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On the Time-Varying Relationship between Closed-End Fund Prices and Fundamentals: Bond vs. Equity Funds

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On the Time-Varying Relationship between Closed-End Fund Prices and Fundamentals: Bond vs. Equity Funds

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Abstract:

Deviations between closed-end investment fund share prices and underlying net asset values represent a historically important anomaly requiring theoretical explanation. In this article, we provide evidence that the processes generating prices and NAVs differ among fund types, implying that explanations of mispricing will necessarily be somewhat parochial. Using a multivariate GARCH model for estimated common factors, we empirically examine discounts of both equity and bond funds, and we find an important asymmetry between them. In particular, we show a structural break in this relationship for bond funds after the Lehman bankruptcy and suggest an explanation based on persistence in NAVs arising from market illiquidity.

Keywords: Closed End Investment Company; Market Efficiency; Market Illiquidity; Dynamic Conditional Correlation

JEL Classification: C32; G01; G12

Closed-end investment funds (CEIFs) have 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 fundamentals, or net asset values (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)), and costly arbitrage (Pontiff (1996)) have all been proposed as sources of discounts and/or mispricing. Most of these explanations have at least some empirical support and plausibility.

However, discounts are not ubiquitous: funds sometimes trade at a premium, and the process of "open ending" closed-end funds results in a rapid adjustment of prices to NAVs. Worse, CEIFs are ordinarily issued *at a premium* to NAV, and this premium usually rapidly disappears (Lee *et al.* (1990)). Thus, one can say there are many "puzzles" attached to CEIFs, of which the discount is only the most well-known.

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.[2]

[1] For a summary of earlier studies on this subject, see Anderson, *et al.* (2002).
[2] 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.

However, the application of the time-invariant relationship assumption seems imprudent for the study of a phenomenon which *might* ultimately prove inconsistent with it. This conundrum motivates our approach in this article. Rather than relying on an estimation technique which restricts the price-NAV relationship in this manner, we estimate the dynamic (time-variant) conditional correlation (DCC) between the price and the NAV combined with a dynamic factor analysis of the common components of returns for both stock and bond closed-end funds. Our focus on these different types of CEIFs is motivated by a profound difference in the behaviors of their discounts over time.

Most empirical work on the fund discount issue has not incorporated information on the *natures* of the funds being analyzed. Whatever explanation for the discount (or the occasional premium, e.g., Pontiff (1996)) is tested, it is implicitly assumed that the explanation is applicable to “closed end investment funds” in general. The present paper demonstrates, however, that there are, in some cases, significant differences in the behavior of fund pricing between funds with different components. These differences suggest that no single explanation for pricing is likely to be satisfactory for all funds. In particular, funds holding bonds differ fundamentally from equity funds, and these differences were starkly highlighted in the wake of the “financial meltdown” of a few years ago.

We find significant differences in the conditional correlations between the price and the NAVs for bond versus equity CEIFs 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 to a fundamental change in the evolution of the NAVs of bond CEIFs, changing 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 the recent financial crisis, implying this type of fund does not suffer as much from mispricing 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 connected as most research strategies might imply.

Second, dramatically different results for bond and stock closed-end funds provide a cautionary tale for "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.

I. The Econometric Model

Most research on the mispricing issue for CEIFS study 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. This is a somewhat restrictive framework to impose, however, particularly in light of the lack of consensus on the mechanisms generating these deviations in price from "fundamental value". 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 argue that both of these methodologies can be improved upon, and that doing so allows the researcher to identify important differences between the stochastic processes generating fund prices, NAVs, and discounts for different sorts of funds. Therefore, we make the following two changes in the ordinary form of 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 factors of the prices and NAVs rather than analyzing individual fund prices and NAVs.

Second, we utilize the estimated common factors to calculate the dynamic conditional correlations as a means to provide strong evidence on the time-varying relationship between them. This technique avoids imprecision in the analysis arising from the idiosyncratic factors which affect particular funds, and which are not relevant to any theory of mispricing. This approach allows us to identify the structural break which occurred 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 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, $r_{i,t}^{p}$ and $r_{i,t}^{n}$ are the continuously compounded *net* returns based on the prices and the NAVs of the fund, respectively.

We assume that these returns have the following factor structures:

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

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

where f_t^p and f_t^n are the $k \times 1$ *common* factor components of $r_{i,t}^p$ and $r_{i,t}^n$, respectively, across all mutual funds $i \in [1, N]$. The parameter vectors λ_i^p and λ_i^n denote the fund-specific $k \times 1$ factor loadings for the common factors f_t^p and f_t^n, respectively. That is, the degree of dependency varies across funds. Lastly, $\eta_{i,t}^p$ and $\eta_{i,t}^n$ are fund i's *idiosyncratic* components in $r_{i,t}^p$ and $r_{i,t}^n$, 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^p and f_t^n. 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.[3] 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.

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

B. The Dynamic Conditional Correlation

To investigate time-varying relations between the NAV and the fund price through f_t^n and f_t^p, we employ the dynamic conditional correlation (DCC) estimator (Engle (2002)) for multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models, as well as the conventional GARCH-BEKK model (Engle and Kroner (1995)). The DCC model can be viewed as a generalization of the constant conditional correlation (CCC) estimator proposed by Bollerslev (1990).

