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THE PORTFOLIO ALLOCATION EFFECTS OF INVESTOR SENTIMENT ABOUT THE ABILITY OF MANAGERS TO BEAT THE MARKET*

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Abstract

I present a model that can transform discounts on closed-end mutual funds into a measure of investor sentiment about the ability of fund managers to beat the market. This measure of sentiment varies positively with capital flows into actively managed open-end mutual funds, but negatively with capital flows into passively managed index funds. Investors appear to re-allocate their portfolios between actively and passively managed investment vehicles based on expectations about by how much managers will beat or trail the market.

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1 Introduction

I present below a model for pricing closed-end mutual funds that incorporates investor expectations about whether fund managers will, through their portfolio management skills, beat the market. I first demonstrate that the model successfully explains many features of closed-end fund pricing, including the average level of discounts and why 56% of the cross-sectional variance in discounts can be explained by two fundamental factors, management fees and the dividend payout rate. Given that the model accurately captures closed-end fund behavior, I use market data to generate a time-series of investor sentiment about the ability of fund managers to beat the market. This time series varies positively with capital flows into actively managed mutual funds but negatively with capital flows into passively managed index funds. This suggests that investor beliefs about the ability of management to beat the market affect investor capital allocation across a wide class of investment vehicles. When sentiment about the ability of managers to beat the market improves, investors move capital from passively managed portfolios into actively managed portfolios, and vice versa.

The model presented below builds upon the work of Lee, Shleifer & Thaler (1990), who argue that "investor sentiment" about anticipated returns is responsible for the time variation observed in discounts on closed-end funds, which are mutual funds whose shares trade like common stock. Because supply and demand determine their prices, closed-end fund shares can be—

and often are—priced by the market at large discounts or premia to the value of their underlying portfolios. It is argued by Lee, Shleifer & Thaler (1991) that this violation of arbitrage pricing results from time variation about anticipated returns on the part of investors. As they grow more or less positive about future returns, investors bid up or down the prices of closed-end fund shares, thereby causing discounts/premia to vary. Because changes in perceptions about returns affect all funds simultaneously, changing investor sentiment also provides a good explanation for the high correlation found among fund discount movements.

This paper builds upon the investor sentiment model by arguing that what matters for investor portfolio allocation decisions is not so much investor expectations about absolute returns as about relative returns. That is, what matters to investors is not simply how high a rate of return a fund will generate but by how much the fund will beat or trail the market. I refer to this as differential sentiment because portfolio allocation decisions are affected by the expected *differential* in returns between the market and mutual funds.

Adding differential sentiment to a model of closed-end fund pricing helps to explain closed-end fund behavior. However, if differential sentiment exists, it should be expected to affect investors portfolio allocation decision in all cases where investors might worry about the ability of fund managers to beat the market. That is, if investors care about the ability of closed-end fund managers to beat the market, they should also care about the ability of managers of other types of investment vehicles to beat the market. To that end, this paper examines capital flows into both open-end mutual funds and index funds. If sentiment is indeed market wide, then we should expect to find that a measure of sentiment derived from closed-end funds is positively correlated with capital flows into open-end funds but negatively correlated with capital flows into index funds. Because closed-end funds and open-end funds are both actively managed investment vehicles, an improvement in differential sentiment should cause investors to want to invest more of their money in both kinds of mutual fund. On the other hand, the improvement in differential sentiment will cause investors to take money out of index funds. This is because investors who truly believe that managers are now more likely to beat the market will withdraw capital from index funds—whose returns are tied to the market—in order to reallocate their portfolios towards actively managed investment vehicles.

It is demonstrated below that these two correlations predicted by the differential sentiment hypothesis are not only found in the data, but are found to be economically and statistically significant as well. Investor beliefs about managerial ability appear to drive portfolio allocation decisions. Furthermore, the negative correlation with respect to index fund capital flows serves to empirically distinguish differential sentiment from investor sentiment. If investors were moved solely by investor sentiment—i.e. expectations about future absolute returns rather than relative returns—then one would expect them to place more capital into *all* investment vehicles when sentiment improved. Instead, the negative correlation with respect to index funds suggests that what is crucial is *differential* sentiment about whether active management can beat passive management.

Section 2 presents the differential sentiment model and shows that it nests rational expectations as a special case. Section 3 argues that because rational expectations fails to explain closed-end discounts, one must invoke differential sentiment. Section 4 uses the model to quantify differential sentiment. Section 5 demonstrates that differential sentiment varies positively with capital flows into open-end mutual funds but negatively with capital flows into exchange-traded index funds. Section 6 concludes.

2 The Differential Sentiment Model

An examination of all closed-end stock funds trading on the NYSE from 1960 to 1999 reveals that one cannot reject the hypothesis that closed-end funds die off in a Bernoulli fashion, with an annual death probability of $\gamma = .0364$.[1] That is, if a fund is in business on January 1st, it has a 3.64% chance of going out of business by the end of the year and a $1 - \gamma = 96.36\%$ chance of continuing in business into the next year.[2] The fundamental value of a closed-end fund is traditionally measured by its Net Asset Value (NAV), the difference between fund assets and liabilities. We will denote the NAV per share at time t by N_t. The market price per share of the fund at time t will be denoted by P_t. If a fund goes out of business at some particular time T, then $P_T = N_T$ because the fund liquidates its holdings and returns the entire NAV to shareholders. In any period t before liquidation takes place, the closed-end fund may choose to pay a dividend, d_t. The current price of a closed-end fund should simply be the present value of expected dividend payments over the period that the fund is expected to remain in business plus the present value of the liquidation payment that will eventually be made when the fund goes out of business. Given the Bernoulli death process, the current price of a closed-end fund is consequently the sum of two terms[3]:

$$\begin{aligned} P_t &= \sum_{i=1}^{\infty} \gamma(1-\gamma)^{i-1} \left(\frac{1}{R^{out}}\right)^i E_t[N_{t+i}] \\ &+ \sum_{i=1}^{\infty} (1-\gamma)^{i} \left(\frac{1}{R^{out}}\right)^i E_t[d_{t+i}] \end{aligned} \tag{1}$$

The first term in equation (1) is the expected present value of liquidation payments, where discounting is done relative to R^{out}, the expected period-on-period total rate of return that fund investors believe is available outside of the fund in alternative investments. For the investor considering whether to place his money into the fund, R^{out} would be the rate of return available in, say, an index fund, and may be thought of as the opportunity cost of returns forgone when investing in the fund. From the perspective of period t, a fund that liquidates at period $t+i$ goes $i-1$ periods without liquidating and then liquidates in the ith period. Hence the liquidation term begins with the product $\gamma(1-\gamma)^{i-1}$. The second term in equation (1) gives the expected present value of dividend payments. For a dividend to be paid out at time $t+i$, the fund must live through period $t+i$. That is why each term in this sum begins with $(1-\gamma)^i$.

