Exploiting Closed-End Fund Discounts: The Market May Be Much More Inefficient Than You Thought

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October 2, 2014

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JEL Classification: G01, G11, G12
Keywords: Closed-end fund puzzle, limits to arbitrage, market efficiency

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Abstract

We find significant evidence of mean reversion in closed-end fund premiums. Previous studies substantially understate the magnitudes of arbitrage profits in the closed-end fund market. Capitalizing on the property of mean reversion, we devise a parametric model to estimate expected fund returns by incorporating the information content of a fund's premium innovation history. Our strategy of buying the quintile of funds with the highest expected returns and selling the quintile of funds with the lowest expected returns yields an annualized arbitrage return of 18.2 percent and a Sharpe ratio of 1.918, which are substantially higher than the corresponding figures produced using the extant methods. The results are robust to a wide range of tests. They greatly deepen the closed-end fund discount puzzle and pose a challenge to the market efficiency in these products.

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Closed-end funds (CEF) are investment companies that issue a fixed number of shares and invest the proceeds based on the objective of the fund. The shares of a CEF are traded on a stock exchange similarly to common stock and unlike an open-end fund cannot be redeemed by the shareholders at its net asset value (NAV). In efficient and frictionless markets, the share price at which a fund trades must equal its NAV. In reality, however, share prices are oftentimes significantly below their respective NAVs (termed as the CEF discount puzzle). Further, the difference between share prices and NAVs, referred to as the premium[1], exhibits tremendous time-series and cross-sectional variation. A large body of research has tried to explain this puzzling behavior. Leading explanations include investor sentiment effects (see, e.g., De Long, et al., 1990 and Lee, et al., 1991); open-ending frictions (see, e.g., Brickley and Schallheim, 1985; Bradley, et al., 2010; and Brauer, 1988); agency costs (see, e.g., Barclay, et al., 1993; Khorana, et al., 2002 and Del Guercio, et al., 2003); managerial skills (Chay and Trzcinka, 1999; Coles, et al., 2000; Johnson, et al., 2006; and Berk and Stanton, 2007); and market segmentation (see, e.g., Bonser-Neal, et al., 1990; Bodurtha, et al., 1995; Gemmill and Thomas, 2002; Nishiotis, 2004; Cherkes, et al., 2009; Froot and Ramadorai, 2008; and Elton, et al., 2013).

This paper reports new evidence that greatly deepens the CEF discount puzzle. First, we formally test for mean reversion in CEF premium for each individual fund and find that the majority of funds exhibit significant mean reversion in the premium. Early explanations for why fund premiums should mean revert are provided by the noise trader model of De Long, et al. (1990) and the investor sentiment hypothesis of Lee, et al. (1991). Alternatively, premiums should also display rational mean reversion as a result of time-varying contingent liabilities as evidenced in the findings of Malkiel (1977), Chay, et al. (2006), and Day, et al. (2011). Our analysis shows that the

[1] A fund's discount is the negative of its premium.

bias-adjusted speed for mean reversion to equilibrium premium levels is 8.6 percent per month, implying an average half-life of 7.7 months for all the funds in our sample. Furthermore, there exists huge cross-sectional variation in the reversion speeds, indicating substantial heterogeneity across funds. In general, funds investing in fixed-income securities have faster speeds of reversion than funds investing in equities. International funds exhibit more significant evidence of mean reversion than funds invested domestically. Even for funds within the same fund type, there exists large cross-sectional heterogeneity in premium mean reversion speeds.

Second, the extant literature has investigated the magnitude of inefficiency in the CEF market. Thompson (1978) finds that portfolios of CEFs trading at discounts outperform the market and Pontiff (1995) shows that funds with premiums accrue negative abnormal returns and funds with discounts accrue positive abnormal returns. We propose a parametric method to optimally exploit the information contained in the history of CEF premiums and premium innovations. Specifically, at each point in time, we estimate the expected fund returns by employing the current fund premiums and the history of premium innovations, and use the expected returns to sort funds to guide investments. While a properly specified parametric model can extract information more optimally, the actual information gain depends to a large extent on whether the model parameters are estimated accurately. Apparently, the more observations are used, the more efficiently the parameters can be estimated. In the real world with limited number of observations, estimation risk can be large, and a parametric method can underperform ad-hoc approaches (see, e.g., DeMiguel, et al., 2009; Kan and Zhou, 2007; and Liu and Timmermann, 2013). How well a parametric model performs compared to some benchmarks is an empirical question worth close investigation.

Using our sample, a strategy of buying the quintile of CEFs with the lowest premiums and selling the quintile of CEFs with the highest premiums in the spirit of Thompson (1978) and Pontiff

(1995), yields an annualized mean return of 14.9 percent with a Sharpe ratio of 1.519. Given the significant evidence of mean reversion in CEF premiums and the large cross-sectional variation in the speeds of reversion, we devise a parametric model to forecast future fund returns for each fund based on its full history of premium innovations. We design a trading strategy which exploits this information content by buying the quintile of funds with the highest expected returns and selling the quintile of funds with the lowest expected returns. This long-short trading strategy produces an annualized mean return of 18.2 percent and a Sharpe ratio of 1.918, which are substantially higher than the corresponding figures produced using the methodology of Thompson (1978) and Pontiff (1995).

Third, trading strategy returns are regressed on commonly used risk factors to test if they are an artifact of taking on systematic risks. We find that these returns cannot be explained by the three Fama and French (1993) risk factors, the Carhart (1997) momentum factor or the Pástor and Stambaugh (2003) tradable liquidity factor. The five-factor risk-adjusted return (the alpha) for our optimal parametric strategy is 17.4 percent which is significant at the 1 percent level. This figure is only slightly lower than the corresponding unadjusted return of 18.2 percent. The results continue to be robust when considering subsamples of domestic funds, foreign funds, equities funds, and fixed-income funds. Returns are not driven by systematically buying foreign funds and selling domestic funds to capture a market segmentation premium or by systematically buying equities funds and selling fixed-income funds to capture the well-known equity premium. Overall, the risk-adjusted return (the alpha) from the subsample of foreign funds is greater than that from domestic funds; and the alpha from fixed-income funds is larger than that from equities funds. Additionally, time period consistency of returns is tested by partitioning the out-of-sample period into two halves. Contrary to what is expected in efficient markets with rational learning, there is no statistically significant difference in mean returns between the first half of the out-of-sample period and the second half. Overall, our results greatly deepen the closed-end fund discount puzzle and pose a challenge to the market efficiency in these products.

The remainder of this paper is organized as follows. Section I presents the empirical methodology used to extract the information content of CEF discounts. Section II discusses the data. Section III presents empirical results quantifying the magnitude of the CEF discount puzzle. Robustness tests are presented in Section IV. Section V contains concluding remarks.

I Empirical Methodology

This section describes the empirical models of expected CEF returns that we employ in our analysis. CEF returns and premiums are respectively calculated as follows:

$$r_{i,t} = \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} - 1 \tag{1}$$

$$prem_{i,t} = p_{i,t} - nav_{i,t} \tag{2}$$

where

$P_{i,t}$ -- market price of the ith CEF at time t;

$p_{i,t}$ -- logarithm of market price, $\ln(P_{i,t})$;

$D_{i,t}$ -- cash dividend disbursement; and

$nav_{i,t}$ -- logarithm of net asset value (NAV).

$prem_{i,t}$ -- difference between log market price and log NAV, which is the price premium in relative terms.

In this framework, discounts are negative premiums. If the closed end-fund market is weak-form efficient, then the state density of the future price is dependent only on the current price. Premiums will not contain information regarding future CEF prices. Contrary to this, if CEF premiums have explanatory power for future CEF prices, then the CEF market is not weak-form efficient.

Two new predictive regression models that restrict the information content of premiums in different ways are used to forecast one-step ahead CEF returns in this paper. Evidence against weak-form efficiency showing that premiums contain explanatory power for future returns is provided by Pontiff (1995), Swaminathan (1996), Neal and Wheatley (1998), and Froot and Ramadorai (2008). Ex-ante evidence that premiums should mean revert is provided by Lee, et al. (1991), who show that investor sentiment affects CEF premiums. Since investor sentiment is mean reverting by definition, premiums should also display mean reverting behavior which may be used to forecast future premiums and returns. CEFs with better investor sentiment should trade at greater premiums than those with poorer investor sentiment. Based on this idea, we use the current fund premium to forecast future returns as follows:

$$r_{i,t} = \alpha_i + \beta_i \, prem_{i,t-1} + \varepsilon_{i,t} \qquad (3a)$$

$$\boldsymbol{E}_t\left[r_{i,t+1}\right] = \hat{\alpha}_i + \hat{\beta}_i \, prem_{i,t} \qquad (3b)$$

where $\boldsymbol{E}_t[\cdot]$ is the mathematical expectation operator, conditional on the time-t information set, and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are regression parameters estimated using data from the first observation in the sample, for fund i, up to time t.