For the DCC, consider the following vector autoregressive process for $y_t = \left[f_t^p, f_t^n\right]'$:

$$y_t = \Gamma(L) y_{t-1} + e_t, \tag{3}$$

where $\Gamma(L)$ is a lag polynomial matrix. We conventionally assume that $e_t = \left[e_t^p, e_t^n\right]'$ obeys the bivariate normal distribution,

$$e_t | \Omega_{t-1} \sim N(0, H_t), \tag{4}$$

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

$$H_t = D_t R_t D_t, \tag{5}$$

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

The equation (5) can be re-parameterized as follows,

$$E_{t-1}\varepsilon_t\varepsilon_t' = D_t^{-1}H_tD_t^{-1} = R_t = \left[\rho_{i,j,t}\right], \tag{6}$$

where $\varepsilon_t = \left[\varepsilon_t^p, \varepsilon_t^n\right]' = D_t^{-1}e_t$ 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,

$$Q_t = S(1-\alpha-\beta) + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta Q_{t-1} \tag{8}$$

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.

II. 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. $-denominated bonds/notes, FNMA not-mortgage backed securities, FNA mortgage-backed securities, and other mortgages. Stock closed-end funds included in our sample have their portfolios allocated in the following sectors: technology, industrials, health care, financials, consumer services, consumer goods, oil and gas, utilities, communications, and basic materials.

When we analyzed the price and the NAV data for the stock and bond funds in our sample, we noticed a significant difference between these two types of funds. For most stock funds, both the NAV and the price started declining in 2007, with a slightly sharper decrease seen in the fall of 2008. Prices and the NAVs of the majority of bond funds did not show any dramatic changes until the fall of 2008. Figures 1 and 2 show the fluctuations in the NAVs and the prices for a representative bond fund and a representative stock fund. (Other funds display similar behavior.)

[insert Figure 1 about here]

[insert Figure 2 about here]

Since all bond funds and stock funds behave similarly to the funds in their groups, we model their returns as a combination of a common component and an idiosyncratic component (eq.1 and eq.2).

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 funds. 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, the relative variance of the common component is greater than one for the majority of funds, implying the relative importance of the common factor (Figure 3 and Figure 4). This finding supports the use of the common factor methodology to analyze the price/NAV relationship. The descriptive statistics for the estimated common factor of both types of funds is presented in Table I.

[Insert Table I about here]

[insert Figure 3 about here]

[insert Figure 4 about here]

Having obtained simple common factor representations for the underlying price and asset value series, we analyze the dynamic conditional correlations between these factors for bond and stock funds. These correlations, then, 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 correlations 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 also report our baseline model estimates with the diagonal BEKK model along with the CCC and the DCC models in Table II and Table III for the bond and the equity fund factors, respectively. All parameter estimates are significant at the 1% level.

[insert Table II and Table III about here]

B. Estimation Results

We estimate the dynamic conditional correlation (DCC, Engle (2002)) between the common component of the funds' price, f_t^p, and the common component of their NAV, f_t^n for both the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model and the conventional GARCH-BEKK model (Engle and Kroner (1995)). The detailed explanation is provided in Section II.

Figures 5 and 6 show the estimated dynamic conditional correlations for a hypothetical bond closed-end fund and a stock closed-end fund, respectively.

[insert Figure 5 here]

[insert Figure 6 here]

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 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 5).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 CEIF, 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 6, 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 CEIFs is quite different, in at least 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.

One possible explanation for the significant decrease in bond fund conditional correlation may be 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 categories. Equity markets, though hammered by the downturn, continued trading virtually uninterruptedly.

This asymmetry had a 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 CEIFs *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 IV).

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., 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.

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

[insert Figure about 7 here]

As can be seen from graphs presented on Figure 7, 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 increases (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.

[insert Figure 8 about here]

As can be seen from Figure 8, 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.

III. Summary and conclusions

CEIFs have much more importance for finance academics than for finance practitioners. This importance is due to the nearly unique opportunity they present 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. On the other hand, the sizes of such funds, and their target customer groups, suggest they are of only limited economic significance.

Many theories of fund share mispricing have been advanced, and a variety of explanations have at least some empirical support. Noise (irrational) traders, 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 CEIF "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 program. First, we show that CEIFs 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 factors behind the prices and asset valuations. We do not impose any cointegration requirement between prices and asset values.

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 show that 2008 saw a structural break in the process generating NAVs for bond CEIFs, 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.

As a critique of the general research program aimed at "explaining" CEIF mispricing (and related paradoxes), our findings constitute a cautionary tale. One should not, as a general matter, assume a cointegrating relationship between NAVs and fund share prices. Further, it appears quite unlikely that any explanation of mispricing will be applicable to *all* types of CEIFs. This is because, rather than proceeding as if there is a single process, in which prices and values share an integrated relationship, one should consider the possibility that there are, in fact, two separate processes: one, generating prices, and the other NAVs, and these may be subject to rather different types of shocks. In the ordinary course of events, the process generating NAVs is quite as well-behaved as that producing share prices: only relatively extreme conditions should be expected to highlight any differences. The Lehman bankruptcy and its related fallout provide just such an opportunity.

