IDENTIFYING REGIME CHANGES IN CLOSED-END FUND DISCOUNTS

By J. Christopher Hughen and Mark E. Wohar*

Abstract
In seeming contradiction of the efficient markets hypothesis, closed-end fund shares typically trade at discounts to their portfolio values. We find that about half of these discounts are non-stationary. Focusing only on those funds that have stationary discounts, this study applies the Bai and Perron (1998, 2003a,b) methodology to test for structural breaks in the mean discounts. Virtually all have structural breaks, and our findings contradict previous studies that indicate closed-end fund discounts revert to a long-term mean value. The data indicate that closed-end fund trading strategies are more risky than they superficially appear. As structural breaks in mean discounts do not occur together, our analysis does not find support for a common factor (possibly investor sentiment) causing these breaks.

Introduction

Closed-end funds, which are investment companies that own portfolios of marketable securities, usually trade at discounts to the values of their portfolios.[1] This paper tests for multiple structural breaks in the mean discounts of 19 funds that have stationary discounts to gain a greater insight into two controversial issues associated with closed-end funds.

The first issue is the role of investor sentiment in the fluctuations of closed-end fund discounts. The noise trader model developed by De Long et al. (1990) provides a theoretical framework in which irrational investors can cause prices to diverge from fundamental values. Such noise traders are influenced by information of seemingly little value, like sentiment. Lee et al. (1991), Chopra et al. (1993), Swaminathan (1996), and Gemmill and Thomas (2002) find that discount fluctuations are related to the sentiment of individual investors. Other researchers fail to support the theory that small investor sentiment causes changes in closed-end fund discounts [Chen et al. (1993); Elton et al. (1998)]. If investor sentiment is influencing these fluctuations, the mean discounts of different funds will change at similar times. Our research utilizes the Bai and Perron (1998, 2003a,b) methodology to test for such structural breaks in the mean discounts.

Our examination of structural breaks in the mean discounts also provides a greater understanding of the profitability of closed-end fund trading strategies. Buying closed-end funds at large discounts and selling when the discounts narrow is a well known trading strategy. Thompson (1978) first documents the abnormal profitability of this strategy, and the persistence of its profitability is confirmed by many other researchers [Pontiff (1995); Anderson (1986); Sias (1997); Cakici et al. (2000); Anderson et al. (2001)].

The existence of closed-end fund discounts and the continued profitability of such simple trading strategies that exploit these discounts appear to contradict the theory of efficient markets,

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[1] In this study, the market price of a closed-end fund share is measured using the end-of-day closing price observed in exchange trading. The fund's portfolio value is regularly reported on a per share basis called the net asset value (NAV). Consistent with Pontiff (1995), we measure the deviation of price and underlying value as the natural logarithm of the fund share price divided by the NAV. A negative value is a discount, and a positive value is a premium.

which suggests that prices represent all available public information regarding underlying value. Why do closed-end fund trading strategies continue to be profitable? Pontiff (1995) attributes the superior performance of funds with large discounts to mean reversion of the discounts instead of discounts providing valuable information about future NAV returns. We examine the frequency and size of structural breaks in the mean, which increase the risk of this strategy and represent a plausible explanation for why it has continued to yield a profit over such a long period.

Our study provides three insights into the time-series properties of closed-end fund discounts. While it is commonly believed that discounts revert to a long-term mean value, our analysis reveals that this is rarely the case over the sample period. We examine 19 funds that have stationary discounts. All but one of these 19 funds are found to exhibit a structural break in the mean discount, and 26% of the funds have five different mean discounts over the sample period. This suggests that trading strategies based on mean reversion involve substantial risk associated with structural breaks.

An additional insight provided by our study is that changes in the mean discount are substantial. The median change in the average discount between regimes is 11.3%. Previous research has failed to explain why fund trading strategies continue to be profitable despite the numerous studies that call attention to their performance. Such large structural breaks introduce considerable risk into these strategies. Finally, our study reveals that structural breaks in mean discounts do not generally coincide. For the period during which most of the funds are in our sample, the maximum number of funds that have regime end dates within a 90-day period is 16%. The data is not consistent with the noise trader model, which suggests that discount changes are driven by fluctuations in investor sentiment.

Literature Review

Financial economists have extensively studied closed-end funds because their shares typically trade at discounts that appear to contradict the efficient markets theory. Malkiel (1977) finds that rational explanations fail to account for the size of the discounts, which apparently constitute a market imperfection. Early research in this area examines the profitability of simple trading strategies. Other studies explore the time-series properties of discounts and the role of investor sentiment in explaining discount fluctuations. We next provide an overview of these findings.

Profitability of Trading Rules

Thompson (1978) provides one of the earliest examinations of closed-end fund performance. A strategy based on buying discounted funds earns an excess return of 4%; furthermore, funds trading at premiums underperform the market. Richards et al. (1980) evaluate trading rules to identify even more profitable strategies. Trading rule strategies, which buy and sell funds based on specific discount levels, produce greater returns than simple buy-and-hold strategies. Anderson (1986) finds these results persist over different time periods and samples. Pontiff (1995), whose study reveals that deeply discounted funds outperform by 6%, concludes that mean reversion in discounts accounts for the relation between discounts and future performance.

Other researchers explore whether the profitability persists under different transaction costs and portfolio weighting schemes. Using expenses in the range of 0 - 4%, Cakici et al. (2000) examine U.S. and U.K. funds to reveal that profitable strategies exist across a variety of different transaction costs. When costs are high, shorting funds with large premiums yields the highest returns. Anderson et al. (2001) also include transaction costs in an analysis of strategies using different spans, which is the difference between the buy and sell point. They find that narrow span strategies are unprofitable in an environment with high transaction costs. Sias (1997) investigates different approaches to forming a portfolio of large discount funds and concludes that a nonlinear weighting of portfolio components provides substantially higher returns. Cakici et al. (2002) find that a short portfolio of high premium funds reduces turnover and produces greater returns than a long portfolio of discounted funds, which has greater turnover and higher transaction costs.

The research on fund trading strategies demonstrates that the profitability of closed-end fund trading strategies is robust to a variety of different transaction costs and weighting schemes. As they find that buying at high discounts and selling at low discounts is profitable, these studies imply that discounts are mean reverting.

Time-Series Properties of Discounts

Pontiff (1995) attempts to explain the abnormal returns of deeply discounted funds within the framework of efficient markets. Through his investigation, he provides a seminal analysis of the time-series properties of these funds. Using NAV data over 25 months, he finds that the majority of funds in his sample have stationary discounts. Pontiff confirms the research described in the previous section by documenting that a fund trading at a 20% discount has an expected monthly return that is 0.7% higher than a fund trading at NAV. However, two statistical tests fail to reject a zero correlation between the discount and future NAV returns. An examination of the risk exposure of funds provides weak support for investor sentiment influencing discounts.