Thompson (1978) finds that portfolios of CEFs trading at discounts outperform the market and Pontiff (1995) shows that funds with premiums accrue negative abnormal returns and funds with discounts accrue positive abnormal returns. Eqns. (3a,b) differ importantly from the methodology that Thompson (1978) and Pontiff (1995) use to form portfolios. Both authors consider only the sign of the premium. They implicitly assume that CEFs trading at the discounts are expected to have high returns and CEFs trading at premiums are expected to have low returns. We assume explicitly in eqns. (3a,b) that future fund returns depend on current fund premium, and we employ current information to forecast future returns using the parametric model estimated with prior data. If fund premiums exhibit mean reversion, which is confirmed with our data, then our parametric model should yield better forecasts of future returns as the parametric model better exploits the information content of the current fund premiums.

Note, however, that eqns. (3a,b) do not fully capture the information content that the history of premiums may have. Brauer and Chang (1990) and Starks, et al. (2006) show that tax-loss selling are present in CEFs. Chay, et al. (2006) and Day, et al. (2011) further provide evidence that CEF premiums display predictable patterns in response to dividend disbursements by funds. Premiums tend to be smallest immediately before a distribution, since this is the time that investors' contingent tax liability is greatest. Following disbursement, premiums increase as a result of the diminished tax liability. To account for the information content of possible patterns in premiums and premium innovations, we add the lagged premium innovations to the return prediction equation, in the spirit of the augmented Dickey and Fuller (1981) regression model, namely:

$$r_{i,t} = \alpha_i + \beta_i\, prem_{i,t-1} + \sum_{j=1}^{k_{i,t}} \gamma_{i,j} \Delta prem_{i,t-j} + \varepsilon_{i,t} \qquad (4a)$$

$$\boldsymbol{E}_t\left[r_{i,t+1}\right] = \hat{\alpha}_i + \hat{\beta}_i\, prem_{i,t} + \sum_{j=1}^{k_{i,t}} \hat{\gamma}_{i,j} \Delta prem_{i,t-j+1} \qquad (4b)$$

where Δ denotes the difference operator. The lag length $k_{i,t}$ is optimally chosen following the procedure suggested by Campbell and Perron (1991), starting at $k_{i,t} = 3$ and reducing the number of lags until the longest lag is statistically significant at the one percent level. Now, expected returns at $t+1$ are not only dependent on current premiums at time t, but also dependent on the history of premium innovations from time $t-k_{i,t}$ to time t.

The return differential between a trading strategy using eqns. (4a,b) and (3a,b) can also be interpreted as a test of the validity of the traditional assumption that for CEFs only the current premium contains explanatory power for future returns. If portfolio returns using eqns. (3a,b) are similar to portfolio returns using eqns. (4a,b), then the traditional assumption holds up. If portfolio returns using eqns. (4a,b) are larger than those from using eqns. (3a,b), then the traditional assumption can be rejected in favor of the alternative hypothesis that CEF returns are dependent on premium path. Those are the hypotheses that we test. We refer to eqns. (3a,b) as the BMR model and eqns. (4a,b) as the RADF model.

II Data

Monthly data are compiled from four different data sources. Data on CEF share prices, total returns, trading volumes, and shares outstanding is obtained from the Center for Research in Security Prices (CRSP) monthly stock file database. There are 693 CEFs in the CRSP universe. CEFs incorporated outside of the United States are excluded from the sample. End-of-month fund NAVs are obtained from Bloomberg. Not all CEF observations in CRSP have the accompanying NAV observation available in Bloomberg. The final sample consists of the intersection of the two databases which leaves 377 CEFs that trade in the United States covering the August 1984 to December 2011 period. Missing values for CEF returns are imputed with the sample mean of that CEF's return time series[2]. Data on the three Fama and French (1993) factors, as well as the Carhart

[2] Results are unchanged when missing returns are imputed with zero.

(1997) momentum factor, are obtained from Kenneth French's website. Data on the Pástor and Stambaugh (2003) tradable liquidity factor is obtained from Luboš Pástor's website.

[Insert Table I about here]

CEF fund type classifications are obtained from Morningstar. Table I presents the cross-section of fund categories and types. Panel A shows that 61.7 percent of the CEFs are categorized as domestic funds, 21.1 percent are categorized as foreign funds, and the remaining 17.2 percent have a miscellaneous categorization. Of those CEFs that invest domestically, 15.5 percent invest in domestic equities and 84.5 percent invest in domestic fixed income securities. Of those CEFs that invest internationally, 79.1 percent invest in foreign equities and 20.9 percent invest in foreign fixed income securities. The last two columns present a snapshot of the cross section of sample CEFs in the latest sample year, 2011. In 2011, the mean market value of equity (MVE) was $370 million for domestic CEFs, $336 million for foreign CEFs, and $140 million for miscellaneous CEFs. There were 192 domestic CEFs, 29 of which invested in equities and 163 of which invested in fixed income securities. 39 funds invested in foreign equities and 11 funds invested in foreign fixed income securities. The remaining 17 funds in the sample in 2011 invested in the miscellaneous category.

Figure 1 plots the time series of the number of CEFs contemporaneously included in the sample in the top panel and the time series of total assets under management of the sample funds in the bottom panel. Total assets under management for CEFs contemporaneously in the sample increase from $0.07 billion in 1984 to a high of $109 billion in 2007.

[Insert Table II and Figure 1 about here]

Table II presents statistics for the distribution of CEF premium observations for the full sample in Panel A and for a snapshot of the CEF market in December 2011. CEFs are also partitioned into domestic, foreign, equities, and fixed income subsamples in the table. CEFs generally trade at a discount. The full sample mean premium is -4.1 percent and the sample standard deviation is 22.4 percent. Premiums are lowest for CEFs investing domestically with a mean premium of -4.8 percent and they are greatest for CEFs investing in foreign securities. That funds investing internationally trade at larger premiums is consistent with the model of Cherkes, et al. (2009) where investors trade in the more easily accessible CEFs rather than trade in the less accessible underlying assets directly. In all partitions of the data, premiums are generally within the range of -15 percent to 5 percent, as indicated by the twenty-fifth and seventy-fifth percentiles.

Since Panel A contains both cross-sectional as well as time series variation in premiums, Panel B presents a snapshot to indicate what the purely cross-sectional dispersion of premiums looks like. This cross-sectional dispersion is arguably more important for our long-short trading strategy which capitalizes on premium mean reversion. The snapshot cross-sectional distribution shows that even in the cross-section there is a large dispersion of premium levels. Figure II presents a time-series plot of the premium for a representative CEF, the Templeton Emerging Markets Fund. Large time-series variation is also observed in premium levels. The representative fund's premium ranges from a low of -20 percent to a high of 35 percent. Informally, mean reverting behavior is also observed.

III Empirical Results

A. CEF Trading Strategy Implementation

When implementing the BMR model (based on eqns. (3a,b)), and the RADF model (based on eqns. (4a,b)), approximately the first one-third of the sample period is used as the base estimation period and the remaining two-thirds of the sample is used as the out-of-sample test period. The first out-of-sample predicted CEF return is February 1998. CEFs are required to have existed for at least 120 months prior to entering the sample and being used in the estimations of eqns. (3a,b) and (4a,b). Requiring a minimum fund life of 120 months provides a good compromise between parameter estimation precision and the avoidance of a survivorship bias. Expected returns are estimated in a cumulative rolling regression method. Since time $t + 1$ expected returns are estimated based only on information available at time t, expected returns are immune to look-ahead bias. After time $t + 1$ expected returns are estimated, CEFs are sorted into five equally weighted portfolios of CEFs based on expected returns. A long-short portfolio is formed by buying the quintile portfolio with the highest expected return and shorting the quintile portfolio with the lowest expected return. Returns using three different trading strategies are estimated: the first two strategies are from the two expected return models, i.e., the BMR model eqns. (3a,b) and the RADF model eqns. (4a,b), and the third is the benchmark case, the traditional naïve strategy of buying the portfolio of CEFs that trade at the lowest current premiums and selling the portfolio of CEFs that trade at the highest current premiums.

B. Mean Reversion in CEF Premiums

The following augmented Dickey-Fuller (ADF) regressions are used to test for mean reversion and to estimate the speed of mean reversion for each CEF individually:

$$\Delta prem_{i,t} = \alpha_i + \beta_i prem_{i,t-1} + \sum_{j=1}^{k_i} \gamma_{i,j} \Delta prem_{i,t-j} + \varepsilon_{i,t} \tag{5}$$

where Δ is the difference operator. The optimal lag length, k_i, is chosen using the Campbell and Perron (1991) method. The tau statistic to test for mean reversion in CFE premiums is computed as $\tau = \frac{\hat{\beta}}{\hat{\sigma}_{\beta}}$.