Figure 1. ACG (Bond Fund)

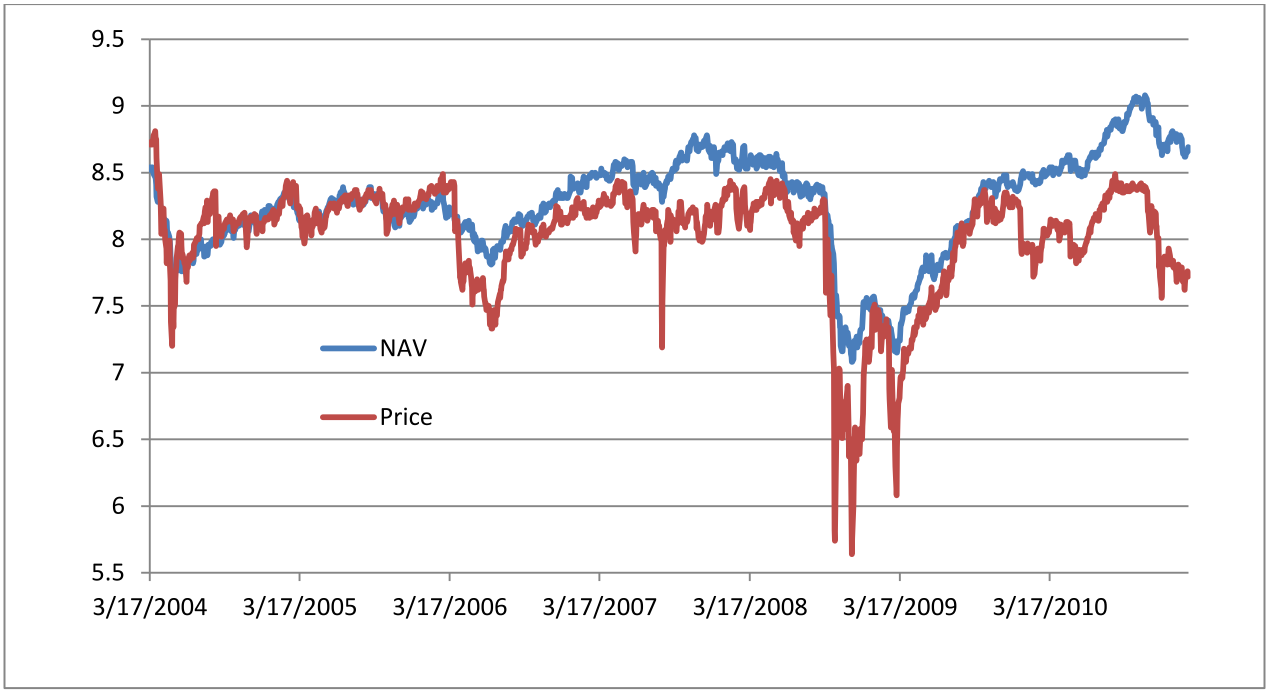


Figure 2. TY (Stock Fund)

