The Closed-End Fund Puzzle:
A Cross-Sectional Analysis of U.S. Closed-End Fund Discounts

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Abstract

This paper examines the effect of systematic beta risk, expense ratios, and fund size on the cross-sectional variation of closed-end fund discounts. Using a methodology similar to that of Gemmill and Thomas (2002) and Flynn (2004) on a sample of 50 U.S. closed-end funds, the data indicate that expense ratios have a significant positive effect on discounts for my entire sample and systematic beta risk has a significant positive effect on debt fund discounts. These results reject hypotheses implied by both noise trader and agency cost theories with respect to closed-end fund discounts.

I. Introduction

The pricing and behavior of closed-end funds[1] has emerged as one of finance's most vexing puzzles. Despite the fact that the net asset value (NAV) of closed-end fund shares is widely disseminated and well-known, closed-end funds typically trade at discounts (or sometimes premiums) to the NAV of their underlying portfolios; and these discounts have been shown to vary significantly both over time and across funds (Lee, Schleifer and Thaler, 1990). The seemingly anomalous behavior of closed-end funds has often been cited as an example of market irrationality. Therefore, closed-end funds have emerged as a battleground in the longstanding debate between proponents of the efficient market hypothesis and behavioral economists. Yet despite a voluminous body of research, the closed-end fund puzzle remains largely unresolved (Russel, 2005).

In this paper, I focus on one of the most perplexing components of the closed-end fund puzzle: the source of discounts and their cross-sectional variation. Economists offer a variety of explanations for the existence of closed-end fund discounts. Efficient market theorists such as Malkiel (1977) focus on NAV measurement biases due to liquidity and unrealized tax consequences. Other economists focus on agency costs, such as expense ratios (Kumar and Noronha, 1992). De Long *et al*. (1990) seek to explain the closed-end fund puzzle with a behavioral model of asset markets in which "noise traders" with unpredictable and systematically erroneous beliefs coexist with rational, risk-averse investors. They argue that rational investors will value closed-end funds at a discount, on average, in order to compensate for systematic noise trader risk. The noise trader theory

[1] Closed-end funds, unlike their open-end counterparts, do not issue new shares or redeem existing shares at the underlying portfolio's net asset value (NAV). Rather, closed-end funds raise assets and issue a fixed number of shares during an initial offering period. The price of closed-end fund shares is determined on an open market such as the New York Stock Exchange by the forces of supply and demand—meaning that closed-end fund shares often trade at a discount or premium to their net asset value.

has been the subject of much debate among economists studying closed-end funds and will be outlined in more depth in Section III. I intend to test hypotheses implied by the agency cost and noise trader theories by empirically investigating the effect of expense ratios, systematic risk, and fund size on the cross-sectional variation of closed-end fund discounts.

However, this is not the first paper to test the effect of these factors on discounts. Gemmill and Thomas (2002) use a sample of U.K. equity closed-end funds and find statistically significant relationships between all three of the aforementioned factors and average discounts. The authors suggest that these factors would have a similar effect on U.S. closed-end funds, but leave this investigation as an avenue for future research. In a working paper, Flynn (2004) applies a similar test to a sample of funds traded in the U.S. and Canada between 1991 and 2000, but finds contradictory results. Therefore, the effect of expense ratios, systematic risk, and fund size on discounts is still unsettled.

I seek to fill this gap by using a more recent sample of 50 U.S. closed-end funds to test the effect of these factors on the cross-sectional variation of average monthly discounts from the beginning of 2002 through the end of 2006. My results reject the agency cost theory of closed-end fund discounts and contradict the findings of both Gemmill and Thomas (2002) and Flynn (2004) by indicating that higher expense ratios lead to lower discounts. Contrary to the hypothesis implied by the noise trader theory, I find that greater levels of systematic risk also imply lower discounts; however, this effect is less robust than the link between discounts and expense ratios. And finally, my results indicate that fund size does not have a statistically significant effect on discounts.

This paper consists of six sections. Section II reviews the existing body of relevant literature by outlining the closed-end fund puzzle and explaining the results of similar studies. Section III provides a theoretical framework for analyzing closed-end fund discounts, leading to three hypotheses regarding the effect of systematic risk, expense ratios, and fund size on the cross-sectional variation of discounts. Section IV describes the data I used in this study. In Section V I specify a three-factor model for testing these hypotheses and discus the results of my empirical investigation. And in section VI, I conclude.

II. Literature Review

Closed-end funds have existed for many years and a large body of research has accumulated to explain their puzzling behavior. Empirical studies have documented and described a number of specific anomalies, such as the persistence of large discounts and their variability both over time and across funds. Theoretical models both within the efficient market paradigm and of a behavioral nature have been proposed to explain these anomalies. However, Russel (2005) notes that the existing body of theoretical work does not satisfactorily explain the pricing of closed-end funds.

To put the closed-end fund puzzle in perspective, Lee, Schleifer and Thaler (1990) describe closed-end fund pricing as a four-part anomaly. 1) Evidence indicates that new funds typically appear at a premium and move to a discount within a few months. Therefore, why do people buy funds when they are first issued knowing that there is a high probability that those funds will move to a discount over a relatively short time-horizon? 2) Closed-end funds usually trade at large discounts. Why is this common? 3) Discounts and premiums appear to vary widely both over time and across funds in similar and differing asset classes. Why do discounts move together and why do they vary so much? 4) Share prices often converge to their NAV when funds are liquidated. This makes intuitive sense given that shares are redeemed at NAV upon liquidation. However, if this is the case, why doesn't the presence of arbitrageurs prevent large discounts from persisting?