The estimated mean reversion coefficients and tau-statistics to test for mean reversion in CEF premiums are presented in Panels A and B of Table III, respectively. The mean of the estimated mean reversion parameter β is -0.138. It is well-known that this parameter estimate is downward biased. To give an estimate of the bias, we simulate time series under the null hypothesis of a random walk with 100 observations, and estimate the β. With 10,000 replications, we estimate the average β to be -0.052, which is the estimated bias of the mean reversion speed under the null of no mean reversion.[3] This gives an average bias-adjusted parameter for our sample of CEFs of -0.086 (=-0.138+0.052). This implies an average half-life of 7.7 (=ln(0.5)/ln(1-0.086)) months for mean reversion in CEF premiums, a very fast speed. From the standard deviation, as well as the twenty-fifth and seventy-fifth percentiles of MRPs, we also observe the wide dispersion of mean reversion coefficients, indicating that the benchmark strategy ignores important heterogeneity in mean reversion speeds.

Under the null hypothesis of no mean reversion, the 5 percent critical value for the sample size of 100 is -2.89 (see Fuller, 1976, p.369). In Panel B, we can see that the null hypothesis can be rejected at the 5 percent significance level in favor of mean reversion in fund premium for approximately 50 percent of CEFs[4]. When CEFs are partitioned by fund type, the mean tau statistic

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[3] Balvers, et al. (2000) suggest estimating the bias under the alternative of mean reversion. We choose not to pursue such a strategy because it would require running a separate set of simulation for each of the CEFs in our sample. We do not expect the difference to be large.

[4] We acknowledge that ADF-type tests have very low power to reject the null hypothesis of a random walk in favor of the alternative of mean reversion in small and moderate samples. See, e.g., Cochrane (1991), and DeJong et al. (1992).

is significant at least at the 5 percent level of those CEFs that invest domestically, internationally, in equities, and in fixed income securities, respectively. These results indicate that funds in the miscellaneous category tend to have less significant mean reversion speeds that make the full sample mean tau statistic somewhat less significant. While the tau-statistics have wide dispersion across funds, there is little evidence of explosive behavior (i.e., $\beta>0$) in fund premium in our sample. Under the null hypothesis of random walk, the 5 percent critical value against the alternative of explosive behavior is -0.08 (see Phillips, et al., 2011, p.213).

Table IV presents statistics of annualized mean monthly returns across CEFs. Mean returns for the full sample are presented in the first row. The remaining rows present annualized mean monthly returns for CEFs that invest primarily domestically, internationally, in equities, and in fixed-income securities, respectively. In general, returns of international funds are more volatile than domestic funds. Unconditionally, the annualized mean return for equities CEFs is 10.4 percent and the annualized mean return for fixed-income CEFs is 7.5 percent. Equity funds also have higher volatility than fixed-income funds. This is broadly consistent with the equity risk premium.

[Insert Table III and Table IV about here]

C. CEF Trading Strategy Returns

Table V presents portfolio performance for the benchmark trading strategy that buys the quintile portfolio of CEFs trading at the lowest current premiums and sells the quintile portfolio of CEFs trading at the highest current premiums with monthly rebalancing. The full sample annualized mean arbitrage return of the benchmark strategy is 14.9 percent and is statistically significant at the 1 percent level. The Sharpe ratio of the arbitrage portfolio is 1.519, which is larger than the market Sharpe ratio of 0.170 over the same period. This return from the benchmark strategy is similar to the strategy returns in Pontiff (1995). Both the long and the short legs of the arbitrage portfolio contribute roughly symmetrically. While the mean return on the portfolio of CEFs trading at the lowest premium outperforms the market by a statistically significant 9.3 percent, the mean return on the portfolio of CEFs trading at the highest premium underperforms the market and is not significantly different from zero.

The PTO, MVE, STO, and DVOL columns give statistics on portfolio turnover, portfolio mean CEF market value of equity, portfolio mean CEF share turnover, and portfolio mean CEF dollar trading volume, respectively. Portfolio positions turnover relatively infrequently with the long-short portfolio turning over at an annualized rate of 2.335 times. The mean CEF market-cap traded is $382.468 million, annualized mean share turnover is 63.8 percent, and annualized mean CEF dollar volume traded is $223.706 million. While CEF share turnover and dollar trading volume do not appear to be large, they coincide with the fourth and fifth deciles of NYSE stocks over the same sample period (not reported). In practice, there would have been sufficient liquidity for this trading strategy to have been a tradable one. The last column of Table V contains average Dickey-Fuller mean reversion parameter estimates (MRP), estimated in a cumulative rolling manner, for CEFs in each portfolio. Whereas the average mean reversion parameter for the full sample of CEFs is -0.117, it is -0.108 for the Q5-Q1 long-short portfolio. Given the estimated bias of 0.052 under the null hypothesis of a random walk reported in Section III.B, these mean reversion parameters correspond to a premium half-life of 10.32 months for the full sample of CEFs and a mean reversion speed of 12.03 months for CEFs in the Q5-Q1 long-short portfolio. The slower mean reversion speeds of CEFs in the Q5-Q1 portfolio provide evidence that neglecting heterogeneity in mean reversion parameters may result in suboptimal portfolio allocation.

[Insert Table V about here]

Table VI presents mean returns from the long-short strategies discussed in Section III.A using the full sample of CEFs and the BMR and RADF models to forecast expected CEF returns. The annualized mean return from the BMR long-short strategy is 17.3 percent. This is 2.4 percentage points greater than the benchmark strategy, indicating that important information about CEF return dynamics is lost by not allowing the coefficients in eqns. (3a,b) to be freely estimated. The Sharpe ratio for the BMR strategy is 1.862. Similar to the benchmark strategy, the long and short positions contribute roughly symmetrically to the mean return. Possible short sale restrictions cannot explain the magnitude of inefficiency as evidenced by the Q5-MRKT portfolio. The mean return from this strategy is 9.8 percent per annum and the Sharpe ratio is 0.795. In contrast to the benchmark strategy, the mean Dickey-Fuller mean reversion speed of CEFs in the Q5-Q1 portfolio is -0.154 (a half-life of 4.14 months), a much quicker mean reversion speed. Taking into account the heterogeneity in CEF mean reversion speeds substantially improves trading strategy returns over the benchmark model, which does not take into account mean reversion speed heterogeneity.

[Insert Table VI about here]

Portfolio mean returns from the trading strategy that uses the RADF model of expected returns are presented in Panel B. If the premium history beyond the current premium contains no explanatory power for returns, then mean returns in Panel B should match those in Panel A. The annualized mean return from the long-short strategy is 18.2 percent. The larger RADF returns indicate that inefficiency in the CEF market is more severe than previously documented and that the histories of premiums have explanatory power for returns. Expected CEF prices are not independent of the path that their premiums have taken. The Sharpe ratio of the Q5-Q1 RADF strategy is 1.918. Similarly to the benchmark model and the BMR model, the long and short portfolios contribute symmetrically to strategy returns. The long portfolio minus market portfolio strategy yields an annualized mean return of 10.7 percent, providing further evidence that short sale restrictions are not the source of predictable trading strategy returns. The mean Dickey-Fuller mean reversion speed of CEFs in the Q5-Q1 portfolio is -0.132 (a half-life of 4.9 months), providing evidence that the RADF model also optimally takes into account heterogeneous MRPs. Since the Q5-Q1 portfolio returns are larger using the RADF model than the BMR model, and since the traded CEF mean reversion speeds are similar, the large increase in trading strategy returns is the result of incorporating the information content of the historic path of premiums.

[Insert Figure 3 and Table VII about here]

Figure 3 plots the realized monthly strategy returns when the RADF model is used to forecast future CEF returns. The realized strategy returns appear to be randomly distributed over time, providing evidence that the excess returns from our long-short strategy are not being driven by tax-loss selling as documented by Brauer and Chang (1990) and Day, et al. (2011). Large return outliers are not present in the time series, suggesting that there is no evidence that a peso problem could explain the consistent arbitrage returns. It is interesting to note that during the 2001 recession following the tech-bubble crash and during the recent 2007-2009 financial crisis, our RADF strategy would have provided a good hedge against the generally falling markets. In an efficient market, an investor should not be able to obtain such predictable returns.

