EXPLORING THE PERSISTENCE OF U.K. EQUITY CLOSED-END FUND PERFORMANCE

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ABSTRACT

This paper examines whether there is any persistence in the value added by U.K. closed-end funds with domestic equity objectives. There is some short-term persistence in value added by the best performing funds when ranking funds by the past Jensen (1968) performance where past performance is divided by residual volatility. However the persistence in value added by funds is short term and disappears after one year. There is also persistence in performance ability by funds when using Net Asset Value (NAV) excess returns. In contrast to open-end mutual fund performance persistence studies, there is no support that there any closed-end funds which consistently destroy value to investors.

I Introduction

There are a large number of studies that examine the persistence in performance of U.S. mutual funds such as Grinblatt and Titman (1992), Elton, Gruber and Blake (1996), Carhart (1997), Cohen, Coval and Pastor (2005), Busse and Irvine (2006), Elton et al (2011,2012) among others. Studies by Fletcher and Forbes (2002) and Cuthbertson, Nitzsche and O'Sullivan (2012) among others examine the persistence in performance of U.K. unit trusts.[1] The prior literature suggests that there is persistence in the relative rankings of open-end fund performance between one period and the next. There is also persistence in inferior fund performance (e.g. Carhart). However whether there is persistence in superior fund performance is less clear as the empirical evidence is more mixed on this issue. There are some studies which suggest that the best performing funds in the past can deliver significant superior performance in the future (Gruber (1996), Kosowski, Timmermann, White and Wermers (2006), Elton et al (1996,2011,2012)).[2]

In contrast to the large body of evidence of the persistence in open-end fund performance, there is little prior literature on the persistence in closed-end fund[3] performance. Prior studies by Bers and Madura (2000) examine the persistence in U.S. closed-end fund performance and Bal and Leger (1996), Dimson and Minio-Paluello (2001), Guirguis (2010), and Bredin, Cuthbertson, Ntizsche and Thomas (2014) examine the persistence in U.K.

[1] Unit trusts are equivalent to open-end U.S. mutual funds.

[2] Cuthbertson et al (2010) provide an excellent overview of the empirical evidence of the performance of open-end U.S. and U.K. mutual funds. See also Elton and Gruber (2013) for a review of U.S. open-end and closed-end mutual funds, and exchange-traded funds.

[3] Closed-end funds are known as investment trusts in the U.K..

closed-end fund performance.[4] In this study, I contribute to this gap in the literature by examining the persistence in performance of U.K. closed-end funds with U.K. equity objectives. This approach differs from the earlier U.K. studies where their samples of funds combine both domestic equity and international equity closed-end funds. I also evaluate the performance of the closed-end funds using domestic linear factor models rather than using global factor models[5] as in Bredin et al.

Why examine the persistence in closed-end fund performance? One reason for examining persistence is that management ability is priced in closed-end funds but not in open-end funds since funds are priced at Net Asset Value (NAV) (Gruber (1996)). Berk and Stanton (2007) argue that since management ability can be priced in closed-end fund stock returns, we should not find persistence in performance using stock returns. Gruber (1996) and Elton, Gruber and Busse (1998) note that the risk and return characteristics of closed-end fund stock returns differs from the risk and return characteristics of the underlying assets that they hold. As a result, we might find persistence or reversals in closed-end fund performance using stock returns due to the momentum or contrarian effects in stock returns that is independent of the trading decisions of closed-end fund managers.

I examine whether there is any persistence in closed-end fund performance using a variety of past performance measures including average excess returns or market-adjusted excess returns, and the Jensen (1968) performance. In most of my tests, I rank funds by the

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[4]Related studies of U.K. closed-end fund performance include Bangassa (1999), Bangassa, Su and Joseph (2012), and Fletcher and Marshall (2014) among others.

[5] Griffin (2002) finds that local versions of the Fama and French (1993) model are more reliable in pricing domestic stock returns rather than global factor models. Fama and French (2012) find that regional versions of the Fama and French (1993) and Carhart (1997) models are more reliable in pricing regional stock returns than global versions of the models.

past performance divided by residual volatility to control for the precision by which the measures are estimated (Kosowski et al, Fama and French (2010)). I consider whether there is any persistence in the short run or long run for up to three years after portfolio formation. I use the Jensen (1968) performance measure to evaluate the out-of-sample performance of the fund portfolios. To evaluate the performance of the funds, I select the linear factor model which has the best performance in correctly assigning zero performance to passive portfolios (Grinblatt and Titman (1989), Chen and Knez (1996)) using the Gibbons, Ross and Shanken (1989) mean-variance efficiency tests. I initially consider five alternative factor models based on the capital asset pricing model (CAPM), the empirical models of Fama and French (1993) and Carhart (1997), the five-factor model of Fama and French (2014a,b), and a six-factor model which includes the five-factor model of Fama and French augmented with the momentum factor (CarhartA model).