Many economists seeking to explain parts two and three of the closed-end fund puzzle—the existence of discounts and their variability both over time and across funds—offer standard economic arguments within the framework of the efficient market hypothesis. Malkiel (1977) explains the closed-end fund puzzle by focusing on NAV measurement biases due to liquidity and unrealized tax consequences. Since many funds own positions in illiquid securities, their reported value overstates the true price managers would receive if they decided to unwind these positions. However, Lee, Schleifer and Thaler (1990) note that illiquid securities make up a small proportion of the portfolios of most closed-end funds and many closed-end funds that only invest in highly liquid securities still trade at substantial discounts. The tax liability argument is based on the fact that US funds must distribute at least 90% of their capital gains in order to avoid corporate taxation. If a manager decides to close-out a profitable position, the corresponding capital gains will be distributed to investors in the form of a taxable dividend. Therefore, NAVs are overstated on an after-tax basis because investors could potentially be forced to pay taxes on capital gains that accrued before they purchased shares in a given closed-end fund. But Malkiel (1977) finds that tax liabilities only account for a limited portion of observed discounts.

Other economists focus on agency costs, such as management fees, as a source of closed-end fund discounts (Kumar and Noronha, 1992). According to this model, management fees—either in terms of expense ratios[2] or expenses as a proportion of cash flows—are a cost reflected by discounts. However, Dimson and Minio-Paluello (2002) find this explanation problematic. They note that agency costs cannot explain part one of the closed-end fund puzzle—the fact that seemingly rational investors purchase new funds at a premium knowing that there is a high likelihood that the funds will subsequently trade at a discount.

[2] Expense ratios are defined as management fees and other expenses divided by NAV.

Given that standard economic arguments within the efficient market paradigm do not satisfactorily account for the closed-end fund anomaly (Lee, Shleifer and Thaler, 1990), many economists seeking to explain the closed-end fund puzzle have gravitated toward the nascent field of behavioral finance. Lee, Shleifer and Thaler (1991) argue that fluctuations in closed-end fund discounts are a function of individual investor sentiment because closed-end fund discount changes are correlated with the performance of small-cap stocks—and both closed-end funds and small-cap stocks are predominantly owned by retail investors. In a complimentary model, De Long *et al*. (1990) explain closed-end fund discounts in terms of noise trader risk. This model assumes that closed-end funds are traded by both rational, risk-averse investors with finite horizons, as well as irrational noise traders who systematically misinterpret and overreact to salient information. The authors argue that discounts are not a function of pessimistic noise trader sentiment, but instead reflect the additional return rational investors demand in order to compensate for the risk of participating in a market alongside noise traders with stochastic sentiments.

Economists have sought to test the effect of factors implied by both the standard economic and behavioral explanations of the closed-end fund puzzle on discounts. Gemmill and Thomas (2002) use a sample of 158 U.K. equity funds to conduct a cross-sectional analysis on factors possibly influencing discounts. The authors calculate average discounts for each fund in their sample over a seven year period between 1991 and 1997. They then run a regression of average discounts on expense ratios, average dividend yields, systematic discount risk[3] (a proxy for noise trader risk), fund age, a

[3] This factor measures the sensitivity of changes in the discount of each individual fund versus the value-weighted average discount of the entire sample. Similar to betas within the capital asset pricing model, this factor seeks to measure the systematic (i.e. undiversifiable) risk of discount changes for each fund relative to a large basket of funds.

measure of how costly it would be to arbitrage each fund, and fund size. They use a weighted least squares regression, with the volatility of each fund's discount over their sample period as the weighting variable.

Gemmill and Thomas (2002) find that the estimated coefficients for each of these variables are significant at the one percent level, except for fund size, which is still significant at the five percent level. The regression produces a weighted R^2 of 0.52 and an un-weighted R^2 of 0.34. The results of this study indicate that funds that are small, difficult to replicate[4] (and thus arbitrage), and that have low dividend yields trade at large discounts. However, a negative estimated coefficient[5] on the systematic risk variable indicates that funds with greater non-diversifiable discount risk trade at smaller discounts. This final result appears counterintuitive given that rational investors are generally believed to be risk-averse rather than risk-seeking. The authors note that this result does not support the noise trader theory. However, they are unable to provide a satisfactory explanation for the effect of systematic discount risk on cross-sectional average discount levels and instead leave it as an outstanding puzzle subject to further analysis.

Another study (Flynn, 2004) finds contradictory results by conducting a similar analysis of cross-sectional average discount levels on a sample of U.S. and Canadian closed-end funds. This study uses a sample of 69 equity funds and 123 debt funds and calculates average monthly discounts over a ten year period between January 1991 and December 2000. Using a methodology similar to that of Gemmill and Thomas (2002),

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[4] Gemill and Thomas (2002) measure replication risk as the residual error from a regression of NAV returns on relevant market indices. Replication risk is not included as a factor in this paper's empirical investigation because the structural complexity of many modern closed-end funds (e.g. combinations of multiple asset classes, the use of leverage, and derivative hedging strategies) renders the process of selecting a relevant market index very difficult.