Using 21 bond funds and 27 equity funds with stationary discounts, Gasbarro et al. (2003) explore mean reversion in closed-end fund discounts using a cointegration analysis of share prices and NAVs. The Johansen (1988) cointegrating λ-max statistics indicates that 85% of the funds are cointegrated, while the trace statistics are consistent with 63% of the funds having cointegrated share prices and NAVs. The authors estimate an error-correction model to determine whether the changes in the NAV or share price or both are responding to deviations from equilibrium. In 70% of the equity funds and 86% of the bond funds, the Johansen method indicates that changes in both share prices and NAVs are contributing to the mean reversion in discounts. The coefficients from the share price changes are larger in about half of the funds. The authors argue that it is these share price changes that are needed to generate excess profits from a trading strategy associated with mean reversion.

Investor Sentiment and Discount Fluctuations

De Long et al. (1990) develop a model of noise traders in financial markets that offers an explanation for the discount fluctuations described in the previous section. This model has two participants: rational investors and noise traders, who make systematic forecasting errors that are influenced by investor sentiment. Closed-end funds have characteristics that are consistent with the parameters of this model. Individual investors own most of the shares in closed-end funds, and they are viewed as being sensitive to sentiment like the noise traders.[2] Like the model, rational investors in closed-end funds face impediments to arbitrage. These include difficulties in identifying the exact portfolio of the fund, the inability to receive the proceeds from short sales, and short-term horizons.

Lee et al. (1991) find that the pricing of closed-end funds is consistent with implications of the noise trader model. Discounts are highly correlated (average of 0.5), and returns on small stocks are large when the discounts for closed-end funds are small. This is consistent with the proposition that risk generated by changes in investor sentiment is not diversifiable because it affects many assets. Chopra et al. (1993) and Swaminathan (1996) also conclude that discounts are related to the returns on small stocks. Brauer and Chang (1990) show that closed-end fund shares experience the

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[2] Several studies examine the ownership of closed-end funds. Weiss (1989) finds that closed-end funds have lower average institutional ownership after their IPOs than a control sample of regular firms. Lee et al. (1991) show that the average institutional ownership for their sample of closed-end funds is 6.6%. A random sample from the largest (smallest) decile of NYSE stocks has 52.1% (26.5%) institutional ownership.

January effect but the securities owned by the funds are unaffected. This implies that closed-end fund investors face risk that owners of regular common stock do not encounter.

Brown (1999) also presents evidence consistent with the noise trader model by examining the association between the sentiment of individual investors and the volatility of closed-end funds. Extreme levels of the American Association of Individual Investors' Sentiment Survey are related to closed-end fund volatility and this volatility typically occurs during the trading day. In a related study of U.K. funds, Gemmill and Thomas (2002) find that fluctuations in the discount are related to retail flows in open-end funds.

Other researchers conclude that the trading of closed-end funds is inconsistent with the implications of the noise trader model. Using a transactions database that identifies institutional investors, Sias (1997) examines closed-end fund discounts and their relation with order-flow imbalance and trader type. The evidence is inconsistent with the noise trader model since institutional investors have as much impact on fund prices and discounts as individual investors. In their analysis of large daily changes in discounts, Hughen and McDonald (2005) find that fluctuations are not associated with the order flow from individual investors.

Additional studies refute the noise trader model using data on small stocks. Chen et al. (1993) find that small capitalization stock returns are not overly sensitive to discounts. Leonard and Shull (1996) do not find a relation between closed-end funds and small stocks in months other than January. Elton et al. (1998) examine the assertion that closed-end fund shares offer a higher expected return than their assets due to the fund's higher sensitivity to small investor sentiment. They fail to find evidence that sentiment is a priced factor in closed-end funds or stocks.

Data and Methodology

Data

In June of 2000, we purchased the Fund-Edge database from CDA/Wiesenberger, which is a division of Thompson that provides fund information to financial professionals. This database contains weekly prices and NAVs on 516 closed-end funds that go as far back as June 26, 1981. We extended this data through the end of 2002 using NAVs from the *Wall Street Journal* and closing prices from the Center for Research in Stock Prices (CRSP) database. As funds investing in foreign securities may face unique risks that contribute to their discount fluctuations, our sample includes only those funds that invest primarily in domestic assets. By restricting possible sample funds to those that CDA/Wiesenberger classifies as investing in the region of the "United States," the number of possible funds drops from 516 to 267.

Prior studies of closed-end fund trading strategies have used samples consisting primarily of equity funds [Anderson et al. (2001); Anderson (1986); and Richards et al. (1980)]. To produce results that can be compared to these studies, we eliminate funds that CDA/Wiesenberger classifies as bond funds. There are 39 funds that have over ten years of data. We use the Ng and Perron (2001) unit root test (detailed results not reported for brevity), which has good size and power, to determine which discounts are stationary. For 19 of the 39 funds, we can reject the null of a unit root, and Table 1 provides a list of these funds. Consistent with their investment objectives, the funds held primarily domestic stocks as of the last financial report filed as of June 2000.

Table 1: Sample Description.

Fund Name	Ticker	Investment Objective	Portfolio Composition Stocks	Bonds	Cash	Other
Liberty All-Star Growth Fund	ASG	Growth - Domestic	98%	0%	2%	0%
Blue Chip Value Fund	BLU	Growth & Income	93%	0%	7%	0%
Central Securities	CET	Growth - Domestic	91%	0%	9%	0%
Duff & Phelps Utilities Income	DNP	Sector - Utilities	69%	25%	0%	6%
Engex	EGX	Growth - Domestic	100%	0%	0%	0%
First Financial Fund	FF	Sector - Financial Services	100%	0%	0%	0%
Gabelli Equity Trust	GAB	Growth - Domestic	97%	2%	0%	1%
General American Investors	GAM	Growth - Domestic	80%	0%	20%	0%
NAIC Growth Fund	GRF	Growth - Domestic	90%	0%	10%	0%
H&Q Healthcare Investors	HQH	Sector - Health/Biotechnology	73%	0%	11%	16%
H&Q Life Sciences Investors	HQL	Sector - Health/Biotechnology	74%	0%	9%	17%
Morgan Grenfell Smallcap Fund	MGC	Growth - Domestic	99%	0%	1%	0%
Petroleum and Resources Corp.	PEO	Sector - Energy/ Natural Resource	87%	0%	3%	11%
Royce Value Trust	RVT	Growth - Domestic	85%	13%	0%	2%
Salomon Brothers Fund	SBF	Growth - Domestic	93%	1%	1%	5%
Source Capital	SOR	Growth & Income	83%	3%	5%	9%
Southeastern Thrift and Bank Fund	STBF	Sector - Financial Services	93%	0%	7%	0%
Tri-Continental Corporation	TY	Growth & Income	89%	7%	4%	0%
Liberty All-Star Equity Fund	USA	Growth & Income	97%	0%	3%	0%

Notes: Table 1 provides a list of the 19 closed-end funds analyzed in this study. The investment objectives and portfolio compositions are obtained from the CDA/Wiesenberger Fund-Edge database. The funds primarily invest in domestic equities. The sample period for each fund starts when historical NAV data is available in Fund-Edge and ends in December 27, 2002.