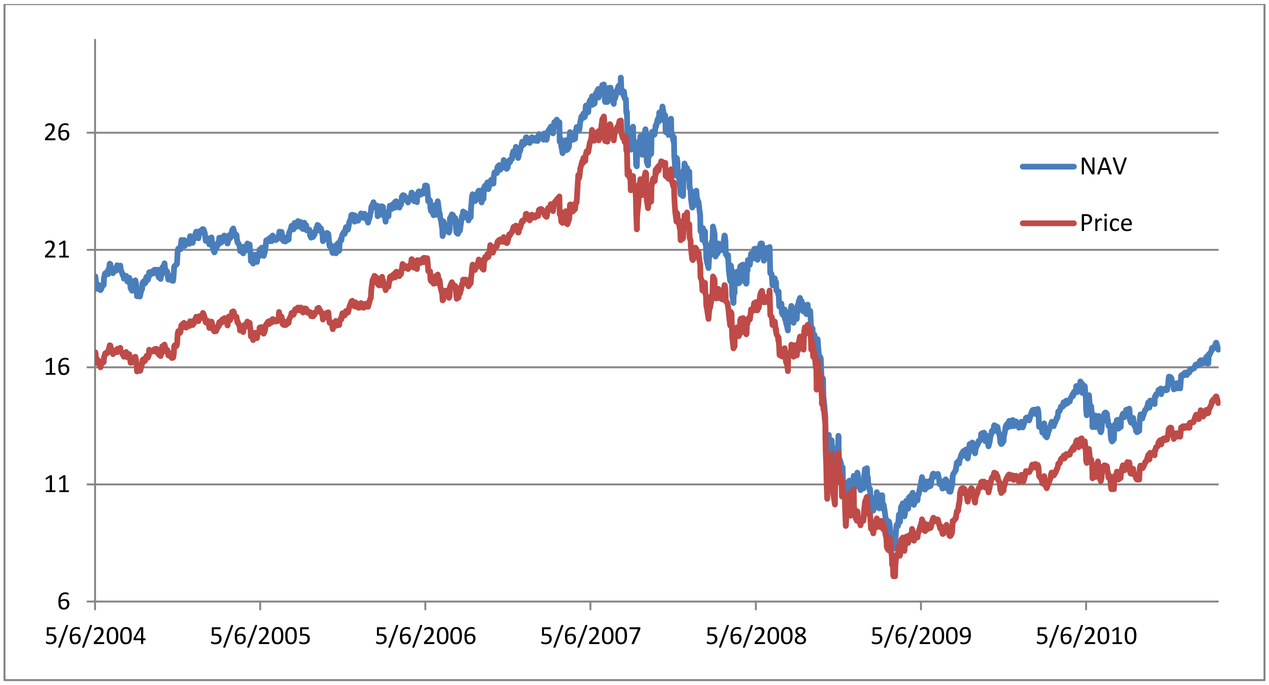
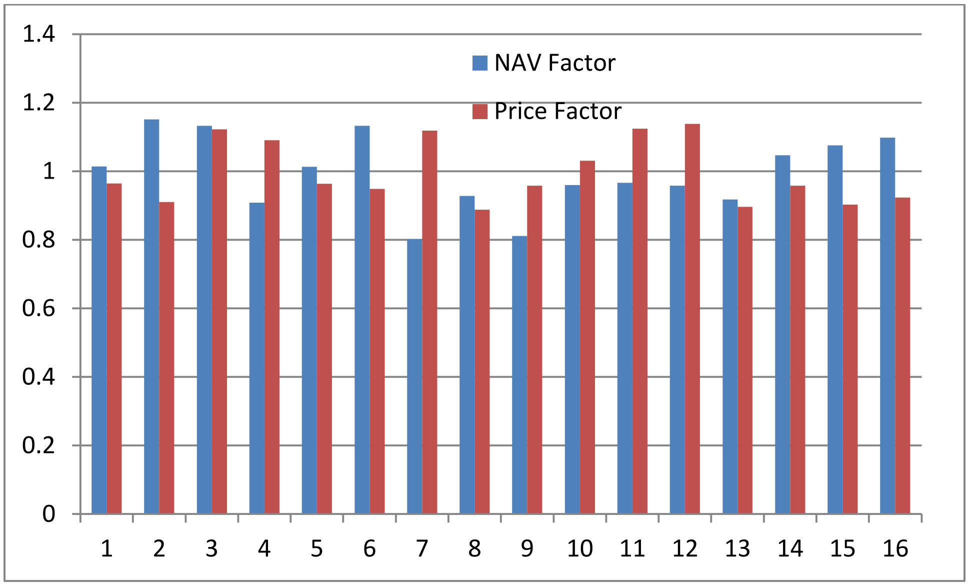
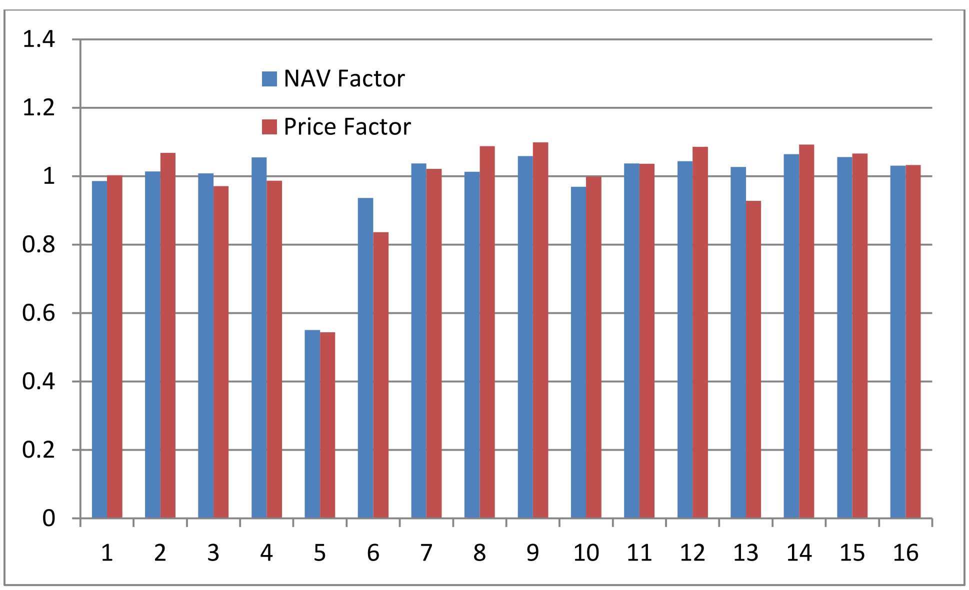