[5] Gemill and Thomas (2002) define discounts as positive and premiums as negative discounts.

the author runs a regression of average monthly discounts for each fund in his sample against the same set of explanatory variables.

Flynn (2004) finds that the estimated coefficients for the systematic risk and fund age variables are significant at the five percent level for stock funds and the systematic risk and dividend yield variables are significant at the one percent level for bond funds. The estimated coefficients on the other factors are statistically insignificant for both tests. In direct contradiction of the results of Gemmill and Thomas (2002), the systematic risk coefficient for this sample is positive[6], implying that non-diversifiable discount risk leads to larger discounts, thus supporting the noise trader theory.

The contradictory nature of these two studies leaves open the debate over the effect of these factors on cross-sectional discount levels. Therefore, I use a similar methodology to test the effect of expense ratios, systematic risk, and fund size on cross-sectional discount levels for a sample of 50 U.S. closed-end funds. I find that higher expense ratios and, to a lesser extent, greater levels of systematic risk, lead to lower discounts. However, my results do not indicate a significant relationship between fund size and discounts.

[6] Flynn (2004) also defines discounts as positive and premiums as negative discounts.

III. Theoretical Framework

In this section, I examine the economic theory underlying each of the three factors tested in my empirical investigation of 50 U.S. closed-end funds. This theory leads to three hypotheses regarding the effect of systematic risk, expense ratios, and fund size on average discount levels.

A. Systematic Risk and the Noise Trader Model

The noise trader model (De Long *et al*., 1990), briefly introduced above, has been used to explain a number of observed financial anomalies, including the closed-end fund puzzle. Under this model, the authors note that not all investors are rational, profit-maximizing decision makers who follow the advice of efficient market theorists by holding the market portfolio. Instead, many investors trade individual securities based on their own research, advice from their financial advisor, or recommendations from popular television personalities such as Jim Cramer, host of CNBC's "Mad Money." Black (1986) believes that these investors, who do not have access to material private signals, often make trading decisions based on immaterial pieces of public information, and thus refers to them as "noise traders."

The presence of speculators with destabilizing and perhaps irrational beliefs is not new. However, according to the classical view of Friedman (1953) and Fama (1965), the presence of rational arbitrageurs mitigates the long-run influence of speculators, such as noise traders, on markets by driving prices toward their fundamental values. But in the postmodern framework of De Long *et al*. (1990), the unpredictability of noise trader sentiment presents a powerful limit to arbitrage for sophisticated investors. Although rational arbitrageurs may recognize situations where security prices deviate from fundamental values, they are often unwilling to bear the risk that noise traders' beliefs will not revert to their mean any time soon. As Keynes is reported to have said, "Markets can stay irrational longer than you can stay solvent" (Wikiquote).[7] In terms of closed-end funds, arbitrageurs may notice that overly bullish noise traders have pushed a fund's price to an unreasonable premium. However, if arbitrageurs with limited investment horizons attempt to exploit this situation by shorting the fund's shares and buying the underlying assets, they may be forced to take a loss if noise trader sentiment becomes even more bullish.

De Long *et al*. (1990) use this implication of the noise trader model to explain many well-known financial anomalies, including the existence of closed-end fund discounts and their variability both over time and across funds. Under the noise trader model of closed-end funds, assume the securities owned by each fund represent a safe asset and the share price of each fund represents an unsafe asset. In the absence of noise traders, both the underlying portfolio of securities owned by closed-end funds and their market value should be priced at the same level in equilibrium because they represent a claim to the same dividend stream. However, assuming that noise traders' expectations about the returns of closed-end fund shares are distinct from their expectations about NAV returns, and noise traders' perceptions of closed-end fund returns are correlated with other sources of systematic risk, then closed-end funds will trade at discounts or premiums and these will vary both over time and across funds. This model accounts for the fact that closed-end funds, on average, trade at discounts (instead of premiums)

[7] The exact source of this quote is unclear. However, a number of online sources, including Wikiquote, attribute it to Keynes but do not offer a more specific reference.

because investing in closed-end fund shares, instead of their underlying portfolio of securities, includes an additional level of noise trader risk.

The assumptions behind this model are supported by evidence that closed-end fund discounts appear to fluctuate together (Lee, Shleifer, and Thaler, 1991), suggesting the presence of some sort of systematic risk factor. This leads to the following hypothesis:

Hypothesis 1: Funds with more systematic risk will trade at larger discounts.

This paper tests and ultimately fails to find support for the noise trader hypothesis by seeking to explain cross-sectional average discount levels in terms of each fund's systematic risk, which is estimated by regressing monthly discount changes for individual funds against those of a weighted sample average.