Equation (1) is unsatisfying because it fails to take into account the fact that a dividend payment made in period t lowers the NAV of the firm in later periods. We must also take account of the fact that management fees paid at time t also reduce the NAV of the fund in later periods, and that our sentimental investors care about the rate of return that the fund manager is expected to generate.

Define R to be the period-on-period total rate of return that the fund manager is expected to earn. Then, if a manager begins with N_t dollars at the beginning of period t, investors will expect that his stock picking will increase the NAV of the fund to RN_t. Not all of that amount will be retained by the fund, however. At some point, the manager must be paid. Closed-end fund management contracts specify that managers will receive a fraction $f < 1$ of fund NAV each year. Therefore, the NAV of the fund after the manager is paid will be $(1 - f)RN_t$. If a fund liquidates, this amount of NAV would be returned to shareholders. If, however, the fund continues in business into the next year, dividends must be paid out of $(1 - f)RN_t$.[4] We model dividends by assuming that a constant fraction α of NAV is paid out each year to investors in the form of dividends.[5] Therefore, if a fund continues in business, its NAV at the start of the next period, after paying dividends of $\alpha(1-f)RN_t$, will be $N_{t+1} = (1-\alpha)(1-f)RN_t$. If we substitute into equation (1) this model of management fees, dividend payments, and expected managerial return, we obtain a convergent geometric series which, when simplified, gives the period t price of the fund as a simple function of period t NAV:

$$P_t = \frac{\frac{R}{R^{out}}(1-f)\gamma}{1-\frac{R}{R^{out}}(1-f)(1-\gamma)(1-\alpha)}N_t + \frac{\frac{R}{R^{out}}(1-f)(1-\gamma)\alpha}{1-\frac{R}{R^{out}}(1-f)(1-\gamma)(1-\alpha)}N_t. \tag{2}$$

As with Equation (1), the first term is the expected present value of expected liquidation payments, while the second term is the expected present value of dividend payments. However, equation (2) incorporates both fundamental and non-fundamental factors into the price of a closed-end fund. The fundamental factors are management fees, dividend payout rates, the current value of the underlying portfolio, and the fund death rate. The non-fundamental factors are given by the differential sentiment ratio, $\frac{R}{R^{out}}$, which captures investor expectations about the fund manager's rate of return relative to the outside, market rate of return.

A nice feature of this pricing model is that it can capture rational expectations as a special case of the differential sentiment ratio. Malkiel (1995) provides evidence that fund managers cannot systematically beat the market over the long run, while Zheng (1999) offers evidence that mutual fund investors are unable to predict which managers will beat the market even in the short run. Because of this, an investor having rational expectations should assume that $\frac{R}{R^{out}} = 1$. That is, the rational investor assumes that the manager of a given fund will on average do neither better nor worse than the market—both because managers cannot systematically beat the market and because the rational investor would not believe that he had the power to predict which managers would in the future beat the market by sheer chance. With rational expectations imposed, our pricing model is reduced to only fundamental factors. Setting $\frac{R}{R^{out}} = 1$ in equation (2) and combining terms gives,

$$P_t = \frac{[\gamma + (1-\gamma)\alpha](1-f)}{1-(1-f)(1-\gamma)(1-\alpha)} N_t. \tag{3}$$

Equation (3) gives the price of a closed-end fund under rational expectations. With a bit of algebra, it can be demonstrated that this price is simply the current NAV less the expected present value of management fee payments. The three parameters f, γ, and α all serve to modulate the future stream of management fee payments and thereby affect the current price of the fund. The higher are fee rates, f, the lower is the price of the fund, as higher rates imply that more of the fund's capital will flow over time to managers rather than investors. A higher value of the death rate, γ, implies a higher price for the fund because the sooner the fund goes out of business, the fewer times management fees will be paid out, thereby leaving more capital to shareholders. And the higher the value of the dividend rate, α, the higher the current price, because any capital paid out to shareholders in the form of dividends is capital out of which management will not be able to take fees during later periods.

2.1 Testing the Differential Sentiment Model

Equation (3) can be used to generate predictions about closed-end fund discounts. These can be tested against discount observations contained in Weisenberger/Thompson Financial's FundEdge data set, which contains daily and weekly data on US-traded closed-end funds over the period 1981-2001. The average management fee rate of the 464 closed-end funds trading in the USA in 2001 was $f = .0081$, while the average dividend payment rate was $\alpha = .0690$. As noted above, the empirically estimated Bernouilli death rate for closed-end funds is $\gamma = .0364$. If we substitute these parameter values into equation (3), we obtain three testable predictions which we examine in turn.

