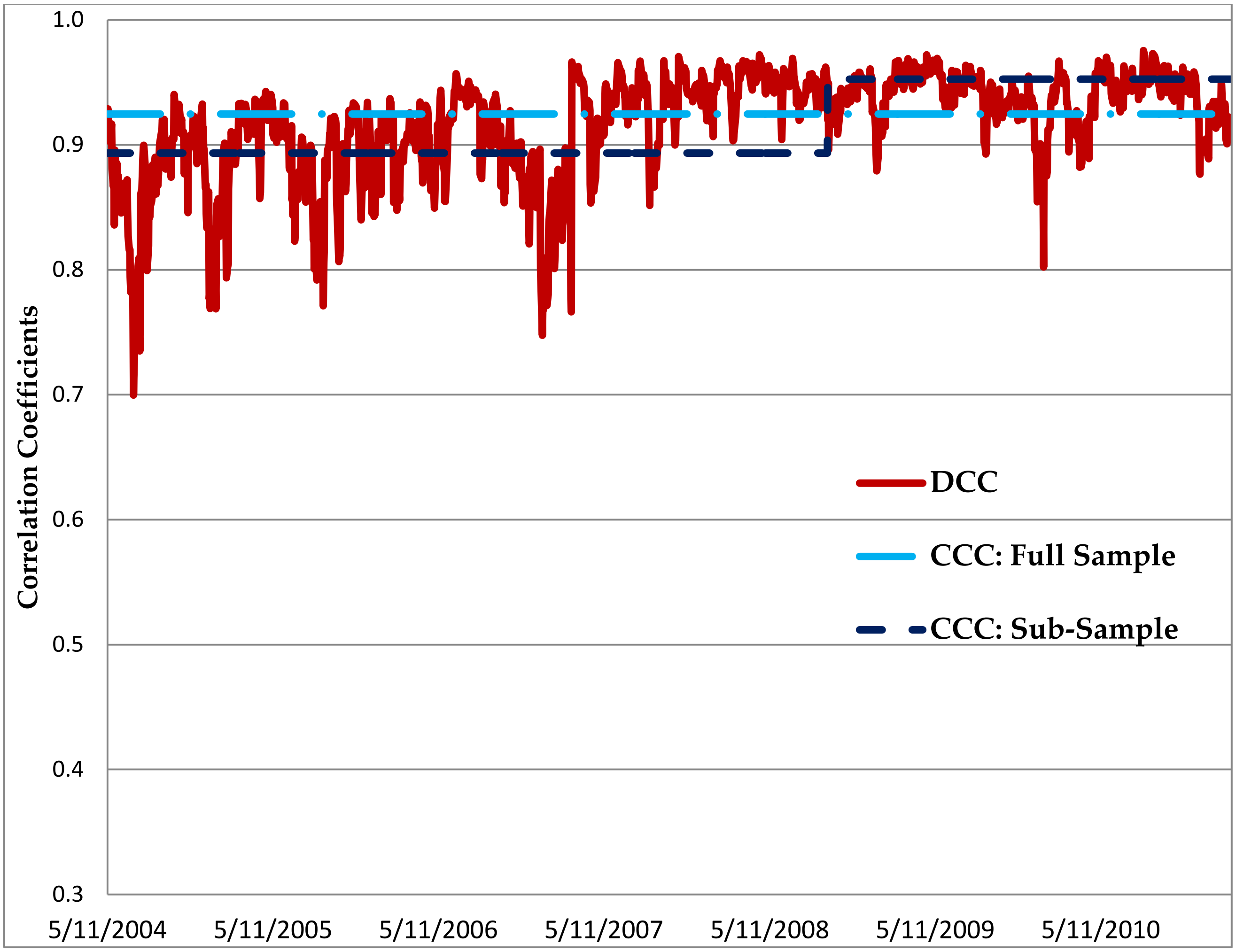
Note: We use the Gaussian kernel to estimate the kernel density functions.

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.