Figure 3. Factor Loadings

(a) Bond Funds



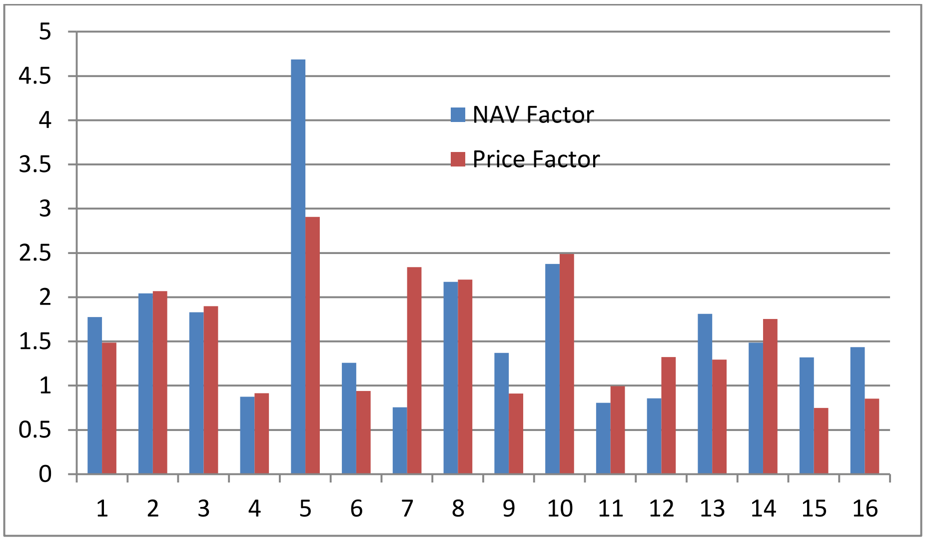
(b) Stock Funds



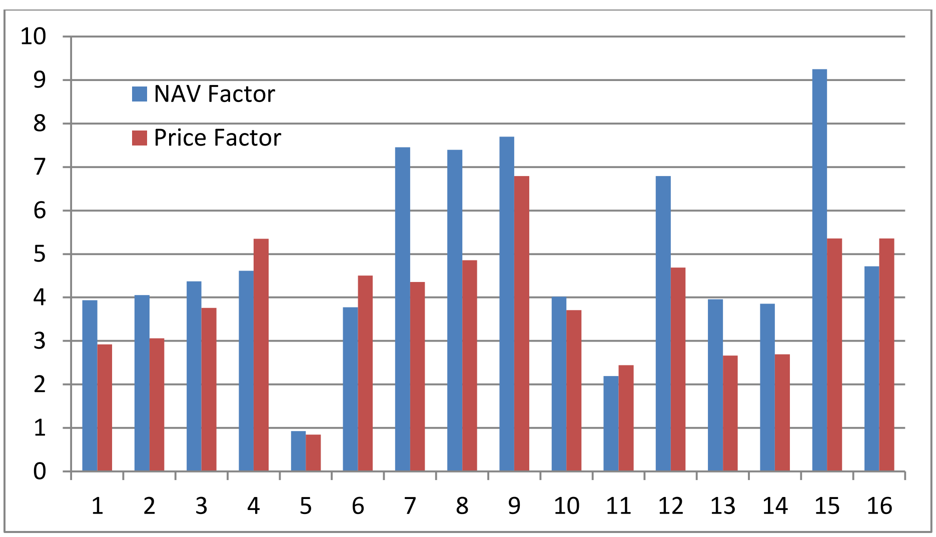
Note: Estimated factor loadings are λ_i^p and λ_i^n in equations (1) and (2). We choose 1 factor for each set of funds, that is, $k = 1$. Therefore, λ_i^p and λ_i^n are scalars. The horizontal axis is a fund's ID.