B. Expense Ratios

Kumar and Noronha (1992) examine the role of expenses in explaining closed-end fund discounts. In order to explicitly demonstrate the relationship between fund expenses and discounts, the authors develop a present value model. They assume that a fund's NAV equals the present value of future cash flows discounted at rate *r*

$$N = \sum_{t=1}^{\infty} \left[CF_t / (1+r)^t \right] \tag{1}$$

where *N* represents a fund's NAV and CF_t represents a fund's cash flow (i.e. investment income) at time *t*. The fund's share price *P* is then calculated by taking the present value of cash flows per share minus expenses per share discounted at rate *r*

(2) $$P = \sum_{t=1}^{\infty} \left[(CF_t - EXP_t) / (1+r)^t \right]$$

where EXP_t represents the amount of expenses per share a fund consumes during period *t*.

If we define the discount *D* at which a fund trades as

(3) $$D = \frac{P - N}{N},$$

then, by substitution, the discount equals

(4) $$D = \frac{\sum_{t=1}^{\infty} \left[EXP_t / (1+r)^t \right]}{\sum_{t=1}^{\infty} \left[CF_t / (1+r)^t \right]}.$$

If we define K_t as the ratio of expenses to cash flows during period *t*,

where $K_t = EXP_t / CF_t$, equation (4) can be written as:

(5) $$D = \frac{\sum_{t=1}^{\infty} \left[K_t CF_t / (1+r)^t \right]}{\sum_{t=1}^{\infty} \left[CF_t / (1+r)^t \right]}.$$

Defining $W_t = CF_t / (1+r)^t$, equation (5) can be written as

(6) $$D = \frac{\sum_{t=1}^{\infty} K_t W_t}{\sum_{t=1}^{\infty} W_t}.$$

Assuming that $E(K_t) = K_0, t = 1,2,...\infty$, then equation (6) reduces to:

(7) $$D = K_0 = EXP_0 / CF_0.$$

This theory implies that discounts should be a function of current expenses. Kumar and Noronha (2002) find that K_0 has a statistically significant positive effect on discounts in their sample of funds between 1976 and 1986. This theory leads to the following hypothesis:

Hypothesis 2: Funds with higher expense ratios will trade at larger discounts.

In my empirical investigation, I test Hypothesis 2 by using expense ratios, which measure current expenses as a proportion of NAV instead of cash flows. Kumar and Noronha criticize this method because EXP_0 / NAV often decreases as asset value increases. However, by including fund size as a factor in my regression, the effect of this confounding factor should be isolated.

C. Fund Size

The theoretical basis for the effect of fund size on discounts relates to liquidity. Trading volume for larger funds is generally higher; therefore liquidity is a function of size. All else being equal, investors should price less liquid funds lower because they demand compensation—in the form of higher returns—for bearing an additional source of risk. This leads to the following hypothesis:

Hypothesis 3: Larger funds will trade at lower discounts.

IV. Data

In order to construct the sample used in this paper's empirical investigation, I downloaded the universe of closed-end funds from the Bloomberg Professional Service and sorted them according to country, inception date, and total assets. The final sample consists of the 50 largest U.S. closed-end funds, according to reported total assets, with an inception date before December 31, 2001. One primary weakness of this sample is that it does not include every existing U.S. closed-end fund. However, the sample still accounts for 24% of the total assets invested in U.S. closed-end funds[8]. Therefore, the results of this paper's empirical investigation should serve as a reasonable generalization of the overall U.S. closed-end fund universe. Despite the deluge of new closed-end funds that have entered the market within the past few years, this sample is limited to funds with at least five years of price and NAV data because the purpose of this paper is to study factors influencing long-run cross-sectional variation among discounts.

For each fund in my sample, I downloaded monthly price and NAV data from Bloomberg. I also gathered data on current expense ratios, total assets, and inception dates for each fund from Bloomberg.

This sample, listed in Appendix A, includes 17 equity funds and 33 bond funds. Table 1 includes descriptive statistics for the sample. The mean average discount is 4% with a standard deviation of 7%. The cross-sectional range in discount levels is quite wide: the largest average premium in the sample is 30% and the largest average discount is 13%. Given that most closed-end funds typically trade at discounts, it is surprising that

[8] This includes funds that were issued after December 31, 2001. Excluding those funds, my sample represents a much higher proportion of assets invested in U.S. closed-end funds.

Table 1.

Descriptive statistics for my sample

This sample includes the 50 largest U.S. closed-end funds (measured by total assets) with an inception date before December 31, 2001.

	Average Discount	*Discount Beta*	*Fund Size*	*Expense Ratio*
Mean	-0.04	0.93	915	0.012
Standard Error	0.01	0.07	56	0.001
Median	-0.05	0.98	815	0.011
Standard Deviation	0.07	0.52	396	0.006
Sample Variance	0.01	0.27	156768	0.000
Range	0.44	2.63	1441	0.038
Minimum	-0.13	-0.54	554	0.005
Maximum	0.30	2.09	1995	0.043

the magnitude of one fund's average premium was more than twice that of the largest average discount in the sample.[9]

The mean discount beta, which measures the systematic risk of discount fluctuations for individual funds versus the asset-weighted average discount, is 0.93 with a standard deviation of 0.53. The lowest discount beta is -0.54, implying that discount returns for that particular fund negatively correlate with the overall sample. The mean fund size, measured by total assets, is $915 million. The largest fund is the sample has almost $2 billion in total assets, compared to slightly more than $500 million for the smallest fund. The mean expense ratio for funds in my sample is 0.012, with a standard deviation of 0.006.