Discounts/premia are by definition $D_t = P_t/N_t - 1$, and can therefore be easily calculated from equation (3). If $D_t < 0$, the fund is trading at a discount, and if $D_t > 0$ the fund is trading at a premium. If we substitute the given parameter values, we obtain a model-predicted discount of -7.2%. Compare this prediction with Figure 1, a histogram of the 225,306 weekly discount observations in our data set over the period 1985 to 2001, which was constructed by totaling all of the discounts/premia that fell into 1-percent wide bins ranging from -50% discounts to +50% premia.[6] As can be seen from Figure 1, discounts/premia are distributed approximately normally around -6%, which is very close to our model's prediction of -7.2% for the typical discount level.[7]

Equation (3) can also be used to generate two predictions that can be tested against cross-sectional regression coefficients. The first predication concerns the responsiveness of the discount to changes in the management fee rate, $\frac{dD_t}{df}$. Taking the derivative of discounts with respect to fees, f, using equation (3) and substituting for our parameters yields -8.49. The second prediction concerns the responsiveness of discounts to changes in the dividend payout rate, $\frac{dD_t}{d\alpha}$. Taking the derivative of discounts with respect to the dividend payout rate, α, using equation (3) and substituting for our parameters gives 0.63. Compare these predictions with Table 1, which presents the results of regressing individual fund management fee and dividend rates on fund discount levels.[8] Regression (3), gives an empirical estimate of the effect of management fees on dividends of -8.82. That is very much less that one standard error away from our model-predicted value of -8.49. The same regression, however, gives 1.96 as the estimated effect of dividend payout rates on discounts. This value is notably higher than our model-predicted value of 0.63, but being that it is highly statistically significant, it does confirm our model's prediction that that higher dividend payout rates lead to a more positive D_t.

Taken together, these results suggest that the model works quite well. It correctly predicts the observed average level of discounts on closed-end funds, correctly predicts that higher fees will result in higher discounts, and correctly predicts that higher dividend payout rates will result in lower discounts. Perhaps most striking, though, is the high R-squared statistic of regression (3), and the fact that the model provides an explanation as to why 56% of the variance in cross-sectional discounts can be explained by management fees and dividend payout rates.

3 The Necessity of Invoking Sentiment

The predictions just successfully tested were made under the rational expectations assumption that $\frac{R}{R^{out}} = 1$. The true utility of the differential sentiment model comes from allowing the ratio $\frac{R}{R^{out}}$ to vary. This is because discounts on closed-end funds vary significantly over time as shown by Figure 2, which plots for 1985 to 2001 the average and standard deviation of the discounts of all funds in operation each week.[9] A fully rational model of closed-end fund pricing is unable to account for such great time variation in discounts because the factors that affect the rational discount level are largely time invariant. Management fees are fixed by contract for several years at a time and are usually renewed at prior levels. There is no evidence that the death rate of funds varies over time. And dividend payout rates are very stable over time as well. Because of this stability, rational models of the discount are hard pressed to explain the large and often precipitous changes in discounts that are observed in the data.[10]

Perhaps the most telling weakness of rational explanations for discounts, though, is their inability to explain why closed-end funds so often trade at premia. Thirty-one percent of the 225,306 weekly observations in Figure 1 are of premia. Under rational expectations, investors would only pay premia if fund managers could not only beat the market, but beat it by enough to make up for their management fees and trading costs. As is well known, however, fund managers are unable to systematically earn such high rates of return.

Even worse for rational explanations of closed-end fund pricing behavior is the fact that discounts and premia are not only often substantial but lingering as well. This is starkly illustrated by Figure 3, which plots initial discounts against discounts 52-weeks later, using one-percent wide bins for initial discounts. For instance, all discounts falling between -25% and -24% were identified and of this subset, the average and standard deviation 52-weeks later were computed. The figure shows that even after 52 weeks, there is only very weak mean reversion. This can be seen by comparing the bold average line with the line of dots, which gives what one would expect if discounts/premia showed absolutely no mean reversion. Fund weeks where the average discount was -20%, for instance, still had, on average, a discount of -16.5% after 52 weeks. This lack of mean reversion is itself *prima facia* evidence that rational models are largely inapplicable in this context. Even if someone in the market does bother estimating a rational discount level, there is only weak arbitrage pressure systematically driving existing discounts/premia towards that level or any other.[11]

Discounts/premia are not, however, without any systematic behavior. To the contrary, they are highly correlated across funds. Lee et al. (1990) find that the average monthly pairwise correlation between the weekly discount levels of the nine US-traded funds in their sample is 0.41. Minio-Paluello

(1998) finds that the average pairwise correlation of discount changes among UK-traded "International General" funds is 0.30. In the FundEdge data set, the pairwise average weekly discount correlation in levels is 0.26 over the period 1985 to 2001. Additionally, if one performs a pooled regression across all 464 funds of first differences of the average weekly discount on first differences of individual fund weekly discounts, one obtains a coefficient of 0.91.[12] That is, a one percentage point change in the average discount series is on average met with a 0.91 percentage point change in the discounts of individual funds.

This evidence supports the idea that the differential sentiment of each particular fund is composed of an idiosyncratic component and a common component. That closed-end funds discounts/premia move in such a coordinated fashion is consistent with closed-end funds being affected by common shocks to differential sentiment. That discounts/premia are only very slowly mean reverting suggests that the cross-sectional distribution of discounts/premia is caused by idiosyncratic differences in differential sentiment that are largely permanent. That is, it appears that investors can grow more or less optimistic about the ability of managers *as a class* to beat the market, while retaining their sentiments about any particular manager's prospects relative to those of other managers. In the next section, I demonstrate that the common component of differential sentiment appears to have market-wide effects. As investors grow more or less optimistic about the ability of managers as a class to beat the market, they don't just bid up or down the prices of closed-end funds. They also shift capital between open-end mutual funds and index funds, depending on whether they believe that open-end fund managers can beat index funds, whose returns of course proxy for market returns.

4 Quantifying Differential Sentiment

4.1 The Measurement of Differential Sentiment

Equation (2) can be re-arranged to measure differential sentiment and how it varies over time. Simply solve equation (2) for the differential sentiment ratio, $S = R/R^{out}$,

$$S = \frac{R}{R^{out}} \quad = \quad \frac{P_t/(1-f)}{P_t(1-\theta) + \theta N_t}, \tag{4}$$

where $\theta = \gamma + (1-\gamma)\alpha$, and then plug in values for each of the parameters f, γ, and α, as well as for price and NAV. We can do this for each fund each week and thereby derive a time-series that captures the differential sentiment of each fund. In essence, we are asking what level of differential sentiment investors must have had for each fund each week to have priced them at exactly the discounts that we observe in the data set. For instance, if we find for a given fund at a given week that $S = 1$, then we know that the market priced the fund that week under the expectation that managers were expected to produce returns equal to the market rate of return. Similarly, an $S > 1$ indicates that investors believed that managers would beat the market, while an $S < 1$ indicates that investors expected managers to trail the market. It should be noted that higher values of S are equivalent to more positive values of D_t (i.e., smaller discounts or greater premia). This makes sense because investors who become more positive about the ability of managers to beat the market will bid up fund share prices; that results in an increase in $D_t = P_t/N_t - 1$.