Table VII presents realized mean returns by ex-ante expected return-sorted CEF quintile in Panel A and tests for a monotonic relationship between mean trading returns and mean ex-ante expected return estimated from the RADF model in Panel B. Only mean quintile returns for quintiles one and two are not significantly different from zero. The first row in Panel A shows that the mean number of CEFs per quintile is approximately 25. Quintiles are well diversified and trading returns are not being driven by a small subset of CEFs. Two tests for monotonicity in returns are conducted: one parametric and one non-parametric. The parametric test is a regression of mean quintile return on a constant and a trend variable ascending from one to five. The non-parametric test is Kendall's rank correlation test[5]. Kendall's tau is bound between -1 and 1. If the rankings of two variables, in this case trading mean returns and forecasted returns, agree in ascending ranking completely, then Kendall's tau equals 1. If they have a completely reversed ranking relationship, then Kendall's tau equals -1. Both tests of monotonic trend indicate that portfolio returns are significantly monotonically higher for CEF quintiles with higher forecasted returns. The trend test indicates that an investor earns an annualized 4.3 percentage points more in expected return by moving to an adjacent quintile with greater forecasted return.

[Insert Table VIII about here]

Since parameters are required to be estimated in the BMR and RADF models, their forecasting ability should be increasing in the time-series length of CEFs because a higher precision in parameter estimation can be obtained with more observations. Table VIII presents mean returns for the benchmark, BMR, and RADF trading strategies conditioned on the minimum number of observations a CEF is required to have prior to entering the sample. The RADF model outperforms both the BMR and the benchmark models when the minimum number of CEF observations is greater than or equal to 120 months. Similarly, the BMR model outperforms the benchmark model when the minimum number of observations required for a CEF to enter the sample is greater than or equal to 120 months. When the required number of observations for a CEF to enter the sample is 36 months or 60 months, the benchmark model outperforms both the BMR model and the RADF model. Even with these short in-sample periods, however, the RADF model obtains mean returns that are approximately equal to those of the benchmark model. That

[5] See Kendall (1938) for test details.

the forecasting performance of the BMR and RADF models improves relative to the benchmark strategy as the minimum in-sample period lengthens indicates that our models are asymptotic in nature. In small samples, there exists a trade-off between proper model specification and estimation precision. How well the parametric model performs relative to the non-parametric one in an actual sample is an empirical question.

D. Risk-Adjusted Returns

This subsection tests if the trading strategy returns reported in the previous section could be the result of taking on greater systematic risks. In the absence of arbitrage opportunities, risk-discounted portfolio returns have a price of zero, i.e.,

$$\boldsymbol{E}\left[m_{t+1} r_{p,t+1}^{e}\right] = 0 \qquad (6)$$

where $r_{p,t+1}^{e}$ is the portfolio excess return and m_{t+1} is the pricing kernel. m_{t+1} is restricted to be linear in k factors

$$m_{t+1} = 1 - \sum_{i=1}^{k} b_i f_{i,t+1} \qquad (7)$$

where $b_i = \boldsymbol{CV}\left[f_{i,t+1}, r_{p,t+1}^{e}\right] / \boldsymbol{V}\left[f_{i,t+1}\right]$, $\boldsymbol{CV}[\cdot]$ is the covariance operator, and $\boldsymbol{V}[\cdot]$ is the variance operator. Eqn. (7) implies a beta pricing model for expected excess returns. The pricing kernel in eqn. (7) is taken in this paper to be the factor model of Fama and French (1993) augmented with the Carhart (1997) winners-minus-losers (WML) factor and the Pástor and Stambaugh (2003) tradable liquidity (LIQ) factor (hereafter referred to as the FFCPS factor model)

$$m_{t+1} = 1 - b_1 r_{MRKT,t+1}^{e} - b_2 r_{SMB,t+1} - b_3 r_{HML,t+1} - b_4 r_{WML,t+1} - b_5 r_{LIQ,t+1} \qquad (8)$$

r^e_{MRKT} is the monthly excess return of the market portfolio over the risk-free rate, r_{SMB} is the monthly return on the small-minus-big (SMB) portfolio, r_{HML} is the monthly return on the high-minus-low (HML) book-to-market portfolio, r_{WML} is the monthly return on the WML portfolio, and r_{LIQ} is the monthly return on the LIQ portfolio.[6] Table IX presents results from regressing benchmark trading strategy returns on the FFCPS factors:

$$r^e_{p,t} = \alpha_p + \beta_{p,1} r^e_{MRKT,t} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t} \qquad (9)$$

[Insert Table IX about here]

Panels A and B of Table IX display results for the full sample of CEFs, using the benchmark trading strategy and the RADF trading strategy, respectively. The alphas (i.e., the risk-adjusted returns) for the long-short strategy are 14.8 percent and 17.4 for the benchmark and RADF strategies, respectively, each of which is statistically significant at the 1 percent level. The alphas are approximately equal to the mean returns, indicating that the FFCPS factors collectively have close to zero explanatory power for the benchmark trading strategy returns. In both panels, Q1 and Q5 returns load positively on the MRKT factor, SMB factor, and LIQ factor. Q1 and Q5 returns load negatively on the WML factor. Q1 returns load positively on the HML factor in the benchmark strategy and there is a negative factor loading on the HML factor for Q5 returns. The Q1 and Q5 returns in the RADF trading strategy do not obtain significant factor loadings on the HML factor. The positive factor loadings for the Q1 and Q5 portfolios indicates that the benchmark strategy tends to trade CEFs holding smaller securities, recent losers, and securities with greater liquidity risk. Once the arbitrage portfolios are formed, both benchmark strategy and RADF

[6] Throughout the paper, risk-adjusted returns obtained using the Fama and French (1993) three factors alone are similar. These results are not reported to conserve space.

strategy returns load significantly positively on the market factor and significantly negatively on the HML factor.

[Insert Table X about here]

Table X presents abnormal RADF trading strategy returns for the subsamples of domestic CEFs and foreign CEFs. Portfolio alphas using the sample of domestic CEFs are presented in Panel A and alphas using the sample of foreign CEFs are presented in Panel B. In Panel A, the annualized alpha for the long-short strategy in the domestic sample is 16.1 percent and the annualized alpha for the arbitrage portfolio in the foreign sample of CEFs, in Panel B, is 18.8 percent, both significant at the 1 percent level. Similarly to the benchmark strategy, in both panels, Q1 and Q5 returns load positively on the MRKT factor and load negatively on the WML factor. Once the arbitrage portfolio is formed, none of the factors obtain consistently significant loadings across samples. In summary, the large arbitrage trading strategy returns cannot be explained by commonly used risk factors and cannot be explained by selling domestic CEFs and buying foreign CEFs to obtain a market segmentation premium.

IV Robustness of the Findings

A. Equity Premium Puzzle Robustness

Since fixed-income securities are in general less risky with lower expected returns than equities securities, the long-short portfolio returns may be an artifact of the equity premium by systematically buying equities CEFs and selling fixed-income CEFs. Table XI presents portfolio alphas, obtained from regressing portfolio returns on the FFCPS factors, when CEFs are partitioned into a subsample of equities funds and a subsample of fixed-income funds. Only returns from the strategy using the optimal RADF model are presented to conserve space. The annualized abnormal long-short portfolio return for the equities subsample is 15.4 percent in Panel A. Q1, Q5, and long-short portfolio returns have significantly positive MRKT betas. MRKT betas for the Q1 and Q5 portfolios are 1.010 and 1.128, respectively. Panel B presents portfolio abnormal returns in the fixed-income subsample. The annualized alpha for the long-short strategy is 17.2 percent. Consistent with fixed-income securities being less variable than equities, Q1 and Q5 returns have MRKT betas of 0.171 and 0.091 (insignificantly different from zero) which are less than those obtained for equities CEFs. While portfolio alphas are slightly larger in the fixed-income funds case, the trading returns cannot be attributed to biased holdings in equities or fixed-income CEFs.

[Insert Table XI about here]

B. Sub-Period Robustness

That the CEF discount continues to be exploitable is puzzling since it was first documented more than 30 years ago. Table XII formally tests the sub-period consistency of returns by partitioning the full sample into two subsamples of equal observations. Trading return results are those obtained from using the RADF model. Given that investors were more fully aware of the potential returns that could be obtained by trading in CEFs in the second half of the sample, mean returns should be lower in the second half of the sample if the CEF market is efficient with rational learning. Contrary to this, however, there is no statistically significant difference between subsample mean returns. The annualized mean return for the long-short strategy in the first half of the sample is 18.8 percent and in the second half of the sample the respective annualized mean long-short return is 17.5 percent. The Q5 mean returns are statistically significantly different from zero in both halves of the sample, while the Q1 returns are insignificantly different from zero. The difference in returns between the first half of the sample and the second half is insignificantly different from zero in all cases. The Q5-MRKT returns are also statistically greater than zero and do not display a tendency to diminish over time. This evidence that such large arbitrage returns remain unexploited greatly deepens the CEF discount puzzle.