Methodology

This study investigates the time-series properties of closed-end funds discounts to gain a greater understanding of whether discount fluctuations are related to investor sentiment and why the profitability of simple closed-end trading strategies persists. We first examine whether discounts are stationary. A stationary time series has a mean and variance that do not change over time. While random shocks will cause such a series to deviate from its mean, it will tend to revert back to this value over time. In other words, shocks in the distant past have little influence on the current value.

For those discounts that appear to be stationary, we will examine whether there are structural breaks in the mean discount for each fund. Such breaks offer an explanation for why previous studies find that simple fund trading strategies continue to yield excess returns. In the presence of changing mean discounts, sophisticated investors are inhibited from reducing the profitability of these strategies. Finally, we will investigate whether breaks in the fund discounts occur at common times. If this occurs, the data will be consistent with a common factor, perhaps investor sentiment, influencing the discounts.

Econometric Procedure

We use the Bai and Perron (1998, 2003a,b, 2004) method to test for infrequent structural breaks in discounts.[3] Monte Carlo experiments reveal that this procedure is quite powerful in detecting structural breaks (Bai and Perron, 2004). To implement this procedure, we regress each fund's discount on a constant and test for structural breaks in the constant (Bai and Perron, 2003a). Consider such a regression model with m breaks ($m+1$ regimes),

$$d_t = \beta_j + \varepsilon_t, t = T_{j-1} + 1, \dots, T_j, \tag{1}$$

for $j = 1, \dots, m+1$, where d_t is the discount in period t and β_j ($j = 1, \dots, m+1$) is the mean level of the discount in the jth regime. The m-partition $(T_1, \dots, T_m)$ represents the breakpoints for the different regimes (by convention, $T_0 = 0$ and $T_{m+1} = T$). Bai and Perron explicitly treat these breakpoints as unknown, and estimates of the breakpoints are generated using the least squares principle. Consider estimating equation (1) via least squares. For each m-partition $(T_1, \dots, T_m)$, the least squares estimates of β_j are generated by minimizing the sum of squared residuals,

$$S_T(T_1, \dots, T_m) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} (d_t - \beta_i)^2 . \tag{2}$$

Let the regression coefficient estimates based on a given m-partition $(T_1, \dots, T_m)$ be denoted by $\hat{\beta}(\{T_1, \dots, T_m\})$, where $\beta = (\beta_1, \dots, \beta_{m+1})'$. Substituting these into equation (2), the estimated breakpoints are given by

$$(\hat{T}_1, \dots, \hat{T}_m) = arg\, min_{T_1, \dots, T_M}\, S_T(T_1, \dots, T_m), \tag{3}$$

where the set of admissable m-partitions is subject to a set of restrictions given below. The breakpoint estimators correspond to the global minimum of the sum of squared residuals objective function. With the breakpoint estimates in hand, it is straightforward to calculate the corresponding least-squares regression parameter estimates as $\hat{\beta} = \hat{\beta}(\{\hat{T}_1, \dots, \hat{T}_m\})$. Bai and Perron (2004) develop an efficient algorithm for the minimization problem in equation (3) based on the principle of dynamic programming.

Bai and Perron (1998) consider testing procedures aimed at identifying the number of structural breaks (m) in equation (1). They begin by specifying a statistic for testing the null hypothesis of no structural breaks against the alternative that there are $m = b$ breaks. Let $(T_1, \dots, T_b)$ be a partition such that $T_i = [T\lambda_i]$ $(i = 1, \dots, b)$. Also define R such that

[3] This section draws heavily from Rapach and Wohar (2005).

$(R\beta)' = (\beta_1 - \beta_2, ..., \beta_b - \beta_{b+1})$. Bai and Perron specify the following statistic:

$$F_T(\lambda_1,...,\lambda_b) = \frac{1}{T}\left(\frac{T-(b+1)2}{2b}\right)\hat{\beta}' R' [R\hat{V}(\hat{\beta})R']^{-1} R\hat{\beta}, \tag{4}$$

where $\beta = (\beta_1, ..., \beta_{b+1})'$ is the vector of regression coefficient estimates, and $\hat{V}(\hat{\beta})$ is a heteroskedastic and autocorrelation consistent estimate of the variance-covariance matrix for $\hat{\beta}$. Bai and Perron next consider a type of maximum F-statistic corresponding to equation (4),

$$SupF_T(b) = F_T(\hat{\lambda}_1, ..., \hat{\lambda}_b), \tag{5}$$

where $\hat{\lambda}_1, ..., \hat{\lambda}_b$ minimize the global sum of squared residuals, $S_T(T\lambda_1, ..., T\lambda_b)$, under the restriction that $(\hat{\lambda}_1, ..., \hat{\lambda}_b) \in \Lambda_\pi$, where $\Lambda_\pi = \{(\lambda_1, ..., \lambda_b); |\lambda_{i+1} - \lambda_i| \ge \pi, \lambda_1 \ge \pi, \lambda_b \le 1 - \pi\}$ for some arbitrary positive number π (the trimming parameter). Bai and Perron develop two statistics, what they call the "double maximum" statistics, for testing the null hypothesis of no structural breaks against the alternative hypothesis of an unknown number of breaks given an upper bound M. The first double maximum statistic is given by

$$\text{UDmax} = max_{1 \le m \le M}\ SupF_T(m). \tag{6}$$

The second double maximum statistic, WDmax, applies different weights to the individual $SupF_T(m)$ statistics so that the marginal p-values are equal across values of m; see Bai and Perron (1998, p. 59) for details. Finally, Bai and Perron specify what they label the $SupF_T(l+1|l)$ statistic to test the null hypothesis of l breaks against the alternative hypothesis of $l+1$ breaks. It begins with the global minimized sum of squared residuals for a model with l breaks. Each of the intervals defined by the l breaks is then analyzed for an additional structural break. From all of the intervals, the partition allowing for an additional break that results in the largest reduction in the sum of squared residuals is treated as the model with $l+1$ breaks. The $SupF_T(l+1|l)$ statistic is used to test whether the additional break leads to a significant reduction in the sum of squared residuals. Bai and Perron (1998, 2003a) derive asymptotic distributions for the double maximum and $SupF_T(l+1|l)$ statistics and provide critical values for various values of π and M.