In the remainder of this paper, I will demonstrate that the differential sentiment ratio moves positively with capital flows into open-end mutual funds but negatively with capital flows into index funds. To ease the interpretation of regression slope parameters, let us define lower case s to be

$$s = 100 * (S - 1) = 100 * \left(\tfrac{R}{R^{out}} - 1\right). \tag{5}$$

Because R/R^{out} is a number near one, lower case s gives the number of percentage points by which the sentiment ratio is above or below one–i.e., s is approximately the number of percentage points by which investors feel that managers will beat or trail the market. In the regressions presented in the next section, this convention will allow us to see how much capital flows into open-end mutual funds and index funds change in response to a one-percentage point change in investor beliefs about by how much managers will beat or trail the market.

In order to capture the common component of differential sentiment, I used equations (4) and (5) to construct s for six closed-end stock funds that were in continuous operation during the period 1985-2001. I chose to use only mature funds because newly formed funds display a systematic movement in discount levels that is unrelated to changes in differential sentiment. As documented by Weiss (1989), newly issued funds are priced at a 10% premia on their first day of trading in order to raise the money necessary to pay off the investment bankers for their IPO services. The funds then systematically move toward discounts over the next 12 months. Because this downward movement in discounts is unrelated to changes in differential sentiment, I examine only mature funds in order to avoid bias. There were actually 10 closed-end stock funds in continuous operation during this time. Two of them, Sterling Capital Corporation and Engex Corporation had to be be excluded because FundEdge lacks complete NAV and price data for these two funds over this time period. I also excluded Adams Express and Petroleum and Resources because they display a huge discontinuous jump, with both falling from large premia of over +35% to discounts of -12% during the same week of 1989. That left six mature closed-end stock funds, Bergstrom Capital, Central Securities, General American Investors, Salomon Brothers Fund, Source Capital Fund, and Tri-Continental Corporation. For each of these funds, I constructed s at each month. I then took a simple average of the six individual s values each month, and used the series thus constructed as my measure of the common component of differential sentiment in the regressions presented in Section 5.[13]

The price and NAV data used to construct s for each fund came from FundEdge. As a proxy for the fee rate, f, I used the expenses-to-NAV data item, which is given in fund annual reports as well as S&P Stock Reports.

This item is only reported once per year, so that I was forced to use the same value when constructing s for all months of a given year. The dividend payout rate rate, α, was proxied by running the regression $Dividends_t = c_1 + c_2 NAV_t$ for each fund over the period 1985-2000 on annual data; the slope coefficient c_2 proxies for α.[14] And, finally, the annual death rate, γ, was presumed to be constant at 0.0364, its empirical value for closed-end stock funds over the period 1960-1999, as explained previously.

4.2 The Identification of Differential Sentiment

The major difference between closed-end funds and open-end funds is in how investors buy into and sell out of their positions. Closed-end funds are closed to new investment. Because of this, they issue a fixed number of shares at their IPO, with the promise that no more shares will be issued thereafter. The shares sold at IPO then trade on a secondary exchange, usually the NYSE or the AMEX. Anyone wishing to buy or sell a position in the fund must purchase or sell shares in the secondary market; the fund neither redeems old shares nor issues new shares. Because the number of shares is fixed, the supply curves of closed-end funds are vertical. Any demand shocks therefore manifest themselves in prices: closed-end funds clear in prices.

By contrast, each open-end fund promises investors that they will be able to purchase and redeem shares at par with the fund's underlying portfolio value. For instance, suppose that an investor who owns 1% of the shares of a given open-end fund wishes to liquidate his position. He does not sell his shares on a secondary market. Rather, he calls the fund, which guarantees to redeem the shares at par. If the investor places his sell order in the morning, the fund waits until the markets close for the day, and then pays the investor 1% of the value of the fund's portfolio, marked to market at closing prices. By guaranteeing to redeem shares at par, open-end funds act as price fixers. An implication of this is that the supply curves of open-end funds are horizontal, pegged to the value of their underlying portfolios. Any demand shocks therefore manifest themselves in quantities: open-end funds clear in capital flows.

Because the supply curves of closed-end funds are perfectly inelastic while those of open-end funds are perfectly elastic, we can fully identify the effects of differential sentiment shocks. If differential sentiment increases, then investors—having increased expectations about the amount by which managers are likely to beat the market—will attempt to reallocate their portfolios towards actively managed assets. That is, the demand curves of both open-end and closed-end funds will shift right simultaneously. Because of their radically different slopes, however, the simultaneous shift in demand will cause purely price changes in the market for closed-end funds but purely quantity changes in the market for open-end funds. Because underlying portfolio values are unaffected by the change in sentiment, the higher prices for closed-end funds will mean more positive discounts/premia. These more positive values of D_t in turn imply larger values of the differential sentiment ratio. Consequently, we should expect to find a *positive* correlation between our sentiment measure, s, and capital flows into open-end funds.

On the other hand, we should expect to find a *negative* correlation between our sentiment measure s and increased capital flows into index funds. This is because index funds, like open-end funds, are price fixers. In the case of index funds, prices are fixed to the value of the underlying index. But whereas an increase in differential sentiment causes the demand curves for actively managed mutual funds to shift right, it will cause the demand curves for index funds to shift left. This is because an increase in differential sentiment means that investors believe that active management is more likely to beat the market. In response, investors should take money out of index funds in order to place it under active management. Therefore, we should expect to see a negative correlation between our sentiment measure, s, and capital flows into index funds.

When examining capital flows into index funds in the next section, we will run regressions on the two largest exchange traded index funds, SPYDERS and DIAMONDS.[15] The underlying index for SPYDERS is the S&P 500, while the underlying index for DIAMONDS is the Dow Jones Industrial Average.