[Insert Table XII about here]

C. Holding Period Robustness

Table XIII presents cumulative abnormal portfolio returns, for holding periods of one, six, nine, twelve, eighteen, and twenty-four months. Note that these are holding-period returns and are *not* annualized. We test how long-lived the information content of premiums and premium innovations is. To conserve space, only FFCPS alphas are presented for trading strategy returns that use the RADF model. Even after twenty-four months there is evidence of return continuation in the arbitrage portfolio. Whereas the long-short mean return for a one-month holding period is 1.5 percent, the mean cumulative return for the twenty-four-month holding period is 10.2 percent. There is evidence of return reversal at the nine-month horizon. Mean cumulative monthly returns decrease from 2.0 percent for a six-month holding period to 1.2 percent (insignificantly different from zero) for a nine-month holding period. That returns remain significant with a holding period of twenty-four months (10.2 percent with a t-statistic of 5.338), however, indicates a high level of inefficiency.

[Insert Table XIII about here]

D. Closed-End Fund Momentum

As a further test of efficiency in the CEF market, we test for momentum effects. Given how long lasting the information content of premiums is, there may be momentum effects in the CEF market. Momentum appears in a wide range of asset classes. Jegadeesh and Titman (1993) first document momentum effects for equities. Momentum spillovers from the equities market to corporate bonds are found by Gebhardt, et al. (2005). Similarly, Okunev and White (2003) and Menkhoff, et al. (2012) report momentum effects for currencies. Asness, et al. (2013) provide comprehensive evidence of momentum effects for a wide range of asset classes, including for commodities. Since CEF premiums mean revert, it is not immediately obvious if momentum effects are present. If market prices and NAVs have similar variability, then momentum may exist. Alternatively, if market prices are much more variable than NAVs, then the effects of mean reversion in fund premiums can dominate and momentum effects are not likely.

Table XIV presents CEF returns from a momentum strategy that buys the quintile portfolio of CEFs with the highest previous period return and sells the quintile portfolio of CEFs with the lowest previous period return. Panel A presents returns from a simple random walk with drift strategy, as a benchmark case. Expected returns in this random walk case are modeled as

$$\boldsymbol{E}\left[r_{i,t+1}\right] = \left(t - t_{i,1} + 1\right)^{-1} \sum_{j=t_{i,1}}^{t} r_{i,j} \tag{10}$$

where $t_{i,1}$ is the first observation of the sample for the i'th CEF. Eqn. (10) models CEF expected return as the cumulative rolling mean return. CEFs are sorted into portfolios based on expected return and the long-short strategy is formed by buying the quintile portfolio with the highest expected return and selling the quintile portfolio with the lowest expected return. Annualized mean returns for portfolio sorts are roughly the same as market returns, as would be expected. Mean returns produced by the long-short strategy are insignificantly different from zero.

[Insert Table XIV about here]

Mean momentum strategy returns are presented in Panel B, where CEFs are sorted into quintile portfolios based on their mean returns over the past $h \in \{3, 6, 9, 12\}$ months and held for the same number of months. The annualized mean return for the long-short momentum portfolio is never significantly higher than zero for all holding periods. Returns in the portfolios of winners and losers tend to cancel each other out as is evidenced by the portfolio returns that buys the past winners and sells the market portfolio. Evidence provided in Table XIV suggests that momentum effects do not seem to exist in the CEF market. This is to be expected if premiums mean revert due to risky arbitrage.

V Conclusion

This paper provides new evidence on the magnitude of inefficiency in the CEF market that greatly deepens the discount puzzle. Our results relieve the traditional imposed assumption that only current premium has explanatory power for future CEF returns in favor of modeling CEF returns as being dependent on the optimally chosen history of premiums. A long-short trading strategy is formed that buys the quintile of CEFs with the highest expected returns and sells the quintile of CEFs with the lowest expected returns. Expected returns are estimated using two new methods that exploit different aspects of the information content of premiums. The first conditions returns on current premiums alone (BMR model) to capture simple mean reversion and the second is an ADF-style model of returns which conditions CEF returns on the history of premium innovations (RADF model) to capture the information content of premium dynamics.

Annualized arbitrage trading strategy returns are 17.3 percent for the BMR model and 18.2 percent for the RADF model, which are larger than the 14.9 percent benchmark CEF trading strategy return. Since portfolio returns using the RADF model are larger than those using the BMR model, the traditional view of modeling expected CEF returns dependent on only the current premium is rejected in favor of modeling expected returns as being dependent on premium path. Sharpe ratios for the strategies using the BMR and RADF models are 1.862 and 1.918, respectively, which are much larger than the Sharpe ratio of 0.170 for market returns and larger than the Sharpe ratio of 1.519 for the benchmark strategy returns.

In contrast to what would be expected in an efficient market with rational learning, returns are not time period sensitive. There is no statistically significant difference between mean returns in the first half of the sample and the second half. A number of robustness tests are conducted to test if the large CEF trading strategy returns result from taking on well-known systematic risks. Arbitrage trading returns cannot be explained by commonly used risk factors. Results are robust to considering subsamples of domestic funds and foreign funds, indicating that the strategy does not simply capture a market segmentation premium. Results are also robust to considering subsamples of equities funds and fixed-income funds, providing evidence that strategy returns are not a result of selling fixed-income CEFs and buying equities CEFs to capture the equity premium. Our findings indicate that inefficiency in the CEF market is far worse than previously thought and deserves further research attention.

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Table I
Sample Fund Categories and Types

This table presents the sample closed-end fund categories on the left-hand side of the table and a snapshot of the closed-end fund market in the latest sample year on the right-hand side. FREQ (%) indicates the number (percentage) of monthly observations in the sample that falls within a specified category or type. FUNDS lists the number of closed-end funds in each category and MVE is the mean market value of equity (in millions of dollars). The full sample is August 1984 to December 2011.

			Year 2011	
CATEGORY	FREQ	%	FUNDS	MVE
DOMESTIC	40,316	61.7	192	370
EQUITY		15.5	29	731
FIXED INCOME		84.5	163	293
FOREIGN	13,776	21.1	50	336
EQUITY		79.1	39	295
FIXED INCOME		20.9	11	496
MISCELLANEOUS	11,199	17.2	17	140

Table II
CEF Premium Statistics

This table presents CEF premium statistics. Panel A presents statistics for the full sample period and Panel B presents a snapshot for December 2011. N is the number of monthly observations, MEAN is the mean, MED is the median, SD is the standard deviation, Q25 (Q75) is the twenty-fifth (seventy-fifth) percentile, and MIN (MAX) is the minimum (maximum) premium. The sample period is August 1984 to December 2011.

	N	MEAN	MED	SD	Q25	Q75	MIN	MAX
Panel A: Full Sample Statistics								
All	63,537	-0.041	-0.047	0.224	-0.101	0.013	-1.000	2.642
Domestic	39,448	-0.048	-0.039	0.160	-0.086	0.014	-0.908	1.587
Foreign	13,398	-0.010	-0.077	0.373	-0.147	0.042	-1.000	2.642
Equities	14,300	-0.040	-0.080	0.387	-0.149	0.049	-1.000	2.642
Fixed Income	33,307	-0.041	-0.037	0.126	-0.080	0.011	-0.886	1.587
Panel B: 2011:12 Snapshot								
All	266	-0.025	-0.010	0.126	-0.089	0.029	-0.788	0.529
Domestic	200	-0.013	-0.001	0.130	-0.060	0.037	-0.788	0.407
Foreign	50	-0.089	-0.100	0.072	-0.117	-0.081	-0.385	0.098
Equities	67	-0.113	-0.106	0.132	-0.135	-0.079	-0.788	0.124
Fixed Income	174	0.003	0.006	0.100	-0.028	0.043	-0.750	0.297

Table III
CEF Premium Mean Reversion Coefficients

This table presents ADF tau-statistics for mean reversion in CEF premiums and the estimated mean reversion coefficients β_i obtained from estimating the following augmented Dickey-Fuller regressions:

$$\Delta prem_{i,t} = \alpha_i + \beta_i \, prem_{i,t-1} + \sum_{j=1}^{k_i} \gamma_{i,j} \Delta prem_{i,t-j} + \varepsilon_{i,t}$$

where Δ is the difference operator, $\tau = \frac{\hat{\beta}}{\hat{\sigma}_\beta}$. The optimal lag length, k_i, is chosen using the Campbell and Perron (1991) method. Under the null hypothesis, the mean value of the estimated β_i is -0.052. Mean reversion parameters, β_i, are presented in Panel A, and tau-statistics are presented in Panel B. The ADF model is estimated for each CEF using its respective full sample of observations. The 5 percent critical value for the null hypothesis of no mean reversion for a sample size of 100 is -2.89. N is the number of CEFs, MEAN is the mean value, MED is the median value, SD is the standard deviation, Q25 (Q75) is the twenty-fifth (seventy-fifth) percentile, and MIN (MAX) is the minimum (maximum) value. The sample period is August 1984 to December 2011.