The Bai and Perron method allows for quite general specifications when computing test statistics and confidence intervals for the break dates and regression coefficients. These include autocorrelation and heteroskedasticity in the regression model residuals, as well as different moment matrices for the regressors in the different regimes. We use the most general Bai and Perron specification that allows for all of these features. Using the notation of Bai and Perron (2004), we set cor_u = 1, het_u = 1 and het_z = 1. These conditions are quite general when no lagged dependent variables are included in equation (1) and are sufficient to capture the serial correlation of discounts. Pontiff (1995) finds that average serial correlation for monthly discounts is 0.85. This is accommodated in the set up described above and need not be modeled explicitly.

Bai and Perron (1998) discuss a sequential application of the $SupF_T(l+1|l)$ statistics—a specific-to-general modeling strategy—as a way to determine the number of structural breaks. While Bai and Perron (2004) find that this procedure performs well in some settings, its performance can be improved upon when multiple breaks are present, as the $SupF_T(1|0)$ statistic can have low power in the presence of multiple breaks. On the basis of extensive Monte Carlo simulations, Bai and Perron (2004) recommend the following strategy to identify the number of breaks. First, examine the double maximum statistics to determine if any structural breaks are present. If the double maximum statistics are significant, then examine the $SupF_T(l+1|l)$ statistics to decide on the number of breaks, choosing the $SupF_T(l+1|l)$ statistic that rejects for the largest value of l. Finally, Bai and Perron (2004) recommend using a trimming parameter of at least 0.15 (corresponding to $M = 5$) when allowing for heteroskedasticity and serial correlation, and we follow this recommendation in our applications.[4]

Empirical Results

Tests for Structural Breaks

Table 2 reports Bai and Perron (1998) statistics for tests of structural change in the mean values of each fund discount. For 18 of the 19 funds, both double maximum statistics (UDmax and WDmax) support rejecting the null hypothesis of no structural breaks. With the exception of the discount on the Duff & Phelps Utilities Income Fund (DNP), the UDmax statistics are significant at the 1% level and the WDmax statistics have p-values of less than 5%.

With the strong evidence of structural change in the mean levels of all but one of the discounts, we next use the $SupF_T(l+1|l)$ statistics to determine the number of breaks for each fund. These statistics are examined in a sequential fashion to find the $SupF_T(l+1|l)$ statistic that rejects for the largest value of l. For example, the significance of $F(1|0)$ indicates that the null of 0 breaks is rejected in favor of the alternative of 1 break.

The $F(4|3)$ statistic is significant at the 5% level for CET, EGX, GAB, GAM, and GRF while the $F(5|4)$ statistic is either insignificant or unable to be calculated due to the limited number of observations. This is consistent with 26% of the funds in our sample having four structural breaks in the mean discount. For BLU, FF, and MGC, the $F(3|2)$ statistic is significant but the $F(4|3)$ is not. We conclude that these funds, which represent approximately 16% of our sample, have three structural breaks. The $F(2|1)$ statistic is significant at the 5% level for ASG, HQH, RVT and SBF, but the $F(3|2)$ statistic fails to reject the null hypothesis. Therefore, the data suggests that these funds have 2 structural breaks. Finally, our analysis concludes that HQL, MGC, PEO, SOR, STBF, TY, and USA (26% of the sample) have one structural break in the mean discount. The $F(1|0)$ statistic is significant at the 10% level for TY and at the 1% level for the other funds.

By providing strong evidence of structural breaks in closed-end fund discounts, Table 2 indicates that the time-series properties are more complex than indicated in previous studies, which support the hypothesis that discounts are mean reverting. Thompson (1978) and Anderson (1986) conclude that a simple trading strategy, which buys fund shares when discounts are large and sells shares when discounts return to the mean, provides abnormal risk-adjusted returns. Pontiff (1995) finds that the discounts on 53% of his sample of 49 funds are stationary over a 25 month period. Gasbarro et al. (2003) identify mean-reverting funds using cointegration procedures. However, our study suggests that many fund discounts are not stationary and almost all of those that appear stationary have infrequent breaks in the mean.

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[4] We implement the Bai and Perron method using the GAUSS program available from Pierre Perron's home page at http://econ.bu.edu/perron/.

Table 2: Bai and Perron (1998) Double Maximum and $SupF_T(l+1 \mid l)$ Statistics for Tests of Multiple Structural Breaks in the Mean of the Discount.

Fund	*UDmax*[a]	*WDmax*(5%)[b]	*F*(1|0)[c]	*F*(2|1)[c]	*F*(3|2)[c]	*F*(4|3)[c]	*F*(5|4)[c]
ASG	29.17**	46.69*	5.13	13.07*	1.43		
BLU	47.51**	86.73*	23.48**	3.62	17.52**	1.52	
CET	106.39**	233.40**	7.05*	33.58**	2.44	18.01*	<
DNP	4.34	8.63	3.05	2.20			
EGX	48.52**	80.17*	48.52**	35.09**	33.87**	25.75**	<
FF	57.63**	82.11*	57.63**	16.78**	14.13*		
GAB	25.11**	55.11*	10.19*	14.55**	13.53*	14.11**	9.39
GAM	44.87**	98.45*	26.90**	7.5*	2.56	55.82**	<
GRF	44.00**	96.54**	27.76**	2.26	68.68**	57.00**	4.25
HQH	30.64**	59.07*	6.80	23.65**	8.67		
HQL	88.06**	88.06*	88.06**	4.29			
MGC	59.80**	71.07*	10.33*	31.95**	12.94*	0.62	
PEO	24.87**	24.87**	24.87**	1.69			
RVT	18.05**	39.61*	2.15	12.25**	2.76		
SBF	28.32**	52.67*	21.02**	17.20**	3.63		
SOR	18.30**	27.86*	18.30**	3.25			
STBF	50.29**	72.40*	21.03**	5.36			
TY	42.92**	94.19*	8.08†	2.71			
USA	63.64**	108.97*	42.20**	2.73			

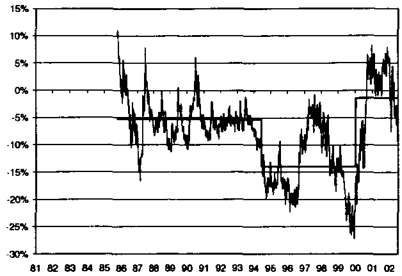
Notes: †,*,** indicate significance at the 10, 5, and 1 percent levels, respectively; < indicates that there was no more place to insert an additional break given the minimal length requirement; [a]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5; [b]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5; [c]One-sided (upper-tail) test of the null hypothesis of l breaks against the alternative hypothesis of $l+1$ breaks; $F(1|0)$, $l=0$; $F(2|1)$, $l=1;\ldots;$ $F(5|4)$, $l=4$.