All exchange traded index funds feature an arbitrage mechanism that serves to fix the price of fund shares to the value of the underlying index despite that fact that fund shares are traded in real time on a secondary market. The mechanism works in the following way. ETF shares are backed by "creation units," which are bundles of the stocks in the underlying index.

If an ETF's share price begins to deviate from the value of the underlying index, then large, predesignated institutional traders have the right to either exchange ETF shares to redeem old creation units or bundle together new creation units in exchange for ETF shares. In this way, these predesignated arbitrageurs increase or decrease the supply of ETF shares until arbitrage pricing again holds. This mechanism is so effective that the prices of ETF shares rarely deviate by more than a few basis points from the value of the underlying index.

Because arbitrage pricing always holds, it must be the case that the level of the underlying index cannot be responsible for the trading volume observed in the market for ETF shares. If investors can buy either the shares of the ETF or the underlying index, and if both have the same price, then decisions about whether to buy ETF shares must be based upon something other than price. This paper suggests that differential sentiment may be responsible for some of the trading volume.

Because the arbitrage mechanism of ETFs keeps ETF share prices pegged to the value of the underlying index, ETF supply curves are horizontal. This means that when changes in differential sentiment cause investors to buy or sell index fund shares, they only affect trading volume. Consequently, when running regressions in the next section, I utilize data on the trading volume of SPYDERS and DIAMONDS as my measure of capital flows into and out of index funds in response to changes in differential sentiment.

5 Sentiment and Portfolio Allocation

5.1 Positive Open-end Fund Capital Flows

Table 2 presents the results of regressions of our differential sentiment measure, average s, on capital flows into, respectively, open-end stock funds and open-end bond funds using monthly data over the period January 1988 to February 1998.[16] The data on open-end capital flows was obtained from the Investment Company Institute, which is the trade group representing all US unit trusts, open-end mutual funds, and closed-end mutual funds. While the Investment Company Institute does not report capital flows into each fund separately, it does disaggregate total open-end fund capital flows between bond funds and stock funds. This disaggregation is convenient because by running separate regressions on capital flows into bond and stock funds, we can gain some insight into how wide ranging the effects of differential sentiment may be. In particular, we can see whether our sentiment measure, which was derived from six closed-end *stock* funds, is related to the capital movements of open-end *bond* funds.

The average s series is used as an explanatory variable, along with percentage yields on 1-year Treasuries and the percentage 1-year trailing return on the CRSP total returns S&P 500 Index.[17] The dependent variables are, for bond and stock funds respectively, the ratios of new sales to redemptions, both measured in dollars. If sentiment improves, then we should expect to see new sales increase and redemptions fall—implying that their ratio should increase as sentiment increases. This conjecture is consistent with the OLS results presented in Table 2.

Whether regressions are run in levels or in first differences, changes in s are positively correlated with the ratio of new sales to redemptions, and this holds true for both stock funds and bond funds. This finding is consistent with Malkiel (1977) and Lee et al. (1991), who find a positive but insignificant relationship between open-end fund net redemptions and discounts using US data, and Levis & Thomas (1999) who find a positive and significant relationship between discounts and individual-investor capital flows into open-end funds in UK data. More interestingly, the effect of differential sentiment remains robust even after the inclusion of short term interest rates and trailing stock returns. This is supportive of our hypothesis that s measures sentiment about expected *differential* or relative returns, rather than sentiment about expected absolute returns. The statistical significance of the coefficient on s, even when outside rates of return are accounted for, demonstrates that differential sentiment has an effect on capital flows that is independent of general expectations about outside rates of return.[18]

It is especially striking that while our measure of s was constructed from *closed*-end *stock* funds, it is highly correlated with capital flows into *open*-end *bond* funds. This holds true even after taking into account the outside rate of return (the interest rate) that should most affect capital flows into bond funds, and indicates that changes in sentiment about whether managers can beat the market affect all managed investment vehicles no matter what their underlying portfolios consist of.

5.2 Negative Index Fund Capital Flows

It is important to examine the sign of the relationship between s and index fund capital flows not only to test the predictions of the differential sentiment hypothesis but also because the sign can distinguish between the differential sentiment hypothesis and the investor sentiment hypothesis of Lee et al. (1991). While the positive relationship between s and open-end capital flows is consistent with both differential sentiment *and* investor sentiment, the two theories predict very different things with respect to index fund capital flows. This difference has to do with the fact that differential sentiment deals with expected relative rates of return, whereas investors sentiment deals with expected absolute rates of return.

As explained above, the differential sentiment hypothesis predicts that there should be an inverse relationship between discounts and capital flows into index funds. As investors become more sure that managers will beat the market, they will pull money out of index funds in order to put it into closed-end funds. The money flowing into closed-end funds will drive up their spot prices, raise $D_t = P_t/N_t - 1$, and thereby generate a negative correlation.

On the other hand, the investor sentiment hypothesis would predict a positive relationship between discounts and index fund capital flows. As investors become more sanguine about asset returns, they should put more money into all types of assets. In particular, there should be increased capital flows into index funds at the same time that the increased capital flows into closed-end funds bid up their spot prices and raise D_t. We can therefore distinguish between investor sentiment and differential sentiment by examining the relationship between index fund capital flows and our s variable, which moves positively with discounts.[19]

To test whether differential sentiment has a positive or negative effect on index fund capital flows, I ran regressions of our six-fund average s series on monthly trading volume data for SPYDERS and DIAMONDS. As explained previously, changes in sentiment will manifest themselves only in trading volume because the ETF arbitrage mechanism prevents sentiment shocks from affecting ETF share prices. The independent variable used in the regressions was total monthly trading volume divided by total shares outstanding, expressed as a percentage. The regressions were performed in both levels and first differences, with the percentage yield on 1-year Treasuries and the trailing percentage 12-month return on each fund's respective underlying index serving as proxies for the outside rate of return.[20] The regressions involving SPDRS were run on monthly Reuters volume data covering 1/1993–12/2000 while those involving DIAMONDS were run on monthly CRSP volume data covering 1/1998–12/2000.[21]

The regression results are presented in Table 3. Consistent with the differential sentiment hypothesis, but inconsistent with the investor sentiment hypothesis, there is a strong negative relationship between s and index fund capital flows. Slope coefficients on s are negative and highly significant for all regressions run in first differences and for three of the four levels specifications. As with the regressions of s on open-end capital flows, the inclusion of proxies for outside rates of return does not weaken the effect of differential sentiment. On the contrary, such proxies increase the statistical significance of s in all specifications. The fact that s has an effect independent of the proxies for outside rates of return is, as mentioned before, indicative of the independent impact that differential sentiment has upon capital allocation.