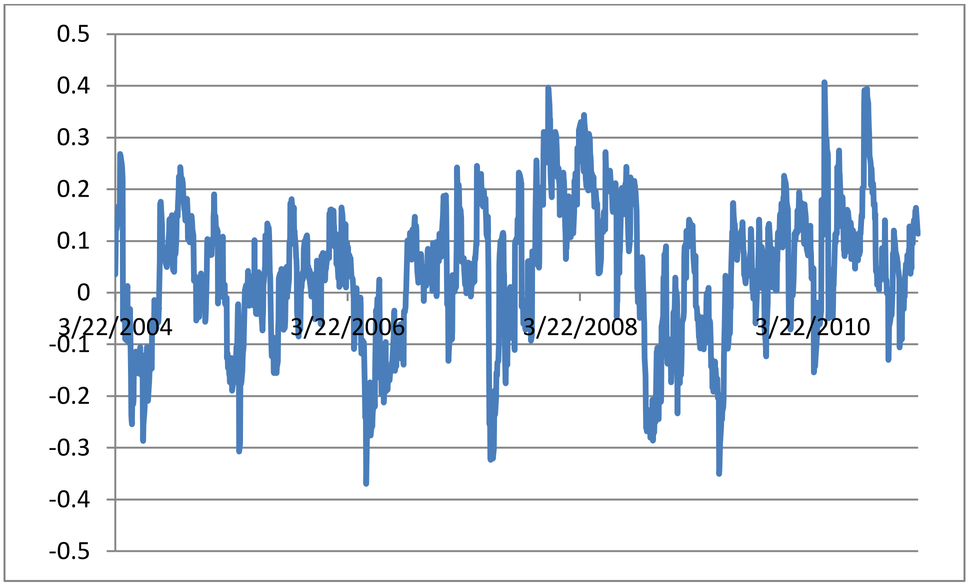
Figure 9. Conditional Correlations: Stock Funds



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.

Figure 10. Dynamic Conditional Correlations: Bond Funds

(a) NAV vs. VIX



(b) Price vs. VIX

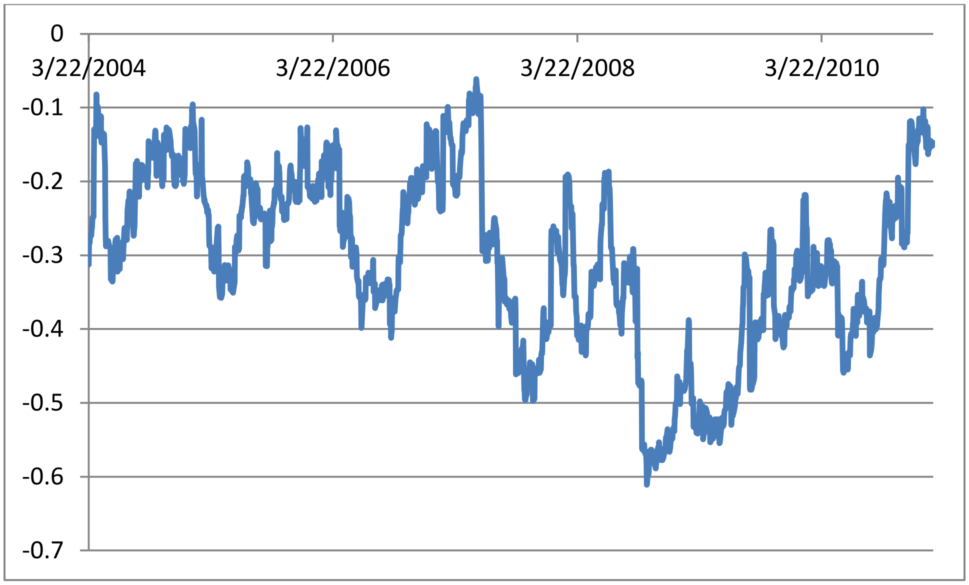
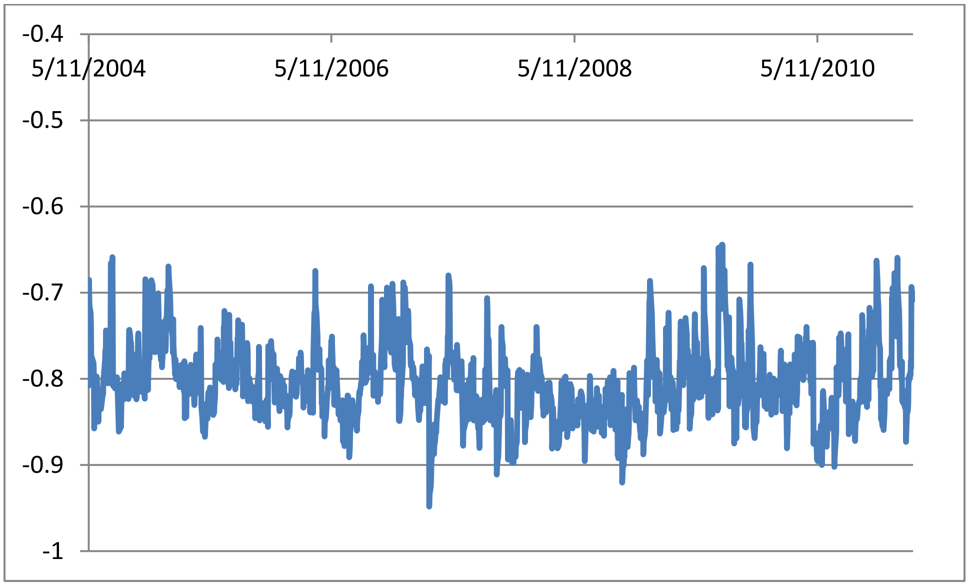