Figure 4. Relative Variations

(a) Bond Funds

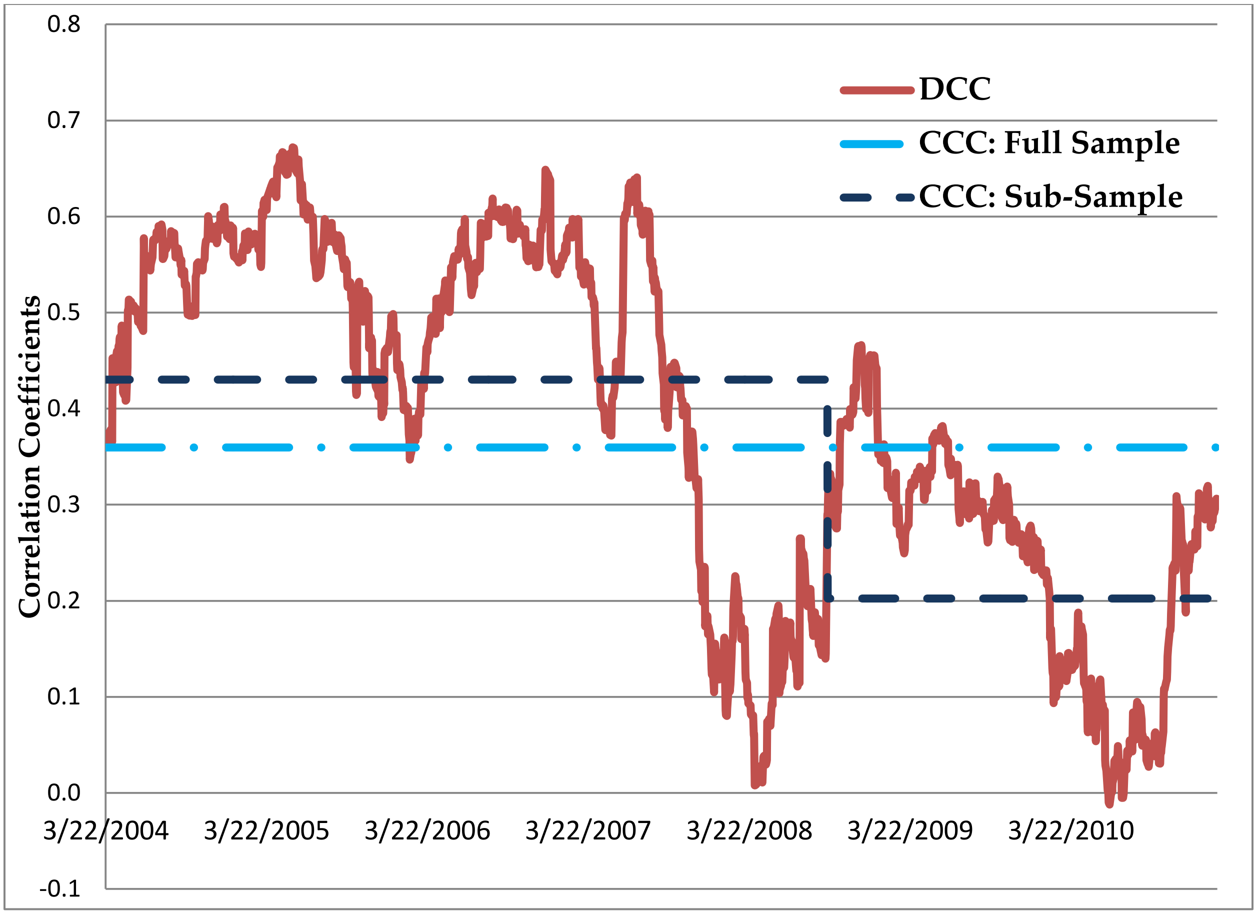


(b) Stock Funds



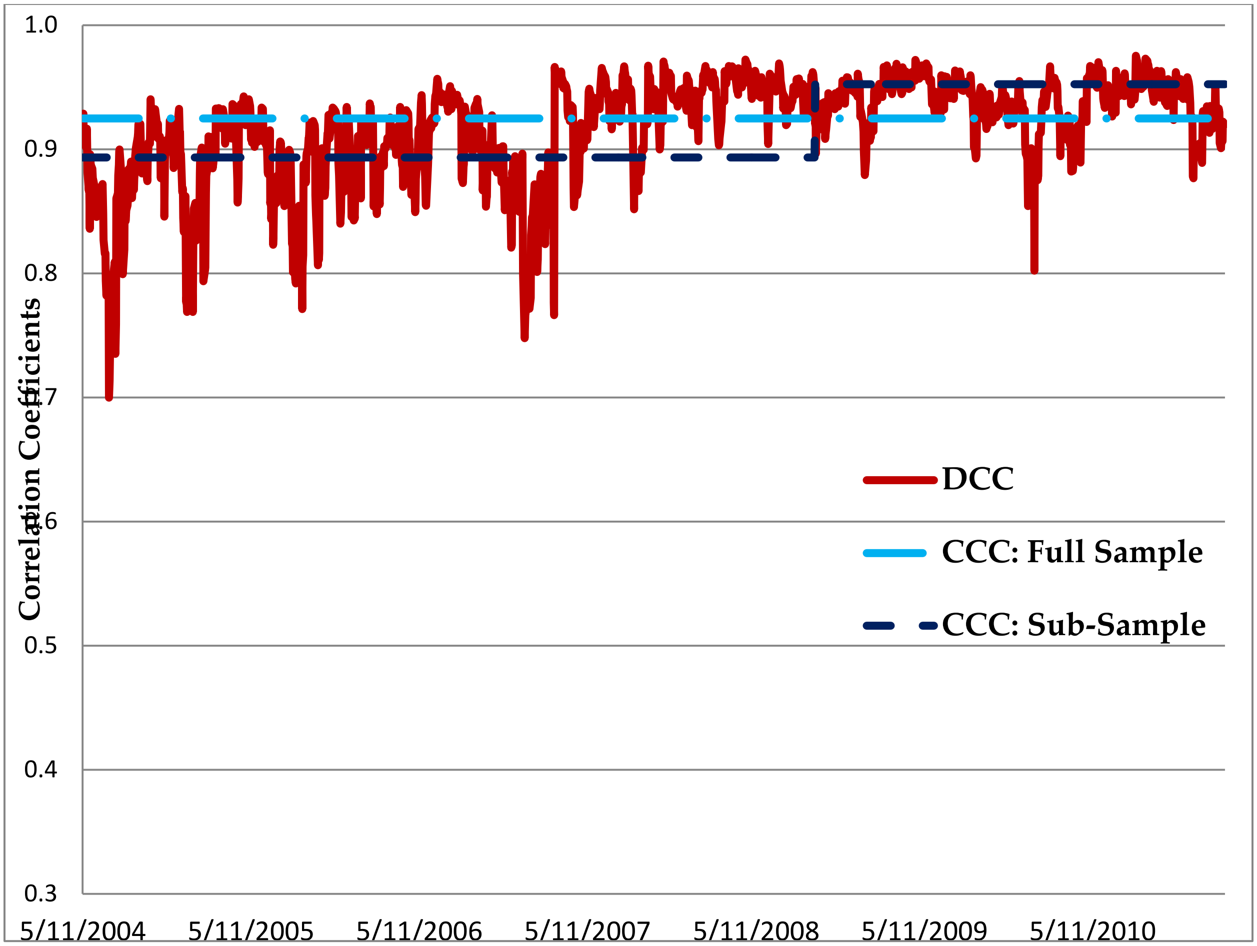
Note: The relative variation is defined by $\sigma(\lambda_i^j f_t^j)/\sigma(\eta_{i,t}^j)$, where σ is the estimate standard deviation and $j = n, p$. Because the common factor and the idiosyncratic component are orthogonal each other, the total variation is the sum of $\sigma(\lambda_i^j f_t^j)$ and $\sigma(\eta_{i,t}^j)$. 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. 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.