6 Conclusion

This paper has argued that the discounts/premia observed on closed-end mutual funds vary over time because of changes in differential sentiment, sentiment as to how much the returns of actively managed portfolios will exceed those of passively held portfolios. A closed-end fund pricing model incorporating differential sentiment was presented and utilized to transform a time series of discounts/premia into a time series of differential sentiment. That sentiment series was demonstrated to be positively correlated with aggregate capital flows into actively managed open-end mutual funds and negatively correlated with capital flows into passively managed exchange-traded index funds. These correlations are consistent with investors re-allocating their portfolios based on their beliefs about the ability of managers to beat the market: when confidence in managers improves, investors move capital from passively managed portfolios into actively managed portfolios, and vice versa.

Future research should examine whether sentiment—be it differential sentiment or some other form of sentiment—has explanatory power for other assets. In an upcoming paper, I demonstrate that differential sentiment strongly affects the prices of Real Estate Investment Trusts (REITs), with discounts on REITs being strongly and significantly correlated with discounts on closed-end funds. This is further proof that differential sentiment has wide-ranging effects. But REITs, like index funds and mutual funds, are pooled investment vehicles. A more fundamental issue is whether sentiment affects the underlying securities that pooled investment vehicles hold in their portfolios.

This paper presents evidence that casts doubt on the assumption that fundamentals-based asset pricing generally prevails for such securities. That is because closed-end funds, while trading like common stock and while meeting the full-information conditions required for rational pricing, still appear to be priced irrationally. Specifically, closed-end funds are required by law to publish their portfolios weekly, and many now update them in real time on their web sites. Closed-end fund investors, therefore, have possession of precise and timely knowledge about the fundamental value of closed-end funds, and therefore of their fundamental share prices. Yet, this full-information environment does not yield rational prices. Figure 1 makes clear that discounts/premia vary significantly from fundamental levels. And Figure 3 shows starkly that price deviations away from fundamental levels are extremely long lasting.

The failure of arbitrage to keep prices at fundamental levels in a market where fundamentals are known immediately and with precision by all participants calls into question how quickly deviations of prices from fundamentals will be corrected in markets—such as those for common stock—where fundamentals are known only very imprecisely. That, in turn, opens up the possibility that sentiment may be able to affect the share prices of common stock. Future research should investigate whether the lack of arbitrage pressure found for closed-end funds extends to operating company stocks, and, if such is the case, whether non-rational sentimental factors are able to influence share prices.

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7 Notes

[1]Let X_t be the number of funds alive at the start of year t and O_t be the number of those that die during year t. Assuming that fund deaths are Bernoulli, with death rate γ, the expected number of deaths in year t is γX_t. A Pearson's Chi-squared test statistic can therefore be constructed as $D^2 = \sum_{t=1960}^{1999} \frac{(O_t - \gamma X_t)^2}{\gamma X_t}$. D^2 is distributed approximately χ^2 with 1999-1960-1 = 39 degrees of freedom. Our estimated D^2 is 30.52 which is significantly less than than the 90% critical value of 51.81. We fail, therefore, to reject the hypothesis that fund deaths follow a Bernoulli process.

[2]Annual fund death rates were regressed against macro variables, fund returns, fund discount levels and other variables that might plausibly affect the decision to liquidate a closed-end fund or convert it to an open-end fund. All were found to be uncorrelated with fund death rates.

[3]We must also impose a transversality condition to rule out speculative bubbles. Formally, we require that $\lim_{n \to \infty} (1-\gamma)^n \left(\frac{1}{R^{out}}\right)^i E_t[P_{t+n} + d_{t+n}] = 0$.

[4]Under US securities law, closed-end funds can avoid paying taxes on the capital gains and dividend payments generated by their underlying portfolios by passing on at least 90% of said gains and dividend payments to the shareholders of the fund. These disbursements are made as dividend payments to fund shareholders. A consequence of this tax law is that fund NAVs are more or less constant over time; any gains they make are passed on to shareholders, leaving the management with about the same principal year after year.

[5]My doctoral dissertation, Flynn (2002), examines several more complicated dividend processes. No plausible model of dividend payments can generate enough variation in fund payment streams to explain the high observed time variation in fund discounts. Consequently, I utilize the most parsimonious dividend process in the model presented here.

[6]This histogram truncates the tails of the distribution. 760 observations (0.33% of the total) were of discounts less than -50% or premia greater than +50%. The lowest discount was -66.5% and the highest premia was 205.4%.

[7]The mode of Figure 1 is 6%, and the mean is 4.3% due to the posi-

tive skewness of the distribution; large premia are more common than large discounts.

[8]The presented regression was run on data for the week of 6/22/2001. That date is the last date for which my version of FundEdge has data. Similar regressions run on earlier dates produce similar slope coefficients with equally high significance.

[9]The weekly standard deviation is much less volatile during later weeks in Figure 2 because the number of funds increased greatly over this time period. The January 4, 1985 Wall Street Journal lists only 25 funds. By June, 2001, there were 464 listed by Weisenberger/Thompson Financial. With so many more funds, the discount of a single firm has only a small effect on the average. It is also interesting to note that when average D_t falls, so does the variance of fund discounts. A preliminary investigation indicates that when average discounts/premia fall, most of the reduction in variance is caused by funds whose large premia suddenly become reduced.

[10]See Dimson & Minio-Kozerski (1999) for an excellent survey of both rational and behavioral explanations for discounts and premia on closed-end funds. Though explanations consistent with rational expectations based on tax frictions, illiquidity of fund shares, agency problems and other considerations are capable of generating discounts near the average observed discount, they cannot explain wide deviations from the mean discount, nor sudden movements in the average discount level across all funds, nor premia.