Identification of the Regime End Dates

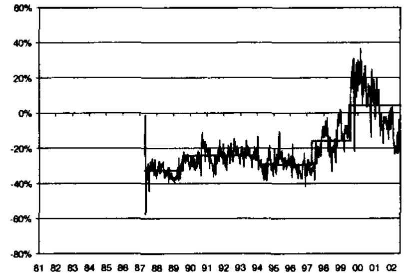
After determining the estimated number of structural breaks, we next use the optimization methodology of Bai and Perron to determine the end date of each regime. Table 3 reports the estimated end dates, the 95% confidence intervals for these end dates, and the mean discount for each regime. For example, the second regime for the Gabelli Equity Trust (GAB) begins on 5/6/89 and ends on 7/7/95. The period from 6/9/95 to 5/24/96 forms a 95% confidence interval for this end date. On average, the fund trades at a slight premium (0.4%) during the second regime. Figure 1 provides a chart of the discount for each fund over its sample period. Each chart contains two lines. The more volatile line is the weekly discount for the fund, and the other line represents the mean discount level over the regimes identified in Table 3.

Figure 1: Closed-End Fund Discounts and Means for Different Regimes Indicated by the Bai and Perron Methodology.

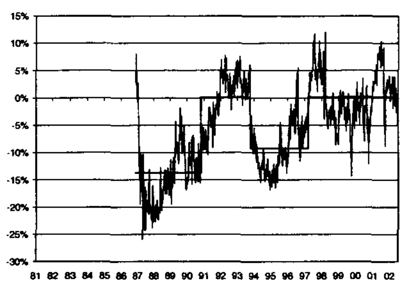
Liberty All-Star Growth Fund
(ASG)



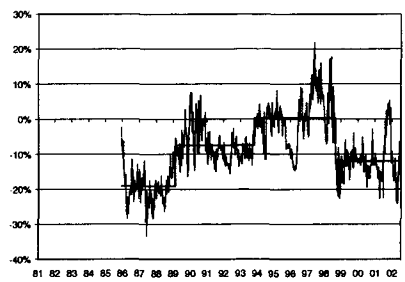
Engex
(EGX)



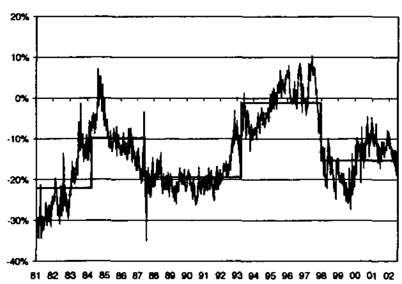
Blue Chip Value Fund
(BLU)



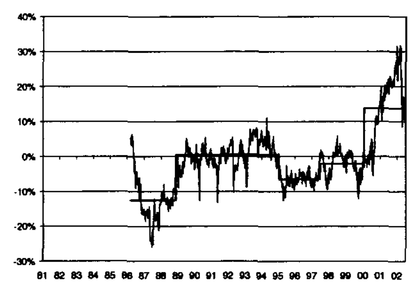
First Financial Fund
(FF)



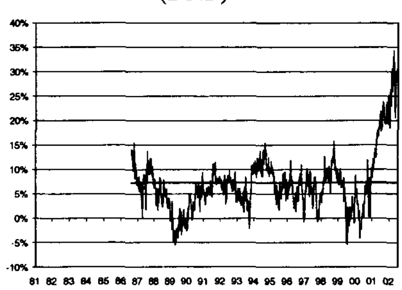
Central Securities
(CET)



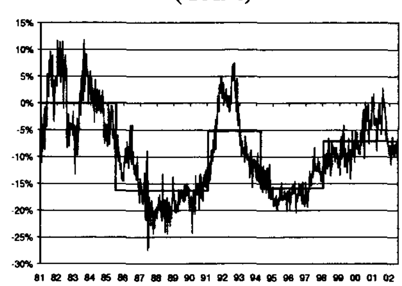
Gabelli Equity Trust
(GAB)



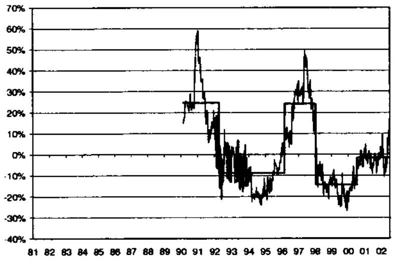
Duff & Phelps Utilities Income
(DNP)



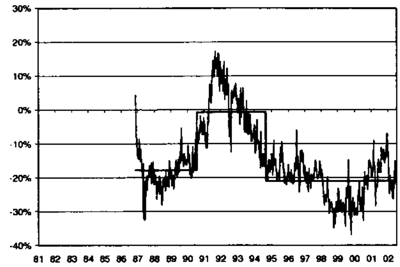
General American Investors
(GAM)



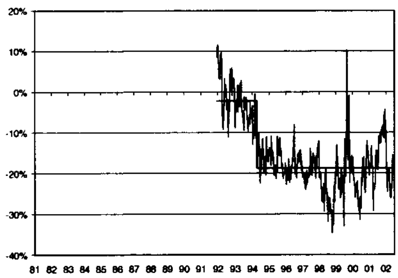
NAIC Growth Fund
(GRF)



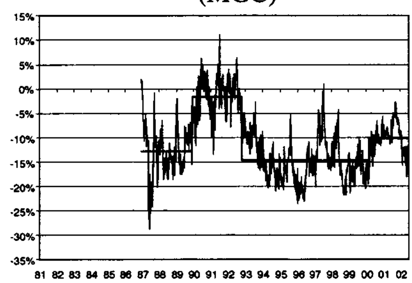
H&Q Healthcare Investors
(HQH)



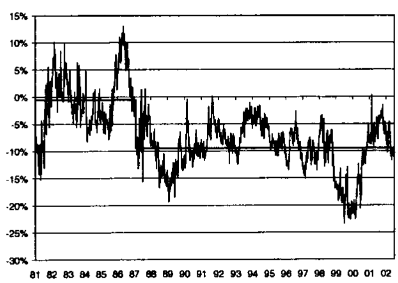
H&Q Life Sciences Investors
(HQL)



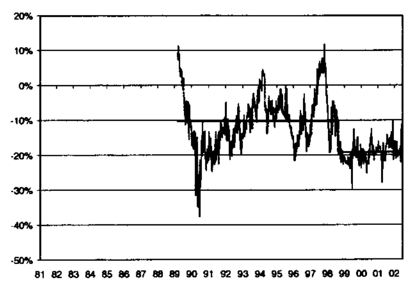
Morgan Grenfell Small Cap Fund
(MGC)



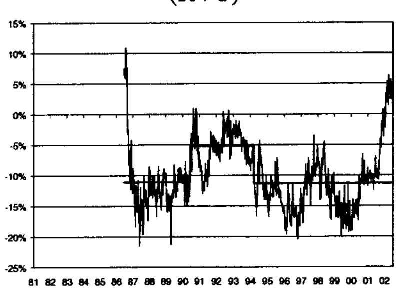
Petroleum and Resources Corp
(PEO)