[9] In order to control for the effect of outliers and possible data errors, my findings section includes results both with and without the DNP Select Income Fund, which trades at a very high premium relative to the sample, and the ING Prime Rate Trust, which has an unusually high expense ratio relative to the sample.

V. Methodology

In my empirical analysis, discounts will be defined as negative numbers. For example, -0.05 will represent a 5% discount and 0.05 will represent a 5% premium. Let $N_{i,t}$ represent the NAV of fund *i* in month *t* and let $P_{i,t}$ represent the share price of fund *i* in month *t*. The discount $d_{i,t}$ of fund *i* during month *t* is expressed as

$$d_{i,t} = \frac{P_{i,t}}{N_{i,t}} - 1 . \tag{8}$$

Discounts can also be calculated by taking the natural log of a fund's price divided by its NAV. However, I will use the above formula to calculate discounts because this is the method used by Gemmill and Thomas (2002) and Flynn (2004) and it is also the method used by the financial press when reporting discounts.

The average monthly discount D_i for each fund *i* is then calculated over the five year period between January 2002 and December 2006 according to the formula

$$D_i = \frac{\sum_{t=1}^{60} d_{i,t}}{60} . \tag{9}$$

Cross-Sectional Analysis

The following least squares regression model is used to test the effect of each factor on cross-sectional average discount levels

$$\Delta D_i = a + bEXPENSE_i + c\beta_i + d\log(SIZE_i) + error_i \tag{10}$$

where $EXPENSE_i$ represents the current expense ratio for each fund *i* and $\log(SIZE_i)$ represents the natural log of each fund's current total assets. [10] The systematic risk factor β_i for each fund is calculated by running a least squares regression of the monthly discount returns of each fund against the corresponding monthly discount returns of a weighted portfolio including each closed-end fund in the sample. The monthly discount return[11] $\Delta d_{i,t}$ for fund *i* in month *t* is defined as the simple difference between the fund's discount in moth *t* and month $t-1$:

(11) $$\Delta d_{i,t} = d_{i,t} - d_{i,t-1} .$$

The monthly discount return $\Delta d_{p,t}$ for the weighted portfolio *p* is expressed by

(12) $$\Delta d_{p,t} = \sum_{i=1}^{50} w_i \Delta d_{i,t} .$$

Each fund's weight w_i represents the current assets A_i of each fund *i* as a percentage of the total assets of all 50 funds included in the sample:

(13) $$w_i = \frac{A_i}{\sum_{i=50}^{50} A_i} .$$

The systematic risk β_i of each fund *i* is estimated by taking the following least squares regression of the time series of monthly discount returns for each fund on a constant and the time series of monthly discount returns for the weighted portfolio:

(14) $$\Delta d_{i,t} = \alpha_i + \beta_i \Delta d_{p,t} + \varepsilon_i .$$

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[10] The natural log of assets was taken in order to be consistent with the methodology of Gemmill and Thomas (2002) and Flynn (2004).

[11] Discount returns are measured as simple differences, rather than of the form $\Delta d_{i,t} = \frac{d_{i,t}}{d_{i,t-1}} - 1$, because of the asymptotic relationship between discount returns calculated in this fashion and zero.

Expected Results

Table 2 lists the predicted coefficients for each factor in the above regression equation according to Hypotheses 1-3.

Table 2.

Expected findings

Factor	Estimated Sign
$EXPENSE_i$	+
β_i	+
$\log(SIZE_i)$	-

VI. Empirical Findings

As discussed in previous sections, I am seeking to test the effect of systematic beta risk, expense ratios, and fund size on average discount levels. In addition to determining which factors explain cross-sectional variation among discounts in my sample, this study also serves as a test for both the noise trader and agency cost theories of closed-end fund discounts. Table 3 reports the results of my cross sectional regression analysis specified in equation (10) above. Column (1) reports the results obtained by running the regression on all 50 funds in my sample. However, two funds suggest the possibility of errors in the reported data. The DNP Select Income Fund (ticker: DNP) traded at an average premium of 30% from 2002-2006, which is almost five standard deviations from the mean of my sample. The ING Prime Rate Trust's (ticker: PPR) expense ratio of 4.27% is also slightly more than five standard deviations from the sample mean. Therefore, in order to control for possible bias, column (2) reports the results obtained by running the same regression with these two funds omitted from the sample. I also follow the methodology of Flynn (2004) by dividing the sample in column (2) into debt and equity funds. These results are reported in columns (3) and (4).

My most striking finding is that higher expense ratios lead to smaller discounts (or larger premiums). This result is significant at the 5% level for both the entire sample of 50 funds and the modified sample excluding two outliers. The coefficient in column (1) of Table 3 implies that if the magnitude of fund A's expense ratio is 1% higher than that of fund B, then the magnitude of fund A's average discount (premium) will be 3% lower (higher). The same relationship between expense ratios and discounts holds across both the equity and debt fund sub-samples. For debt funds, this result is significant at the

Table 3.