[11]However, there was very strong mean reversion prior to 1985. I obtained the Lee et al. (1990) discount data for the 1965-1985 period from Charles Lee. If we construct a diagram like Figure 3 using that data, we find very quick mean reversion. In fact, if we plot initial discounts against discounts 52-weeks later, the line in the diagram is horizontal at about -12%. That is, after 52-weeks, initial discount levels do not matter because discounts/premia always reverted to the mean discount of -12%. Why discounts were so much more mean-reverting before 1985 is an open topic for investigation, as is why the level to which discounts reverted during that period was so much lower (-12% versus -6%) than in more recent years.

[12]The coefficient is unaffected by use of fixed effects or random effects and in either case has a t-statistic of at least 75.2. If one runs separate regressions for each fund of first differences of fund discounts on first differences of the average discount series, the mean slope coefficient over the 464 firms is .98,

with 424 of the regressions featuring t-statistics in excess of 2.0. (The average t-statistic is 6.19.) Thus, whether one runs a pooled regression or individual regressions, individual fund discount innovations are found to be extremely highly correlated with innovations of the average discount series.

[13]A simple average, rather than a capital weighted average, is appropriate because the common component of differential sentiment should affect all funds discounts/premia equally, regardless of fund size; capital weighting simply gives more weight to the idiosyncratic component of the largest fund. However, if the regressions of Section 5 are run on a capital weighted s series, they give about the same slope coefficients, but have weaker t-statistics. The results of this paper are not dependent on the weighting scheme.

[14]If we instead take the ratio of annual dividend payments to year-end NAV as our proxy for the dividend rate, the average s series thus created is not very different and the regression results of Section 5 not substantially affected.

[15]I run regressions on data through the year 2000, up to which time SPYDRS and DIAMONDS were the two largest ETFs by market capitalization. Currently, SPYDRS are still the largest exchange traded fund, but DIAMONDS have slipped to fifth place.

[16]The data ends with February 1998.

[17]The index is "total returns" because it includes re-invested dividends. Using the CRSP index that excludes dividend re-investment had no meaningful effect on the results.

[18]The regressions presented utilized trailing S&P 500 stock returns to help (along with interest rates) proxy for outside rates of return, R^{out}. One may object that trailing returns do not capture investor expectations. To see if this mattered, I also ran the regressions using one-year horizon ex post stock returns, as though investors had perfect foresight. The results were insignificantly affected.

[19]If you run regressions of discounts on capital flows into open-end funds and index funds, you get the same positive and negative signs as you get when running regressions on s. However, s contains more information, and therefore the regressions involving s possess better fits statistically.

[20]As with open-end funds, using 12-month ex post returns on each fund's underlying index, in order to give investors perfect foresight and thereby

model forward looking expectations, does not affect the regression results.

[21]SPDRS began trading in January of 1993, and DIAMONDS in January of 1998. Reuters provides SPYDR total shares outstanding under the ticker symbol ˆsxvso. Shares outstanding data for DIAMONDS were available only through CRSP.

Figure 1: 225,306 Weekly Discount Observations, 1985-2001

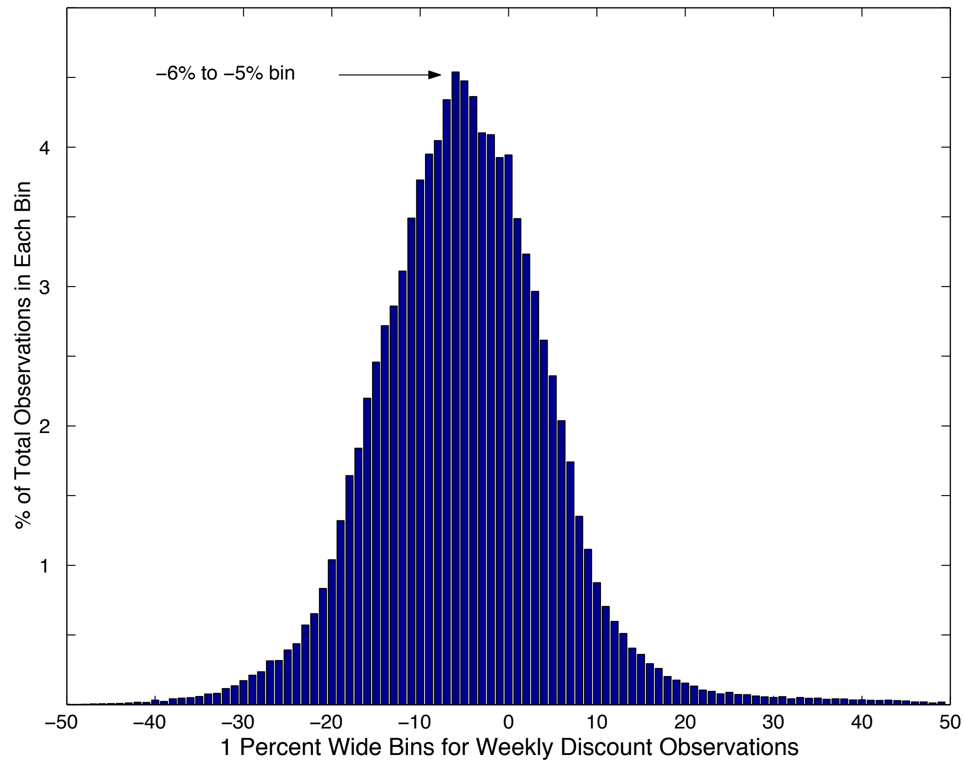

Table 1: Regressions of Fee and Dividend Rates on Discounts

	(1)	(2)	(3)
Constant	1.12	-12.60	-10.74
	(0.51)	(-7.84)	(-5.62)
Fee Rate	-7.19		-8.86
	(-2.48)		(-5.86)
Dividend Rate		1.27	1.96
		(5.52)	(9.46)
R^2	0.04	0.32	0.56
F-statistic	10.11	199.7	145.3
Observations	234	422	234

The dependent variable is the discount level expressed as a percent. The t-statistics given in parentheses were constructed using Newey & West (1987) standard errors, which are consistent under heteroskedasticity. As can be seen from regression (3), 56% of the cross-sectional variance of closed-end fund discounts is explained by management fee and dividend payout rates. These results are for OLS regressions run on the last date available in the FundEdge data set, 6/22/2001. Regressions run on other dates produce similar results. 234 of the 464 funds in the data set contained complete price, net asset value, fee and dividend data and were included in these regressions. The dividend payout rate for each fund was proxied by totaling the dividends paid by a fund in the year leading up to 6/22/2001 and dividing by the fund's portfolio value on that date.