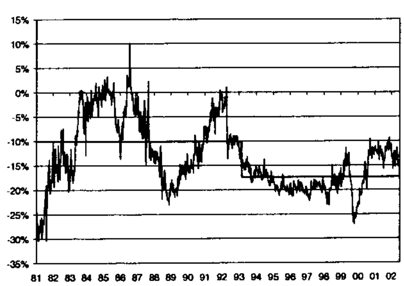
Southeastern Thrift and Bank
Fund (STBF)



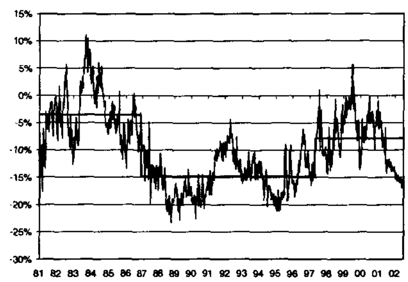
Royce Value Trust
(RVT)



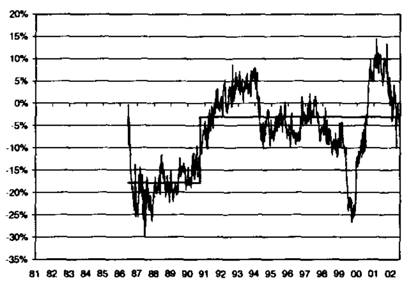
Tri-Continental Corporation
(TY)



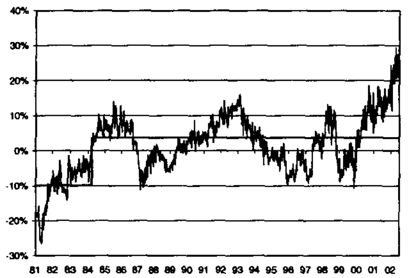
Salomon Brothers Fund
(SBF)



Liberty All-Star Equity Fund
(USA)



Source Capital
(SOR)



As the median (mean) length of the regime shown in Table 3 is 4.1 (5.2) years, we conclude that the structural breaks are generally infrequent. The longest regime occurs for Source Capital (SOR) from 9/8/84 to 12/27/02; this period contains 6,684 days or about 18.4 years. The shortest regime, which lasts 684 days or about 1.9 years, occurs for the NAIC Growth Fund (GRF) from 8/17/96 to 7/2/98.

While structural breaks in the mean discounts are generally infrequent, the changes in the mean are often substantial. Consider the third regime for the Morgan Grenfell Smallcap Fund (MGC) which lasts from 4/9/93 to 8/25/00. The average discount in this period is -14.60% while the mean in the preceding regime is -1.70%. The shift in the mean discount (measured as the absolute value of the change) between these regimes is 12.90%.

For all of the regimes shown in Table 3, the median (mean) change is 11.30% (13.12%). The smallest change is 4.5%, and it occurs at the start of the final regime for MGC (8/26/00 to 12/27/02). The discount on the NAIC Growth Fund (GRF) exhibits the three largest changes: 38.5% at the start of the fourth regime, 33.4% at the start of the second regime, and 33.0% at the start of the third regime. For the entire sample, the mean discount has 20 negative changes and 23 positive changes. The median (mean) change is 10.95% (13.87%) for the decreases and 11.7% (12.48%) for the increases. The Wilcoxon rank sum test fails to reject the hypothesis that the populations of the decreases and increases are identical (p-value = 0.83 for a two-sided test).

These results provide new insight into previous studies on closed-end fund trading strategies. Anderson et al. (2001) investigate various trading strategies over different time periods and assumptions regarding transaction costs. They conclude that strategy performance is sensitive to the period analyzed. The structural breaks documented in this study may be causing these inconsistent results.

Table 3: Bai and Perron (2001) Estimates of the Mean Discount and End Date for Each Regime.

Fund	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
ASG	-0.053 (0.007)**	-0.140 (0.002)**	-0.014 (0.003)**		
Beg. Date:	12/2/94	6/23/00	12/27/02		
4/4/86	[4/12/90,4/7/95]	[3/19/99,8/16/02]	(end of sample)		
BLU	-0.137 (0.016)**	0.000 (0.017)	-0.092 (0.015)**	-0.0015 (0.011)	
Beg. Date:	4/12/91	3/31/94	9/5/97	12/27/02	
5/1/87	[10/12/90,11/29/91]	[4/16/93,4/21/95]	[10/18/96,8/14/98]	(end of sample)	
CET	-0.221 (0.03)**	-0.097 (0.02)**	-0.194 (0.01)**	-0.011 (0.016)	-0.153 (0.013)**
Beg. Date:	9/07/84	11/27/87	9/10/93	6/12/98	12/27/02
6/26/81	[11/18/83,7/31/87]	[4/10/87,8/4/89]	[3/19/93, 11/12/93]	[1/9/98, 3/12/99]	(end of sample)
EGX	-0.327 (0.0078)**	-0.243 (0.0068)**	-0.294 (0.0075)**	-0.16 (0.026)**	0.043 (0.043)
Beg. Date:	1/05/90	7/8/94	10/3/97	1/14/00	12/27/02
10/2/87	[8/25/89,3/23/90]	[10/1/93, 6/2/95]	[9/27/96,10/24/97]	[6/5/98,5/5/00]	(end of sample)
FF	-0.192 (0.0101)	-0.075 (0.0088)	0.004 (0.0189)	-0.120 (0.0128)**	
Beg. Date:	7/28/89	4/15/94	2/19/99	12/27/02	
6/6/86	[3/31/89,11/3/89]	[12/7/90,9/30/94]	[9/25/98,6/23/00]	(end of sample)	
GAB	-0.125 (0.027)**	0.004 (0.008)	-0.065 (0.004)**	-0.021 (0.011)**	0.138 (0.052)**
Beg. Date:	5/5/89	7/7/95	12/12/97	7/14/00	12/27/02
9/5/86	[3/3/89,9/14/90]	[6/9/95,5/24/96]	[1/12/96,1/30/98]	[10/1/99,7/28/00]	(end of sample)
GAM	-0.000 (0.015)	-0.163 (0.0096)**	-0.052 (0.029)**	-0.158 (0.006)**	-0.071 (0.01)**
Beg. Date:	1/3/86	7/19/91	10/7/94	7/17/98	12/27/02
6/26/81	[10/11/85,6/13/86]	[12/9/88,11/8/91]	[9/16/94,10/6/95]	[11/7/97, 9/25/98]	(end of sample)
GRF	0.245 (0.06)**	-0.089 (0.018)**	0.241 (0.05)**	-0.144 (0.015)**	-0.016 (0.008)**
Beg. Date:	9/25/92	8/16/96	7/2/98	12/29/00	12/27/02
8/3/90	[8/21/92, 7/16/93]	[2/2/96,9/20/96]	[6/19/98,11/20/98]	[11/24/00,5/25/01]	(end of sample)
HOH	-0.179 (0.012)**	-0.008 (0.033)	-0.211 (0.015)		
Beg. Date:	1/4/91	2/17/95	12/27/02		
5/1/87	[3/3/89, 2/15/91]	[9/23/94,5/31/96]	(end of sample)		
HOL	-0.022 (0.015)	-0.188 (0.01)**			
Beg. Date:	9/30/94	12/27/02			
6/5/92	[5/27/94,12/16/94]	(end of sample)			
MGC	-0.128 (0.012)**	-0.017 (0.008)**	-0.146 (0.009)**	-0.101 (0.015)	
Beg. Date:	5/18/90	4/8/93	8/25/00	12/27/02	
6/5/87	[3/23/90,10/26/90]	[11/6/92,5/14/93]	[10/29/99,12/27/02]	(end of sample)	
PEO	-0.006 (0.015)	-0.095 (0.01)**			
Beg. Date:	7/24/87	12/27/02			
6/26/81	[3/22/85,4/28/89]	(end of sample)			
RTV	-0.111 (0.015)**	-0.052 (0.008)**	-0.113 (0.016)**		
Beg. Date:	11/30/90	9/2/94	12/27/02		
12/5/86	[4/6/90, 10/29/93]	[12/31/87,1/20/95]	(end of sample)		
SBF	-0.035 (0.014)**	-0.148 (0.009)**	-0.078 (0.014)**		
Beg. Date:	5/22/87	10/10/97	12/27/02		
6/26/81	[9/19/86,6/10/88]	[3/31/95,7/9/99]	(end of sample)		
SOR	-0.099 (0.026)**	0.037 (0.018)**			
Beg. Date:	9/7/84	12/27/02			
6/26/81	[2/5/82,6/7/85]	(end of sample)			
STBF	-0.103 (0.019)**	-0.192(0.0042)**			
Beg. Date:	2/5/99	12/27/02			
9/1/89	[1/29/99, 2/12/99]	(end of sample)			
TY	-0.101 (0.024)	-0.174 (0.01)			
Beg. Date:	8/13/93	12/27/02			
6/26/81	[9/11/92, 12/27/02]	(end of sample)			
USA	-0.178 (0.009)**	-0.031 (0.021)**			
Beg. Date:	3/15/91	12/27/02			
12/5/86	[11/3/89, 4/5/91]	(end of sample)			