Results from cross-sectional analysis of factors affecting discount levels

The table reports cross-sectional regressions for U.S. closed-end funds over the period 2002-2006. Column (1) reports the results of running the regression specified in equation (10) in Section IV on all 50 funds in my sample. Column (2) excludes two outlier funds due to possibly misreported data. Columns (3) and (4) separate the sample in Column (2) into equity and debt funds. Negative coefficients imply larger discounts (or smaller premiums) and positive coefficents imply smaller discounts (or larger premiums). Numbers in parentheses are *t* -values.

	Dependent Variable			
Independent Variables	Average Discount (1)	Average Discount (2)	Average Equity Fund Discount (3)	Average Debt Fund Discount (4)
Constant	-0.28	-0.09	-0.41	-0.08
	-(1.65)	-(0.66)	-(0.84)	-(0.94)
Discount beta	+0.03	+0.01	-0.05	+0.05**
	(1.44)	(0.32)	-(1.08)	(2.91)
Expense ratio	+3.62*	+4.62*	+12.09	+3.18**
	(2.35)	(2.43)	(1.46)	(2.82)
Log of size	+0.03	0.00	+0.04	-0.01
	(1.00)	-(0.07)	-(0.52)	-(0.56)
R^2	0.22	0.16	0.17	0.48
Number of funds in sample	50	48	16	32

*Significance at the five percent level; **Significance at the one percent level

1% level. In the case of equity funds, the positive estimated coefficient for expense ratios is not statistically significant; however, this is likely due to the small number of funds in the equity sub-sample. Chart 1 in Appendix B illustrates the positive linear relationship between expense ratios and average discounts for the entire sample. Chart 2 omits the two outlier funds and Charts 3 and 4 show the relationship between expenses and equity and debt funds.

My results clearly reject Hypothesis 2, which states that funds with higher expense ratios should trade at larger discounts. Therefore, this study does not find support for agency costs theories of management expenses, such as Kumar and Noronha (1992). However, one possible weakness in my analysis is the fact that I calculate expenses as a proportion of a fund's NAV. Kumar and Noronha (1992) argue that measuring expenses as a proportion of current cash flows is a superior methodology because of the effect of fund size on expenses. But including *log (size)* as a factor in my regression should have controlled for the effect of this confounding factor. Therefore, given the contradictory nature between my results and those of Gemmill and Thomas (2002) and Flynn (2004), the effect of expense ratios on cross-sectional discount levels remains unclear.

My results also indicate that higher systematic risk leads to smaller discounts. However, when two outlier funds are omitted from the sample, the coefficient on the discount beta variable is very close to zero and statistically insignificant—suggesting that systematic risk is not a meaningful predictor of discount levels. However, for my sub-sample of bond funds, the coefficient of +0.05 on the discount beta factor is significant at the 1% level. This result rejects Hypothesis 1 and fails to support the noise trader theory. With respect to Hypothesis 3, my results indicate that fund size does not meaningfully explain varying cross-sectional discount levels.

VII. Conclusion

In this paper I set out to explain one component of the closed-end fund puzzle by answering the question: Why do discounts vary across different funds? I used a cross-sectional regression analysis to test the effect of systematic risk, expense ratios, and fund size on a sample of 50 U.S. closed-end funds. My results indicate that higher expense ratios lead to smaller discounts and this relationship is statistically significant. For bond funds in my sample, funds with greater systematic risk trade at smaller discounts. This result appears counterintuitive and does not support the noise trader theory.

One possible caveat of my study is its limited sample size. Gemmill and Thomas (2002) and Flynn (2004) use larger samples; therefore a further cross-sectional analysis of discounts may want to include all U.S. closed-end funds. But even if my results are representative of the overall U.S. closed-end fund universe, it is possible that the primary factors affecting discount levels are changing over time as the strategy and structure of closed-end funds continue to evolve. If this is the case, then it would be very difficult to draw meaningful conclusions from this type of study and explain why discounts vary across different closed-end funds.

Another potential weakness in my study is its scope. Although expense ratios, systematic risk, and fund size were able to partially account for cross-sectional variation among discounts in my sample, other factors might have greater explanatory power. Closed-end funds are often bought and sold on the basis of yield; therefore a comprehensive study on the effect of dividend yields and investor expectations regarding the future interest rate environment might make an interesting avenue for further research.[12]

The fact that my results contradict the findings of Gemmill and Thomas (2002) and Flynn (2004) indicates that the effect of expense ratios, systematic risk, and fund size on discounts is still unclear. Since my results do not support the agency cost and noise trader theories, a better theoretical framework for closed-end funds is still needed. Most importantly, the results of my study serve as further evidence that the pricing and behavior of closed-end funds is still a puzzle.

[12] My study did not test the effect of dividend yields on discounts because accurate data on past dividend yields was difficult to obtain.

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Appendix A.