Table 2: Regressions of Differential Sentiment on Open-end Capital Flows

A. Regressions in Levels

	Stock Fund New Sales to Redemptions	Stock Fund New Sales to Redemptions	Bond Fund New Sales to Redemptions	Bond Fund New Sales to Redemptions
Constant	1.75	2.19	1.41	2.07
	(8.57)	(5.91)	(8.18)	(5.07)
s	0.19	0.20	0.30	0.23
	(2.02)	(1.84)	(3.22)	(2.70)
1-yr Treas Ylds		-0.11		-0.13
		(-1.80)		(-2.32)
1-yr SP 500 Rtrn		0.01		0.004
		(3.15)		(1.34)
Error Model	AR(3)	AR(3)	AR(3)	AR(3)
R-squared	0.84	0.87	0.81	0.82
DW	1.99	2.03	1.97	1.96
BG Prob	0.85	0.81	0.66	0.70

B. Regressions in First Differences

	d(Stock Fund New Sales to Redemptions)	d(Stock Fund New Sales to Redemptions)	d(Bond Fund New Sales to Redemptions)	d(Bond Fund New Sales to Redemptions)
Constant	0.003	0.0003	0.005	0.002
	(0.32)	(-0.04)	(0.43)	(0.23)
d(s)	0.19	0.22	0.26	0.22
	(1.76)	(2.23)	(2.78)	(2.43)
d(1-yr Treas Ylds)		-0.06		-0.15
		(-1.04)		(-2.17)
d(1-yr SP 500 Rtrn)		0.01		0.004
		(3.32)		(1.54)
Error Model	AR(2)	AR(2)	AR(2)	AR(2)
R-squared	0.18	0.32	0.15	0.21
DW	2.01	2.06	1.97	1.97
BG Prob	0.92	0.65	0.57	0.63

This table presents the results of regressions run in both levels and first differences of differential sentiment, s, and control variables on aggregate monthly ratios of new sales to redemptions of open-end funds over the period 1/1988–1/1998. T-statistics based on Newey & West (1987) standard errors (which are consistent under heteroskedasticity and autocorrelation) are given in parentheses. Results are reported separately for open-end stock funds and open-end bond funds. Consistent with our hypothesis that differential sentiment has market-wide effects, as our measure of differential sentiment that was derived from closed-end funds rises, the ratio of new sales to redemptions of open-end funds rises. This relationship is statistically significant for 7 of the 8 specifications. The inclusion of short-run interest rates and stock-market returns demonstrates that the effect of differential sentiment is independent of investor perceptions of alternative, manager-independent rates of return. This is consistent with our hypothesis that s measures investor sentiment about the ability of managers to beat such alternative, manager-independent rates of return. The reported Breusch-Godfrey probability (BP Prob) is the probability under the null of having no autocorrelation at up to 4 lags.

Table 3: Regressions of Differential Sentiment on Index Fund Capital Flows

A. Regressions in Levels

	SPYDRS New Capital Flows, Pct.	SPYDRS New Capital Flows, Pct.	DIAMONDS New Capital Flows, Pct.	DIAMONDS New Capital Flows, Pct.
Const.	2.73	2.87	2.28	11.34
	(1.99)	(0.73)	(1.79)	(5.07)
s	-1.81	-2.01	-1.25	-1.02
	(-2.47)	(-2.56)	(-1.50)	(-2.44)
1-yr Treas Ylds		-0.06		-1.62
		(-0.09)		(-4.37)
12-mo Own Rtrn		-0.14		-0.009
		(-2.75)		(-0.28)
Error Model	AR(1)	AR(1)	AR(2)	AR(2)
R^2	0.61	0.66	0.21	0.47
DW	2.07	2.03	1.80	2.01
BG Prob	0.80	0.75	0.61	0.92

B. Regressions in First Differences

	d(SPYDRS New Capital Flows, Pct.)	d(SPYDRS New Capital Flows, Pct.)	d(DIAMONDS New Capital Flows, Pct.)	d(DIAMONDS New Capital Flows, Pct.)
Const.	-0.07	-0.07	0.01	0.06
	(-0.42)	(-0.44)	(0.07)	(0.30)
d(s)	-1.84	-2.01	-2.34	-2.66
	(-2.19)	(-2.74)	(-2.85)	(-3.28)
d(1-yr Treas Ylds)		-0.21		-2.86
		(-0.28)		(-2.25)
d(12-mo Own Rtrn)		-0.14		-0.02
		(-3.01)		(-0.58)
Error Model	AR(0)	AR(0)	AR(2)	AR(2)
R^2	0.07	0.20	0.30	0.41
DW	2.29	2.21	2.19	2.21
BG Prob	0.08	0.10	0.48	0.53

This table reports the results of running regressions in both levels and first differences of differential sentiment, s, and control variables on capital flows into SPYDRS and DIAMONDS exchange-traded index funds as measured by the ratio of trading volume to total shares outstanding, expressed as a percentage. T-statistics based on Newey & West (1987) standard errors (which are consistent under heteroskedasticity and autocorrelation) are given in parentheses. Whether run in levels or differences and with or without control variables, increases in sentiment coincide with decreased flows of capital to DIAMONDS and SPYDRS. The inclusion of short-run interest rates and index own returns as controls demonstrates that the effect of differential sentiment is independent of investor perceptions of alternative rates of return. This is consistent with our hypothesis that s measures investor sentiment about the ability of managers to beat the market. The reported Breusch-Godfrey probability (BP Prob) is the probability under the null of having no autocorrelation at up to 4 lags.

Figure 2: Average and Standard Deviation of Discounts, Weekly

Figure 3: Initial Discounts/Premia vs. Average and Standard Deviation 52 Weeks Later