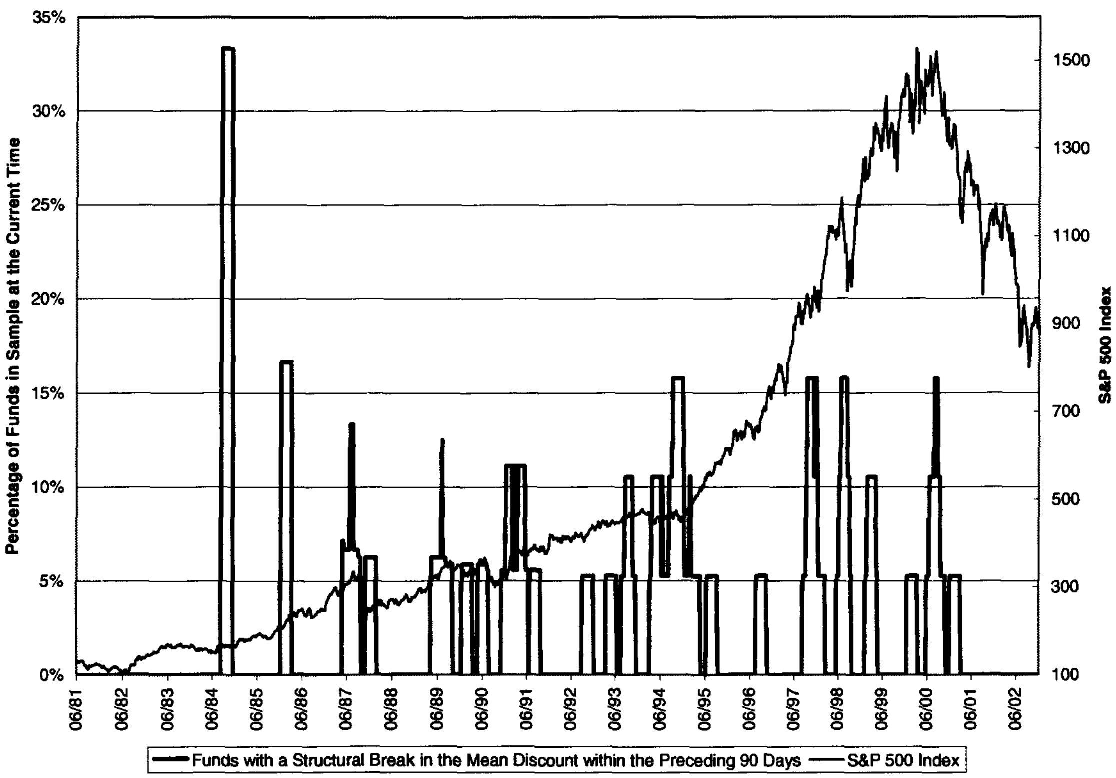
Notes: The number of regimes for each fund is selected according to the results in Table 1. The first number in each cell is the estimated mean for the regime; standard errors are reported in parentheses. The end date for the regime is below the mean; 95% confidence intervals for the end dates are reported in brackets.

Concurrence of Regime End Dates

The noise trader model of De Long et al. (1990) suggests that prices may deviate from fundamental values when impediments to arbitrage prevent rational investors from offsetting the influence of noise traders. Closed-end funds are primarily owned by small investors, who are commonly thought to be more sensitive to market sentiment. Some researchers [Lee et al. (1991); Chopra et al. (1993); Swaminathan (1996); Gemmill and Thomas (2002)] conclude that the noise trader model explains the fluctuations in closed-end fund discounts. Others [Chen et al. (1993); Leonard and Shull (1996); Sias (1997); Elton et al. (1998); Hughen and McDonald (2005)] find that the data are not consistent with this conclusion. If changes in investor sentiment are causing shifts in fund discounts, then the structural breaks in the mean discounts will tend to coincide.

To examine whether this occurs, we determine the percentage of funds in our sample that have a structural break in the mean discount within a 90-day rolling period. A three month period is of sufficient length for investors to detect a credible change in sentiment and react to it. Figure 2 shows this percentage and the value of the S&P 500 Index. The index is included in the graph because previous research suggests that market returns cause changes in sentiment [Brown and Cliff (2004); Wang et al. (2004)].