Sample description

Name	Ticker	Inception Date	Asset Class Focus	Fund Objective
ABERDEEN ASIA-PAC INCOME FD	FAX	16-Apr-86	Debt	Region Fund-Geo Focused-Debt
ADAMS EXPRESS COMPANY	ADX	1-Oct-29	Equity	Growth
ALLIANCEBERNSTEIN GL HI INC	AWF	28-Jul-93	Debt	Government/Corporate
ALLIANCEBERNSTEIN INC FUND	ACG	28-Aug-87	Debt	Government/Agency
BLACKROCK DEBT STRATEGIES FD	DSU	31-Mar-98	Debt	Corporate/Preferred-High Yld
BLACKROCK MUNICIPAL INC TRST	BFK	27-Jul-01	Debt	Municipal
BLACKROCK MUNIHOLDINGS CA IN	MUC	2-Mar-98	Debt	Muni-California
BLACKROCK MUNIVEST FUND	MVF	1-Sep-88	Debt	Municipal
BLACKROCK MUNIYIELD FUND	MYD	16-Dec-91	Debt	Municipal
BLACKROCK MUNIYIELD INSURED	MYI	13-Apr-92	Debt	Municipal
BLACKROCK MUNIYIELD NY INSUR	MYN	16-Mar-92	Debt	Muni-New York
CENTRAL EUROPE & RUSSIA FUND	CEE	7-Feb-90	Equity	Region Fund-Eastern European
CENTRAL SECURITIES CORP	CET	1-Oct-29	Equity	Growth & Income
COHEN & STEERS ADV INC REAL	RLF	31-May-01	Equity	Sector Fund-Real Estate
DNP SELECT INCOME FUND INC	DNP	28-Jan-87	Equity	Sector Fund-Utility
DREYFUS STRATEGIC MUNICIPALS	LEO	23-Sep-87	Debt	Municipal
GABELLI EQUITY TRUST	GAB	28-Aug-86	Equity	Value
GENERAL AMERICAN INVESTORS	GAM	1-Feb-27	Equity	Growth
INDIA FUND INC	IFN	23-Feb-94	Equity	Country Fund-India
ING PRIME RATE TRUST	PPR	12-May-88	Debt	Government/Corporate
JOHN HAN BK & THRIFT OPP FD	BTO	23-Aug-94	Equity	Sector Fund-Financial Service
KOREA FUND INC	KF	22-Aug-84	Equity	Country Fund-South Korea
MFS CHARTER INCOME TRUST	MCR	20-Jul-89	Debt	Government/Corporate
MFS INTERMEDIATE INC TRUST	MIN	18-Mar-88	Debt	Govt/Agency-Short/Intermed
MFS MULTIMARKET INC TRUST	MMT	1-Mar-87	Debt	Government/Corporate
MORGAN STANLEY ASIA PACIFIC	APF	2-Aug-94	Equity	Region Fund-Asian Pacific
MORGAN STANLEY INDIA INVEST	IIF	25-Feb-94	Equity	Country Fund-India
MORGAN STANLEY MUNI INC OPP	OIA	19-Sep-88	Debt	Municipal
NUVEEN DIVIDEND ADV MUNI 3	NZF	1-Sep-01	Debt	Municipal
NUVEEN DVD ADVANTAGE MUNI FD	NAD	1-May-99	Debt	Municipal
NUVEEN INSD MUNI OPPORTUNITY	NIO	19-Sep-91	Debt	Municipal
NUVEEN INSD QUALITY MUNI FD	NQI	19-Dec-90	Debt	Municipal
NUVEEN INV QUALITY MUNI FD	NQM	15-Jun-90	Debt	Municipal
NUVEEN MUNI ADVANTAGE FUND	NMA	1-Dec-89	Debt	Municipal
NUVEEN MUNI MKT OPPORTUNITY	NMO	22-Mar-90	Debt	Municipal
NUVEEN MUNICIPAL VALUE FUND	NUV	1-Jun-87	Debt	Municipal
NUVEEN PERFORMANCE PLUS MUNI	NPP	1-Jun-89	Debt	Municipal
NUVEEN PREMIUM INC MUNI FD 2	NPM	24-Jul-92	Debt	Municipal
NUVEEN PREMIUM INC MUNI FD 4	NPT	19-Feb-93	Debt	Municipal
NUVEEN PREMIUM INC MUNI FUND	NPI	18-Jul-88	Debt	Municipal
NUVEEN QUALITY INCOME MUNI	NQU	1-Jun-91	Debt	Municipal
NUVEEN REAL ESTATE INCOME FD	JRS	15-Nov-01	Equity	Sector Fund-Real Estate
PETROLEUM & RESOURCES CORP	PEO	1-Jan-29	Equity	Sector Fund-Energy
PUTNAM MASTER INTER INC TST	PIM	29-Apr-88	Debt	Government/Corporate
PUTNAM PREMIER INCOME TRUST	PPT	29-Feb-88	Debt	Government/Corporate
ROYCE VALUE TRUST	RVT	19-Nov-86	Equity	Value-Small Cap
SOURCE CAPITAL INC	SOR	1-Jun-68	Equity	Growth & Income
TEMPLETON DRAGON FUND INC	TDF	20-Sep-94	Equity	Country Fund-China
TEMPLETON EMERG MKTS INC FD	TEI	23-Sep-93	Debt	Emerging Market-Debt
WESTERN ASSET HIGH INC FD II	HIX	28-May-98	Debt	Corporate/Preferred-High Yld

Appendix B.

Chart 1.