	N	MEAN	MED	SD	Q25	Q75	MIN	MAX
Panel A: Mean Reversion Parameters (MRP) β								
All	334	-0.138	-0.120	0.079	-0.171	-0.085	-0.541	-0.002
Domestic	202	-0.139	-0.122	0.075	-0.174	-0.085	-0.541	-0.027
Foreign	64	-0.135	-0.127	0.078	-0.165	-0.094	-0.534	-0.030
Equities	69	-0.121	-0.108	0.061	-0.168	-0.070	-0.281	-0.034
Fixed Income	161	-0.136	-0.126	0.065	-0.166	-0.089	-0.444	-0.030
Panel B: Mean Reversion Tau Statistics τ								
All	334	-2.863	-2.878	0.879	-3.319	-2.393	-8.256	-0.053
Domestic	202	-2.913	-2.919	0.757	-3.294	-2.475	-5.287	-0.810
Foreign	64	-3.130	-3.018	1.024	-3.603	-2.505	-8.256	-0.925
Equities	69	-2.906	-2.886	0.841	-3.465	-2.359	-5.368	-0.955
Fixed Income	161	-3.017	-2.970	0.739	-3.399	-2.531	-5.287	-0.925

Table IV
CEF Expected Return Statistics

This table presents statistics for annualized unconditional monthly mean returns for the CEF sample. N is the number of CEFs, MEAN is the mean value, MED is the median value, SD is the standard deviation, Q25 (Q75) is the twenty-fifth (seventy-fifth) percentile, and MIN (MAX) is the minimum (maximum) value. The sample period is August 1984 to December 2011.

	N	MEAN	MED	SD	Q25	Q75	MIN	MAX
All	336	0.079	0.073	0.046	0.064	0.095	-0.241	0.244
Domestic	202	0.074	0.073	0.038	0.066	0.084	-0.241	0.212
Foreign	65	0.105	0.107	0.061	0.066	0.145	-0.111	0.244
Equities	69	0.104	0.100	0.056	0.066	0.132	-0.106	0.244
Fixed Income	162	0.075	0.073	0.024	0.067	0.083	-0.066	0.152

Table V
Benchmark Returns

This table presents portfolio performance from the benchmark trading strategy that buys the quintile portfolio of CEFs trading at the lowest premiums and sells the quintile portfolio of CEFs trading at the highest premiums. Portfolios are rebalanced monthly. Q5 denotes the quintile of CEFs with the lowest premiums, Q1 denotes the quintile of CEFs with the highest premiums, and MRKT denotes market returns. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions of dollars. MRP is the mean Dickey-Fuller mean reversion parameter for CEFs in a portfolio. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.148***	0.735	2.126	371.855	0.593	190.802	-0.119
	(3.339)						
Q1	-0.001	-0.180	2.543	393.081	0.682	256.609	-0.098
	(-0.013)						
Q5-Q1	0.149***	1.519	2.335	382.468	0.638	223.706	-0.108
	(5.667)						
Q5-MRKT	0.093***	0.854	.	.	.	.	.
	(3.185)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.117

Table VI
Trading Strategy Returns: Full Sample Results

This table presents portfolio performance from trading strategies using the full sample of CEFs. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns and portfolios are rebalanced monthly. In Panel A, expected returns are obtained from eqns. (3a,b) and in Panel B expected returns are obtained from eqns. (4a,b). Q5 (Q1) denotes the quintile of CEFs with the highest (lowest) expected returns and MRKT denotes market returns. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions dollars. MRP is the mean Dickey-Fuller mean reversion parameter for CEFs in a portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: BMR Model							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.153***	0.785	2.675	311.850	0.626	196.309	-0.148
	(3.543)						
Q1	-0.020	-0.332	3.204	301.989	0.571	164.342	-0.159
	(-0.541)						
Q5-Q1	0.173***	1.862	2.939	306.919	0.598	180.325	-0.154
	(6.946)						
Q5-MRKT	0.098***	0.795	.	.	.	.	.
	(2.967)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.133
Panel B: RADF Model							
PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.163***	0.829	5.686	322.454	0.654	217.767	-0.128
	(3.695)						
Q1	-0.019	-0.321	5.964	309.417	0.572	171.416	-0.137
	(-0.503)						
Q5-Q1	0.182***	1.918	5.825	315.936	0.613	194.591	-0.132
	(7.154)						
Q5-MRKT	0.107***	0.871	.	.	.	.	.
	(3.250)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.117

Table VII
Monotonicity in Returns

This table presents results from monotonicity tests of closed-end fund optimal trading strategy returns. Q5 (Q1) denotes the quintile of CEFs with the highest (lowest) expected returns. Expected returns are obtained from eqns. (4a,b), i.e., the RADF model. Panel A presents annualized realized portfolio mean returns. Panel B reports the trend test result from the following regression:

$$\bar{r}_p = \alpha + \beta x + \varepsilon$$

where $x = (1,2,3,4,5)'$. TAU is the measure of rank correlation between realized portfolio mean returns and quintile number using the Kendall (1938) methodology. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Portfolio Returns					
	Q1	Q2	Q3	Q4	Q5
N	24.994	25.263	25.347	25.263	25.665
MEAN RETURN	-0.019	0.042	0.086***	0.109***	0.163***
T-STAT	(-0.503)	(1.307)	(2.764)	(3.323)	(3.695)

Panel B: Monotonicity Tests		
α	β	TAU
-0.053***	0.043***	1.000***
(-4.821)	(12.957)	(<0.010)

Table VIII
Selection Bias Robustness

This table presents mean portfolio returns from trading strategies varying the minimum number of observations that a CEF is required to have prior to entering the sample. The benchmark trading strategy buys the quintile portfolio of CEFs that are trading at the lowest premiums and sells the quintile portfolio of CEFs that are trading at the highest premiums. The BMR and RADF strategies buy the quintile with highest expected return and sell the quintile with lowest expected return where expected returns are estimated using eqns. (3a,b) for the BMR model and eqns. (4a,b) for the RADF model. MINOBS denotes the minimum number of observations that a CEF is required to have prior to entering the sample. All out-of-sample periods end December 2011. The out-of-sample period begins January 1995 when MINOBS is 36 and 60, February 1998 when MINOBS is 120, February 2003 when MINOBS is 180, and February 2008 when MINOBS is 240. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

MINOBS	Benchmark	BMR	RADF
36	0.155***	0.142***	0.153***
	(6.158)	(5.578)	(6.807)
60	0.159***	0.139***	0.153***
	(5.940)	(5.428)	(6.468)
120	0.149***	0.158***	0.182***
	(5.667)	(6.946)	(7.154)
180	0.137***	0.144***	0.171***
	(4.508)	(4.356)	(5.269)
240	0.121*	0.158	0.201**
	(1.793)	(1.629)	(2.399)

Table IX
Abnormal Returns: Full Sample Abnormal Returns

This table presents results from regressing benchmark trading strategy returns on the three Fama and French (1993) factors, the Carhart (1997) winners-minus-losers factor, and the Pástor and Stambaugh (2003) tradable liquidity factor:

$$r_{p,t}^{e} = \alpha_p + \beta_{p,1} r_{MRKT,t}^{e} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The benchmark trading strategy buys the quintile portfolio of CEFs trading at the lowest premiums (denoted by Q5) and sells the quintile portfolio of CEFs that are trading at the highest premiums (denoted by Q1). The RADF strategy buys the quintile with highest expected return and sell the quintile with lowest expected return where expected returns are estimated using eqns. (4a,b). Portfolios are rebalanced monthly. The alphas are annualized. Panel A uses the benchmark trading strategy and Panel B uses the RADF trading strategy. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Benchmark Strategy						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.086***	0.644***	0.147**	-0.128**	-0.125***	0.194***
	(3.335)	(13.560)	(2.422)	(-2.075)	(-3.397)	(3.951)
Q1	-0.062**	0.507***	0.144**	0.136*	-0.117***	0.151***
	(-2.132)	(9.398)	(2.088)	(1.936)	(-2.792)	(2.704)
Q5-Q1	0.148***	0.137***	0.003	-0.264***	-0.008	0.043
	(6.095)	(3.045)	(0.051)	(-4.525)	(-0.236)	(0.929)
Panel B: RADF Strategy						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.100***	0.590***	0.141**	-0.079	-0.123***	0.204***
	(3.388)	(10.840)	(2.022)	(-1.115)	(-2.909)	(3.619)
Q1	-0.074***	0.431***	0.140**	0.093	-0.161***	0.147***
	(-2.665)	(8.389)	(2.131)	(1.395)	(-4.047)	(2.766)
Q5-Q1	0.174***	0.159***	0.001	-0.172***	0.038	0.057
	(7.198)	(3.565)	(0.014)	(-2.965)	(1.110)	(1.230)