There are four main findings in my study. First, the Carhart (1997) and CarhartA models do the best job in correctly assigning zero performance to passive portfolios, although all the factor models are formally rejected. As a result, I use the CarhartA model to evaluate the performance of the closed-end funds. Second, when ranking funds by the past average excess returns or market-adjusted excess returns during the prior 12 months, there is some persistence in mean excess returns but this persistence is driven by the factor betas on the momentum factor. Third, there is significant persistence in value added when ranking funds by the Jensen (1968) performance. However this persistence is short-run and disappears after one year. There is also significant persistence in the performance ability by the closed-end funds. Fourth, there is little evidence of persistence in inferior performance by closed-end funds.

The paper is organized as follows. Section II describes the research method of the paper. Section III discusses the data used in my study. Section IV reports the empirical results. The final section concludes.

II Research Method

I evaluate the persistence in closed-end fund performance using the portfolio approach of Carhart (1997) as adapted by an earlier version of the Fama and French (2010) study.[6] At the start of each month between 1990 and 2012, I estimate the past performance of each fund with continuous monthly return data during the estimation window. All funds are then ranked and grouped into quartile portfolios with an equal number of funds in each portfolio as an approximation. I calculate the monthly buy and hold return for each portfolio during the next 36 months. I set the initial weights in each portfolio to be equal weighted. If a trust dies during the next 36 months or has missing return data, I assign a zero return to that month following Liu and Strong (2008). I use a calendar-based approach to calculate portfolio returns over a multi-month period. The portfolio return at time t over a multi-month interval is given by the EW average of the monthly returns at time t for portfolios formed during the interval. As an example, consider the 4-6 months horizon after portfolio formation. The month t return on this portfolio is given by the average of the month t returns on the portfolios of funds formed during the past 4 to 6 months. I use the one-month Treasury Bill return to calculate the excess returns on the portfolios.

I evaluate the out-of-sample performance of the closed-end portfolios over different multi-month horizons. I focus on excess returns for the first three months, the second, third, and fourth quarters after portfolio formation, and the first, second, and third year after portfolio formation. My main focus is on the performance of the quartile portfolios with the best past performing funds (Winners) and the worst past performing funds (Losers). My

[6] The earlier version of their paper was titled Mutual Fund Performance.

main performance measure is to use the Jensen (1968) performance[7] of each portfolio relative to a linear factor model. The Jensen performance is given by:

$$r_{pt} = \alpha_p + \Sigma^{K}_{k=1}\beta_{pk}r_{kt} + e_{pt} \tag{1}$$

where r_{pt} is the excess return of the closed-end fund portfolio p during period t, r_{kt} is the excess return on factor k during period t for k=1,…,K, e_{pt} is a random error term during period t, K is the number of factors in the linear factor model, and β_{pk} is the beta of portfolio p relative to factor k. The intercept α_p is the Jensen performance measure of the fund portfolio. Under the null hypothesis of no abnormal performance, $\alpha_p = 0$. The Jensen performance can be viewed as either the abnormal return of the fund compared to a given asset pricing model such as the Capital Asset Pricing Model (CAPM) or the abnormal return of the fund compared to a passive combination of the risk-free asset and the K factors in the model with the same factor betas as the fund (see Aragon and Ferson (2008) and Elton and Gruber (2013)).

Under the null hypothesis that there is no persistence in value added by the Winners portfolio, then α_p will equal zero. By focusing on performance over different holding periods, it is possible to examine whether any persistence in value added holds over the short run and/or long run. Under the null hypothesis that there is no persistence in inferior performance by the Losers portfolio, then α_p will equal zero. Prior research in open-end mutual funds would suggest that persistence in inferior performance is more common.

To evaluate the performance of the closed-end funds, I consider five different linear factor models. To evaluate which model is most appropriate to use, I test the mean-variance efficiency of each model using the Gibbons et al (1989) test during the same period as which I evaluate the out-of-sample performance of the closed end fund portfolios. I test the mean-variance efficiency of each model using passive portfolios formed on the basis of stock

[7] Connor and Korajczyk (1986) generalize the Jensen performance to a multifactor model.

characteristics. The mean-variance efficiency test examines whether the N α_i's from equation (1) are jointly equal to zero, where N is the number of passive portfolios. Grinblatt and Titman (1989) point out that a good benchmark model is one which correctly assigns zero performance to passive trading strategies (see also Chen and Knez (1996)).