The effect of expense ratios on average discounts for all 50 funds

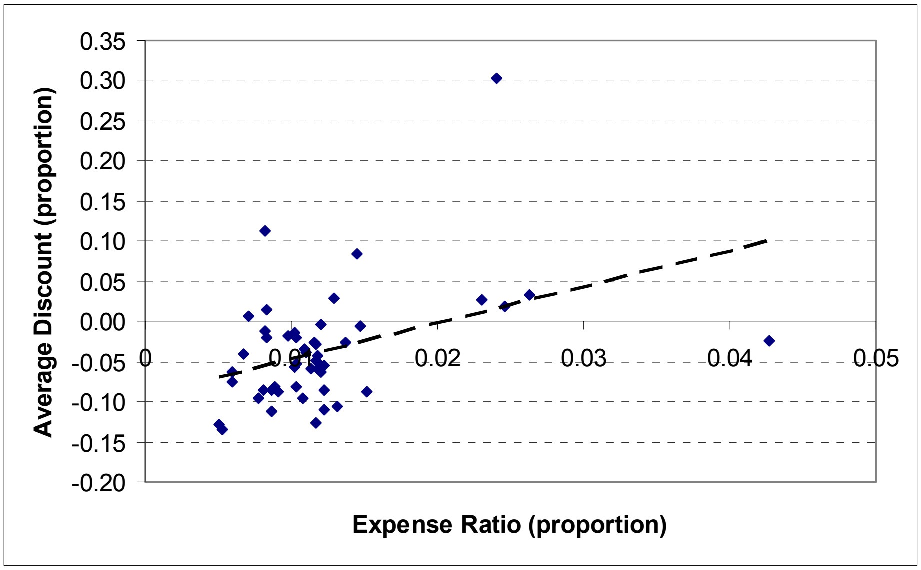

Chart 2.

The effect of expense ratios on average discounts on 48 funds (outliers removed)

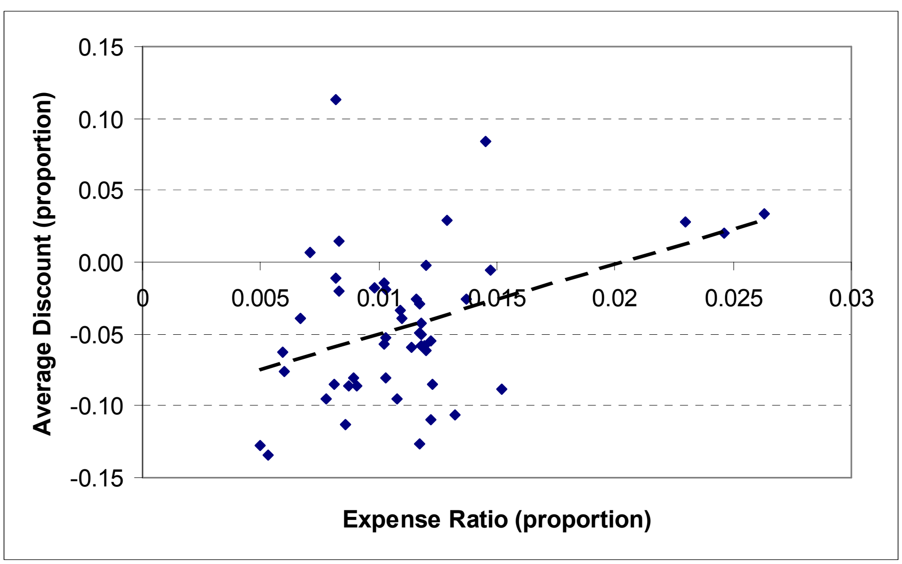

Chart 3.

The effect of expense ratios on average discounts for 16 equity funds (outliers removed)

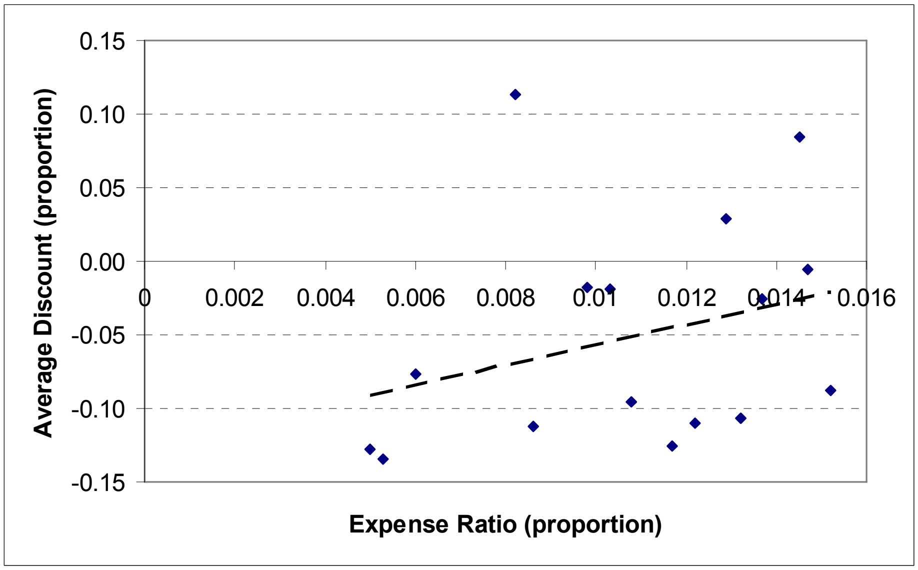

Chart 4.

The effect of expense ratios on average discounts for 32 debt funds (outliers removed)