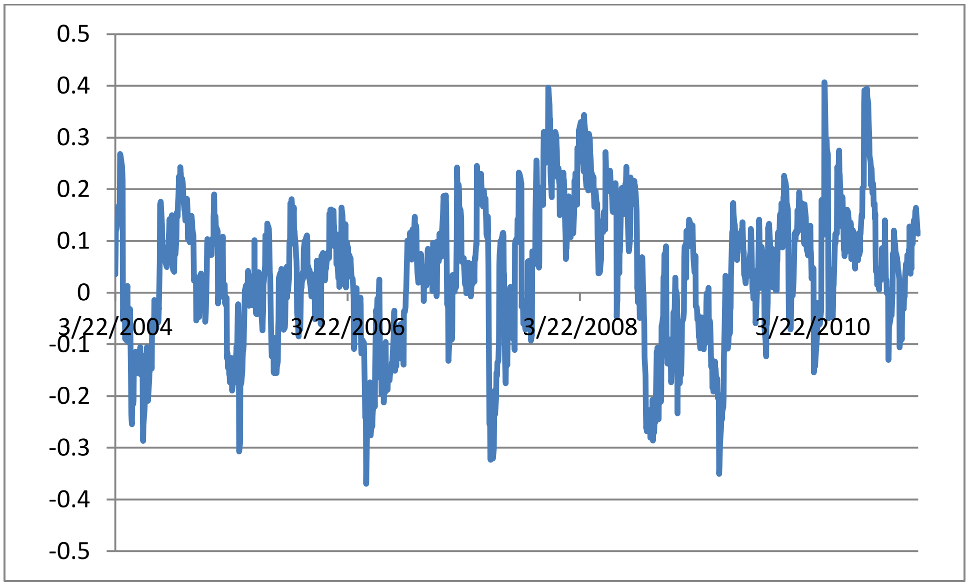
Figure 6. Conditional Correlations: Stock Funds



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 7. Dynamic Conditional Correlations: Bond Funds

(a) NAV vs. VIX



(b) Price vs. VIX

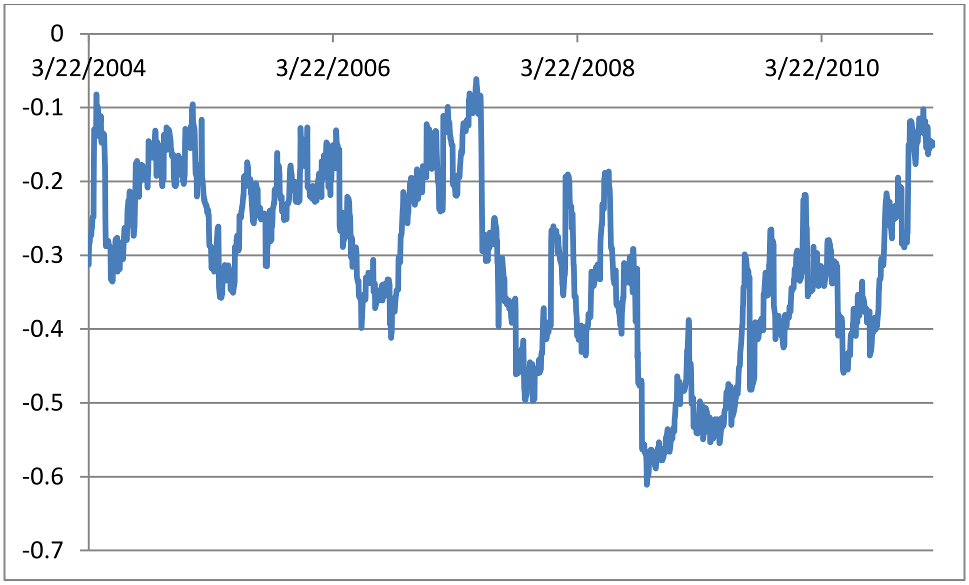
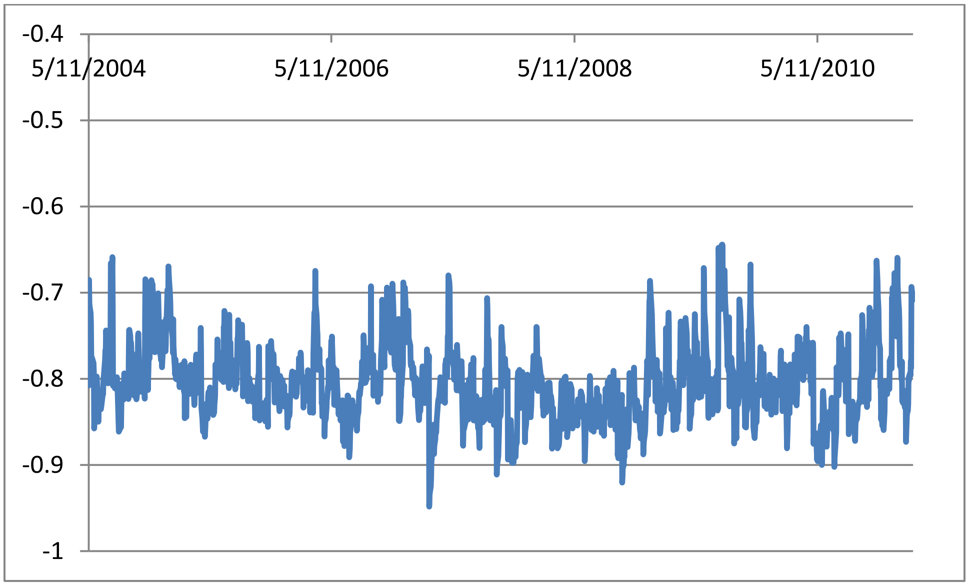