Table X
Abnormal Returns: Domestic and Foreign CEFs

This table presents results from regressing RADF trading strategy returns on the FFCPS factors using the full sample of CEFs in Panel A, the subset of domestic CEFs in Panel B, and the subset of foreign CEFs in Panel C. The regression model is

$$r_{p,t}^{e} = \alpha_p + \beta_{p,1} r_{MRKT,t}^{e} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The alphas are annualized. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4a,b) and portfolios are rebalanced monthly. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Domestic Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.098***	0.295***	0.088	0.082	-0.113***	0.152***
	(3.600)	(5.835)	(1.360)	(1.243)	(-2.883)	(2.913)
Q1	-0.063**	0.279***	0.094	0.049	-0.120***	0.133***
	(-2.389)	(5.709)	(1.509)	(0.775)	(-3.168)	(2.628)
Q5-Q1	0.161***	0.015	-0.007	0.032	0.007	0.019
	(7.826)	(0.401)	(-0.136)	(0.651)	(0.248)	(0.485)
Panel B: Foreign Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.101**	1.071***	0.198*	-0.075	-0.113*	0.253***
	(2.145)	(12.239)	(1.773)	(-0.660)	(-1.663)	(2.788)
Q1	-0.087	0.987***	0.142	0.129	-0.171**	0.141
	(-1.572)	(9.680)	(1.093)	(0.972)	(-2.168)	(1.330)
Q5-Q1	0.188***	0.084	0.056	-0.204*	0.059	0.112
	(4.206)	(1.021)	(0.528)	(-1.897)	(0.912)	(1.310)

Table XI
Abnormal Returns: Equities and Fixed Income Samples

This table presents results from regressing RADF trading strategy returns on the FFCPS three factors:

$$r_{p,t}^{e} = \alpha_p + \beta_{p,1} r_{MRKT,t}^{e} + \beta_{p,2} r_{SMB,t} + \beta_{p,3} r_{HML,t} + \beta_{p,4} r_{WML,t} + \beta_{p,5} r_{LIQ,t} + \varepsilon_{p,t}$$

The alphas are annualized. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4a,b) and portfolios are rebalanced monthly. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. Panel A presents results when the subsample of equity CEFs is used. Panel B reports results when the subsample of fixed-income CEFs is used. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Equities CEF Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.108***	1.128***	0.198**	0.066	-0.108**	0.242***
	(2.859)	(16.106)	(2.222)	(0.724)	(-1.993)	(3.332)
Q1	-0.046	1.010***	0.101	0.180*	-0.119*	0.131
	(-1.089)	(12.834)	(1.011)	(1.766)	(-1.957)	(1.600)
Q5-Q1	0.154***	0.118*	0.097	-0.114	0.011	0.112*
	(4.486)	(1.856)	(1.194)	(-1.383)	(0.226)	(1.687)
Panel B: Fixed Income CEF Sample						
PORTFOLIO	ALPHA	MRKT	SMB	HML	WML	LIQ
Q5	0.113***	0.091	0.123*	0.079	-0.113**	0.143**
	(3.645)	(1.595)	(1.679)	(1.066)	(-2.562)	(2.428)
Q1	-0.060*	0.171***	0.141*	0.078	-0.132***	0.131**
	(-1.907)	(2.947)	(1.897)	(1.049)	(-2.958)	(2.202)
Q5-Q1	0.172***	-0.079**	-0.018	0.000	0.019	0.012
	(8.591)	(-2.139)	(-0.371)	(0.007)	(0.667)	(0.308)

Table XII
Sample Period Robustness

This table presents portfolio returns from the RADF trading strategy using the first half of the sample (denoted by H1) and the second half of the sample (denoted by H2). The difference between them is denoted by DIF. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4a,b) and portfolios are rebalanced monthly. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

PORTFOLIO	H1	H2	DIF
Q5	0.163***	0.163***	0.000
	(2.611)	(2.599)	(-0.001)
Q1	-0.025	-0.012	-0.013
	(-0.479)	(-0.230)	(-0.175)
Q5-Q1	0.188***	0.175***	0.013
	(5.559)	(4.596)	(0.255)
Q5-MRKT	0.101**	0.114**	-0.012
	(2.165)	(2.420)	(-0.182)

Table XIII
Portfolio Returns with Varying Holding Periods

This table presents the alphas from regressing portfolio strategy cumulative returns over the holding period from t to $t+h$ on the FFCPS factors:

$$r^e_{p,t:t+h} = \alpha_p + \beta_{p,1} r^e_{MRKT,t:t+h} + \beta_{p,2} r_{SMB,t:t+h} + \beta_{p,3} r_{HML,t:t+h} + \beta_{p,4} r_{WML,t:t+h} + \beta_{p,5} r_{LIQ,t:t+h} + \varepsilon_{p,t:t+h}$$

The alphas for the various holding periods are *not* annualized. MRKT is the excess market return, SMB is the small-minus-big portfolio, HML is the high-minus-low book-to-market portfolio, WML is the winners-minus-losers portfolio, and LIQ is the tradable liquidity portfolio. CEFs are sorted into quintile portfolios of equally-weighted CEFs based on expected returns obtained from eqns. (4a,b). t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

	Holding Period *h* (in months)					
Portfolio	1	6	9	12	18	24
Q5	0.008***	0.022***	0.024***	0.042***	0.054***	0.066***
	(3.388)	(3.703)	(3.199)	(4.908)	(4.426)	(4.333)
Q1	-0.006***	0.002	0.012*	-0.002	-0.014	-0.036**
	(-2.665)	(0.372)	(1.719)	(-0.279)	(-1.251)	(-2.420)
Q5-Q1	0.015***	0.020***	0.012	0.044***	0.068***	0.102***
	(7.198)	(3.172)	(1.405)	(4.438)	(4.690)	(5.338)
Q5-MRKT	0.008***	0.022***	0.024***	0.042***	0.054***	0.066***
	(3.388)	(3.703)	(3.199)	(4.908)	(4.426)	(4.333)

Table XIV
CEF Momentum Strategy

This table presents portfolio performance from trading strategies using the full sample of CEFs. In Panel A, CEFs are sorted into quintile portfolios of equally-weighted CEFs based on mean returns over the entire past history (random walk strategy). In Panel B, CEFs are sorted into quintile portfolios of equally-weighted CEFs based on cumulative returns over the previous *h* months (momentum strategy), and portfolios are held for *h* months, where *h* = 3, 6, 9, and 12. MEAN is average return, SHARPE is Sharpe ratio, PTO is portfolio turnover, STO is CEF share turnover, and DVOL is dollar trading volume in millions, each of which is annualized. MVE is CEF market-cap in millions of dollars. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample period is February 1998 to December 2011.

Panel A: Portfolio Performance of Random Walk Strategy

PORTFOLIO	MEAN	SHARPE	PTO	MVE	STO	DVOL	MRP
Q5	0.091	0.292	0.620	462.077	0.810	336.998	-0.096
	(1.525)						
Q1	0.087***	0.508	1.621	211.394	0.513	121.734	-0.125
	(2.739)						
Q5-Q1	0.005	0.027	1.121	336.735	0.661	229.366	-0.111
	(0.103)						
Q5-MRKT	0.036	0.316	.	.	.	.	.
	(1.180)						
MRKT	0.055	0.170	.	.	.	.	.
	(1.199)						
FULL SAMPLE	.	.	.	284.831	0.596	162.238	-0.110

Panel B: Mean Return of Momentum Strategy

	Holding Period *h* (in months)			
PORTFOLIO	3	6	9	12
Q5	0.094***	0.082***	0.073***	0.085***
	(3.274)	(4.094)	(3.952)	(4.807)
Q1	0.059*	0.074***	0.099***	0.112***
	(1.866)	(2.898)	(5.116)	(8.018)
Q5-Q1	0.035	0.008	-0.026	-0.027*
	(1.227)	(0.381)	(-1.475)	(-1.646)
Q5-MRKT	0.043**	0.034**	0.021*	0.033***
	(1.993)	(2.102)	(1.647)	(2.958)