Figure 2: Percentage of Funds with Structural Breaks in the Mean Discount within the Preceding 90 Days of a Particular Date. The Structural Breaks are Determined Using the Bai and Perron Methodology.



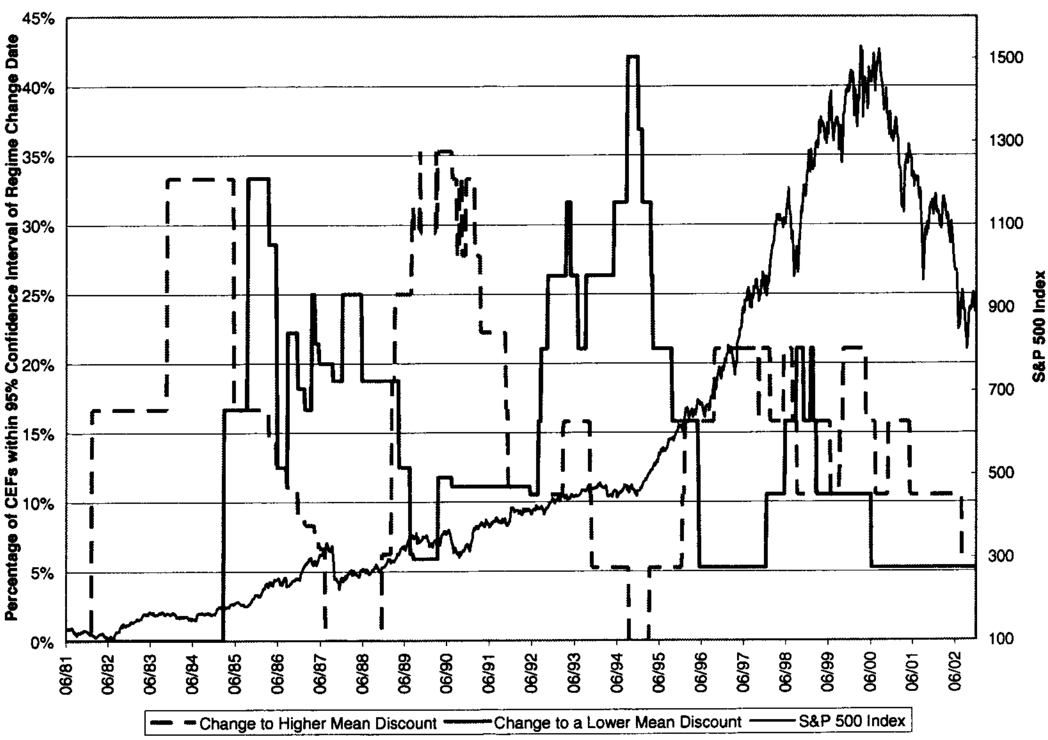
Consider September 30, 1994 as an example. On this date, the percentage of funds with structural breaks within the preceding 90 days increases to 16%. This is shown in Figure 2 as an upward spike after the label "06/94." The 90-day rolling period for this date starts on July 2, 1994.

The following three regime end dates are within this period: regime 2 for EGX ends on July 8, 1994; regime 1 for HQL ends on September 30, 1994; regime 2 for RTV ends on September 2, 1994.

The percentage of funds with a structural break has its highest point at 33% in September 1984. As our sample only includes six funds at that time, it is unlikely that this accurately represents the pricing of closed-end funds. After June 6, 1992 our sample included nineteen funds. On the following four occasions the percentage of funds with structural breaks in the 90-day period reached 16% (3 of the 19 funds): September 1994, October 1997, July 1998, and August 2000. The data does not suggest that the structural breaks coincide even when the window of time is large.

The results shown in Figure 2 do not distinguish the structural breaks that result in positive changes in the discount from those that result in negative changes. However, Figure 3 shows separate results for positive and negative changes in the mean discount. It illustrates the percentage of sample funds that have a 95% confidence interval for a regime change end date that includes a particular date. On two sequences of dates, at least one-third of the funds have structural breaks that result in higher means. For example, 35% (6 of 17) of the funds have a 95% confidence interval for a regime change that includes April 6, 1990. This is represented in Figure 3 as a dashed line between the labels "06/89" and "06/90" on the x-axis. The confidence intervals for the following six regime end dates contribute to this percentage: regime 1 for GAB, regime 2 for GAM, regime 1 for HQH, regime 1 for MGC, regime 1 for RTV, and regime 1 for USA. The second sequence of dates starts in November 1983 when the percentage reaches 33%.

Figure 3: Percentage of Funds within the 95% Confidence Interval for a Regime Change End Date that Results in a Higher or Lower Mean Discount. The Structural Breaks are Determined Using the Bai and Perron Methodology.



Our sample period contains two sequences of dates that are within the 95% confidence intervals for negative shifts in the mean discount for at least one-third of the funds. Two of the six funds in the sample have confidence intervals that include October 1985. Eight of the 19 funds (42.1%) have confidence intervals that include September 1994. By using the 95% confidence intervals to examine whether regime end dates coincide, our study is using a liberal definition of simultaneous occurrence. The confidence intervals for the regime end dates are typically long periods; the median (mean) is 1.7 (2.1) years. Even with a loose standard for concurrence, a majority of the funds do not have structural breaks in the mean discount that occur at the same time.

Conclusions

Economists have failed to fully explain the pricing anomaly associated with closed-end funds. These investments often trade at substantial discounts to their underlying value, and these discounts fluctuate over time. Many studies assume that these discounts are mean reverting. Our paper finds that the time-series properties of discounts are more complex than previously thought. We employ the Bai and Perron (1998, 2003a,b, 2004) method to test for structural breaks in the mean discounts. After determining the number of breaks, we find the end dates for each regime and provide the 95% confidence interval for these dates. All but one closed-end fund in our sample have a structural break in their mean discount.

While the structural breaks in the mean discount are infrequent, the changes in the mean between regimes are substantial. The median regime length is 4.1 years, and the average change in the mean is 13.12%. Five changes in our sample period exceed 20%. Numerous studies since 1978 have documented the excess returns associated with simple closed-end fund trading strategies. Our analysis supports a plausible explanation for the continued profitability of such strategies, which depend on mean reversion in discounts. The risk of the infrequent but substantial structural breaks in the mean discounts inhibits investors from reducing the excess returns from this strategy.

Our results also provide insight into a possible explanation for discount fluctuations. Lee et al. (1991) suggest that the noise traders, who are influenced by changes in investor sentiment, cause changes in discounts. This implies that discount changes will tend to coincide as sentiment shifts affect the pricing of all closed-end funds. Our study finds that no more than 16% of funds have regime end dates within a 90-day period. This suggests that idiosyncratic factors are primarily responsible for large changes in mean fund discounts.

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