Figure 11. Dynamic Conditional Correlations: Stock Funds

(a) NAV vs. VIX



(b) Price vs. VIX

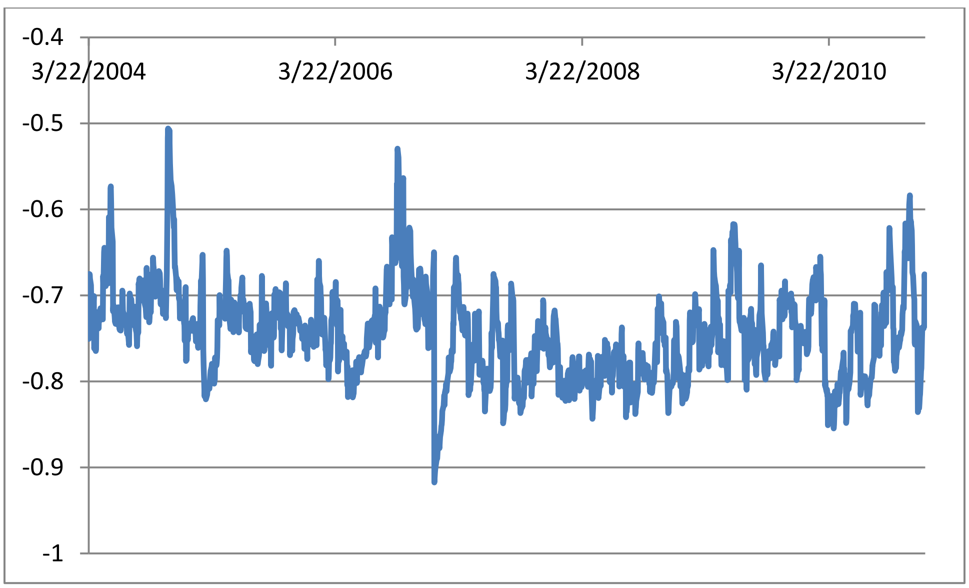


Table I. Descriptive Statistics of Individual Bond Fund Returns

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

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

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

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

	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

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

		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

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

		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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