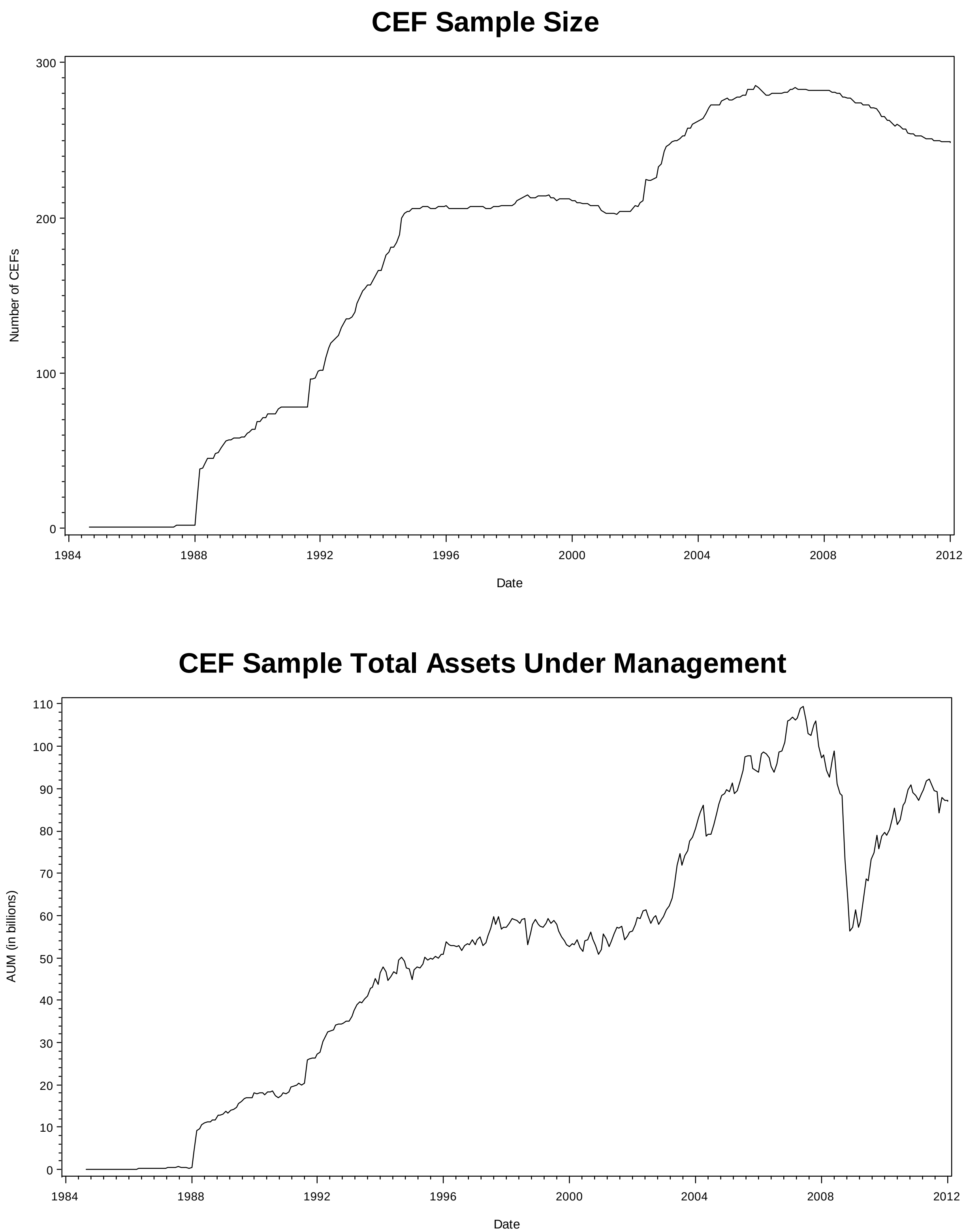

Figure 1. Time Series of Closed-End Fund Sample Size. This figure plots the time series of CEF sample size in the top panel and the time series of total assets under management of the CEF sample in the bottom panel.

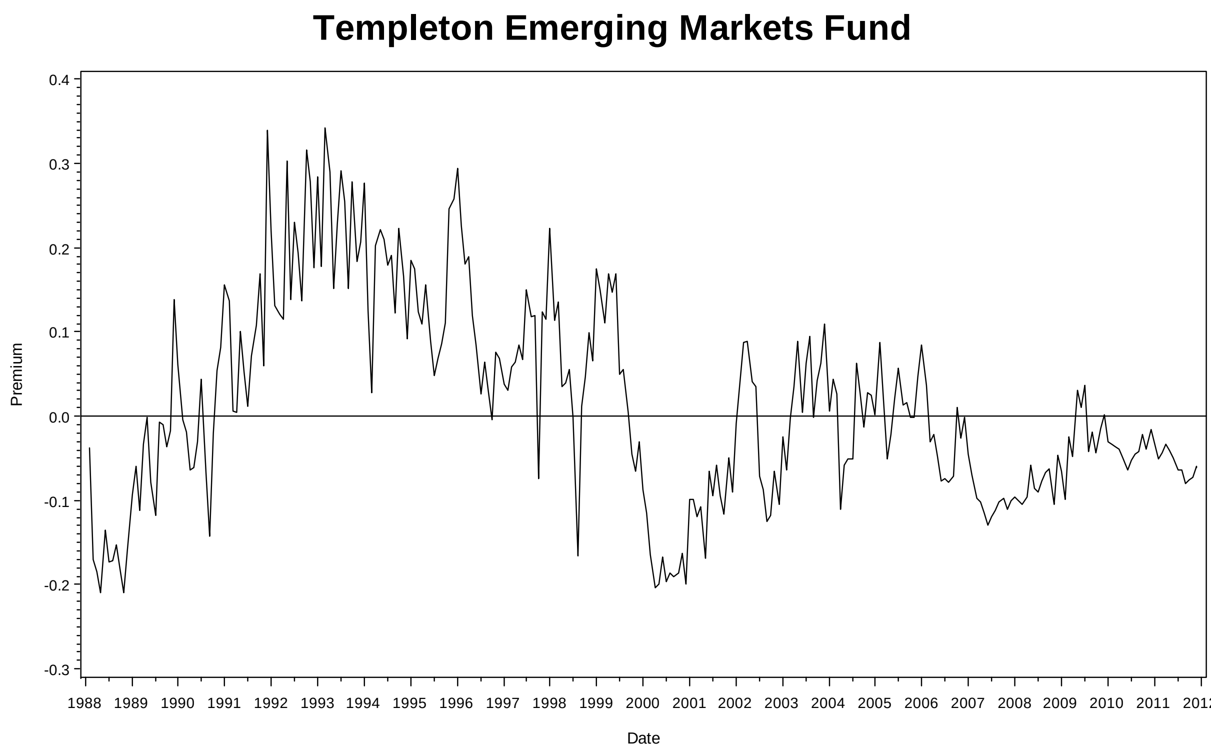

Figure 2. Time Series of Representative CEF Premium. This figure presents a time series plot of a representative CEF's premium. The representative CEF is the Templeton Emerging Markets Fund.

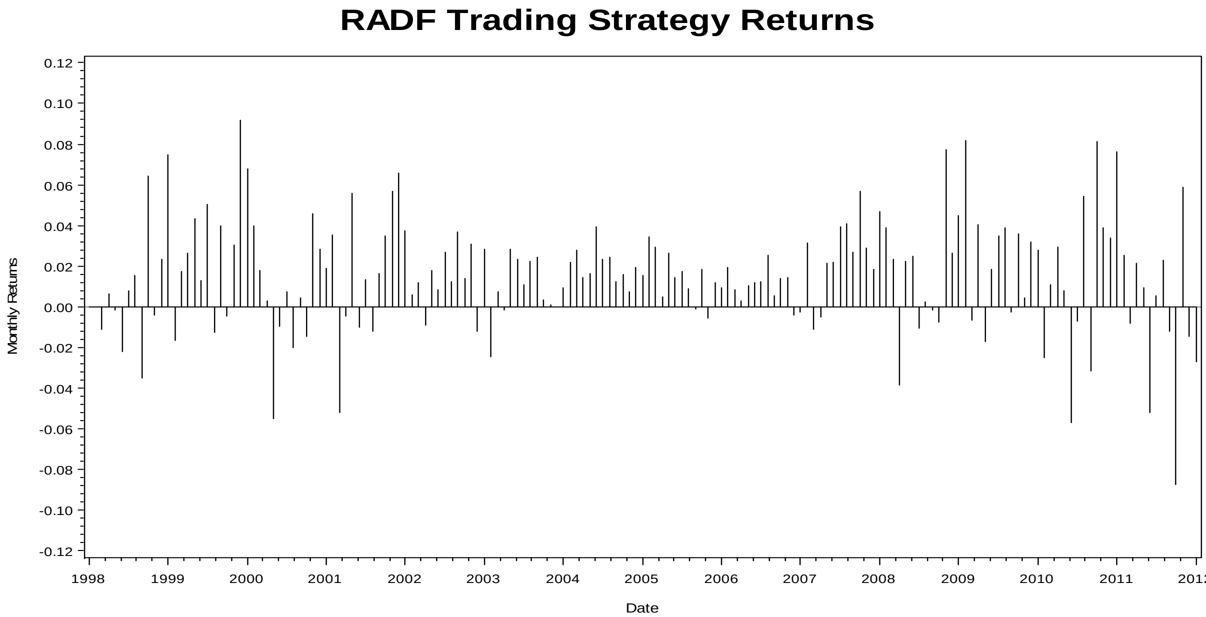

Figure 3. Monthly Returns. This figure plots monthly trading strategy returns for the Q5-Q1 portfolio using the RADF model. Portfolios are equally weighted and rebalanced monthly. The out of sample period is February 1998 to December 2011.