Figure 8. Dynamic Conditional Correlations: Stock Funds

(a) NAV vs. VIX



(b) Price vs. VIX

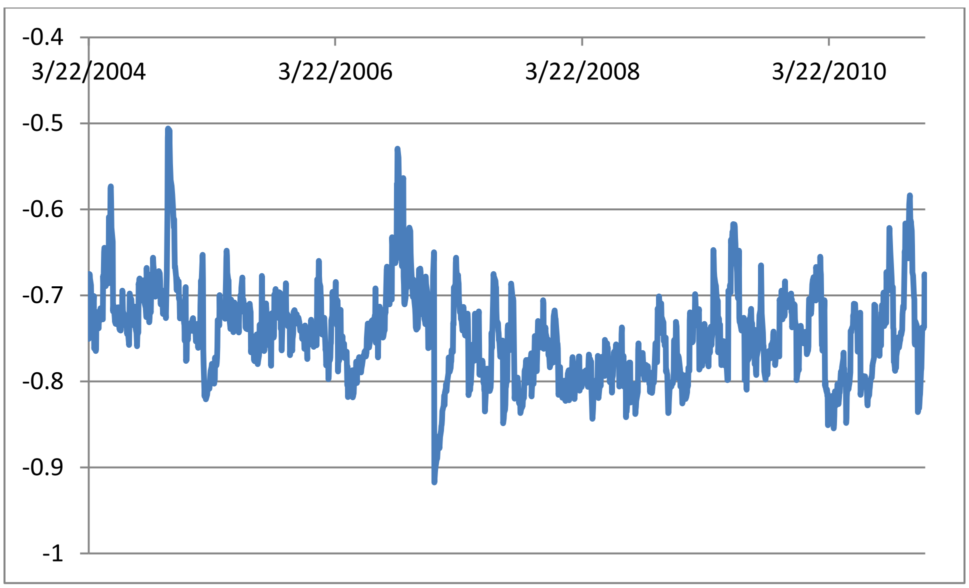


Table I. Descriptive Statistics

	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 II. Model Estimation: Bond Funds

$$\textbf{BEKK:} \boldsymbol{Y_t = \Phi Y_{t-1} + e_t, Y_t} = \begin{bmatrix} f_t^n & f_t^p \end{bmatrix}'$$

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

$$\boldsymbol{M} = \begin{bmatrix} \boldsymbol{\omega_{11}} & \boldsymbol{\omega_{12}} \\ \boldsymbol{\omega_{12}} & \boldsymbol{\omega_{22}} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \boldsymbol{\alpha_1} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\alpha_2} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \boldsymbol{\beta_1} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\beta_2} \end{bmatrix}$$

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

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

		Estimate	Standard Error	t-Stat
BEKK	$\boldsymbol{\omega_{11}}$	7.271444	1.346760	5.399214
	$\boldsymbol{\omega_{22}}$	8.124040	1.621381	5.010568
	$\boldsymbol{\omega_{12}}$	-0.001550	0.000001	-1056.670
	$\boldsymbol{\alpha_1}$	0.198994	0.000390	509.6174
	$\boldsymbol{\alpha_2}$	0.527182	0.003548	148.5895
	$\boldsymbol{\beta_1}$	0.973555	0.000022	43281.12
	$\boldsymbol{\beta_2}$	0.841746	0.001207	697.3823
	$\boldsymbol{-lnL}$	18067.72		
CCC	$\boldsymbol{\rho_{1,2}}$	0.359680	0.000524	685.7799
DCC	$\boldsymbol{\alpha}$	0.015311	0.000065	237.1669
	$\boldsymbol{\beta}$	0.984687	0.000168	5874.187

Note: The BEKK model is based on Engle and Kroner (1995). 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 III. Model Estimation: Stock Funds

$$\textbf{BEKK:} \boldsymbol{Y_t = \Phi Y_{t-1} + e_t, Y_t} = \left[f_t^n \quad f_t^p\right]'$$

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

$$\boldsymbol{M} = \begin{bmatrix} \boldsymbol{\omega_{11}} & \boldsymbol{\omega_{12}} \\ \boldsymbol{\omega_{12}} & \boldsymbol{\omega_{22}} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \boldsymbol{\alpha_1} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\alpha_2} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \boldsymbol{\beta_1} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\beta_2} \end{bmatrix}$$

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

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

		Estimate	Standard Error	t-Stat
BEKK	$\boldsymbol{\omega_{11}}$	8.910059	2.244327	3.970036
	$\boldsymbol{\omega_{22}}$	6.331860	1.816642	3.485475
	$\boldsymbol{\omega_{12}}$	2.584336	0.145375	17.77700
	$\boldsymbol{\alpha_1}$	0.300085	0.000420	713.8121
	$\boldsymbol{\alpha_2}$	0.349882	0.000832	420.7379
	$\boldsymbol{\beta_1}$	0.944047	0.000057	16659.39
	$\boldsymbol{\beta_2}$	0.929901	0.000132	7057.653
	$\boldsymbol{-lnL}$	16975.70		
CCC	$\boldsymbol{\rho_{1,2}}$	0.924676	0.000011	83995.53
DCC	$\boldsymbol{\alpha}$	0.086007	0.000501	171.8038
	$\boldsymbol{\beta}$	0.848063	0.002781	304.9611

Note: The BEKK model is based on Engle and Kroner (1995). 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 IV. 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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