The Gibbons et al (1989) test of mean-variance efficiency is a test of model specification. To compare the performance across the factor models, I use a number of metrics as in Fama and French (2012,2014a,b). I calculate the average absolute alpha ($|\alpha|$) as a measure of average mispricing, where α is a (N,1) vector of α_i. I also calculate the ratio of the average absolute alpha to the average absolute deviation of mean excess returns ($|r|$) of the passive portfolios to the global average mean excess return across portfolios For factor models that are well specified, both the $|\alpha|$ and $|\alpha|/|r|$ measures will equal zero. Factor models that do a better job in pricing the passive portfolios will have a lower $|\alpha|$ and $|\alpha|/|r|$.[8]

I also estimate the Sharpe (1966) performance of the alphas (SR(α)). The Sharpe performance of the alphas is the Sharpe performance of the optimal orthogonal portfolio and is given by $(\alpha'\Sigma^{-1}\alpha)^{1/2}$ where Σ is the (N,N) residual covariance matrix from equation (1). The optimal orthogonal portfolio is the portfolio that can be combined with the K factor portfolios in the benchmark model to give a portfolio that lies on the mean-variance frontier of the N+K assets (Jobson and Korkie (1982), Gibbons et al (1989)).[9] The optimal orthogonal portfolio is the portfolio that delivers the maximum abnormal returns relative to

[8] A more formal approach of model comparison tests using the cross-sectional regression approach is developed in Kan, Robotti and Shanken (2013). A recent study by Harvey and Liu (2014) propose an approach for selecting factors among competing factor models that controls for multiple testing.

[9] See also MacKinlay (1995). Ferson and Siegel (2015) extend the analysis of optimal orthogonal portfolios in the presence of conditioning information.

variance that an investor can generate by deviating from the portfolio weights of a given benchmark model. If a factor model is well specified, then SR(α) will equal zero. Although the SR(α) measures are not strictly comparable across models, they do provide the magnitude of the mean-variance benefits of deviating from a given benchmark model.

I use three different past performance measures. The first is either the average excess returns or average excess returns divided by residual volatility during the past 12 months.[10] In most tests, I focus on the performance of the fund divided by residual volatility as it controls for the precision in which the measure is estimated (Kosowski et al (2006), Fama and French (2010)). The second measure is the past average market adjusted excess returns divided by residual volatility during the prior 12 or 60 months. The third performance measure is the Jensen performance divided by residual volatility[11]estimated during the past 60 months.

III Data

All of the data for this study is collected from the London Share Price Database (LSPD) unless otherwise specified.

A) Sample of Closed-End Funds

My sample of funds includes all U.K. closed-end funds with a U.K. equity objective between January 1990 and December 2012. The U.K. equity sectors include the U.K. Growth, U.K. Growth and Income, U.K. Small Companies, and U.K. High Income

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[10] This test is equivalent to ranking funds by the standard *t*-test of the mean as I only include funds with continuous returns during the estimation window.

[11] This is equivalent to the Information Ratio. The square of the Information ratio is the Treynor and Black (1973) appraisal ratio. Jobson and Korkie (1984) show that the funds with the highest appraisal ratio leads to the largest increase in squared Sharpe (1966) performance for an investor who holds the benchmark model.

investment sectors. The investment sector information for each fund is collected each year[12] from Money Management, the Association of Investment Companies (AIC) web site, and the Investment Trusts magazine. I provide details of the construction of the sample of funds in the Appendix. There are 223 closed-end funds in my sample. My sample of funds should be relatively free of survivorship bias (Brown, Goetzmann, Ibbotson and Ross (1992)).

I collect the monthly stock returns for each fund. Since the Jensen performance measure is estimated over the prior 60 months, I collect the monthly stock returns of the funds between January 1985 and December 2012. The use of stock returns captures the value added to investors (Aragon and Ferson (2008)) by closed-end funds, which is the main concern to investors. The value added depends not only on the performance ability of the fund, trading costs, expenses, but also on the behavior of the fund premium.[13] I also collect

[12] The investment sectors have changed names over the years. The four sectors are the current names of the U.K. investment sectors as at the end of the sample period. In the early part of the sample period, there was a U.K. General sector. I allocate trusts in the U.K. General sector to the U.K. Growth sector since most trusts transferred to this sector when the classifications changed.

[13] See Dimson and Minio-Paluello (2002) and Cherkes (2012) for excellent reviews of alternative explanations and evidence of the closed-end fund premium. Recent studies developing theoretical models to explain the closed-end fund premium include Berk and Stanton (2007) and Cherkes, Sagi and Stanton (2009). Elton, Gruber, Blake and Shachar (2013) show that the ability to use leverage is a major factor why U.S. closed-end bond funds exist and has a significant impact on the level of fund premium and performance. Ramadorai (2012) finds support for the rational theories of the premium in explaining the closed hedge fund premium.

the NAV returns for each fund from Datastream as I also consider the persistence in the performance ability of closed-end funds.

B) Linear Factor Models

I consider five different linear factor models to evaluate the out-of-sample performance of the Winners and Losers portfolios of funds. Details on how the factors are constructed are provided in the Appendix.[14] I use the following factor models:

1. CAPM

This model uses the excess returns on the value weighted U.K. market index as a proxy for the market portfolio.

2. Fama and French (1993) (FF)

This model is a three-factor model. The factors include the excess returns on the market index and two zero-cost portfolios that capture the size (SMB) and value/growth (HML) effects in stock returns.

3. Carhart (1997)

This model is a four-factor model. The factors include the three factors in the FF model and a zero-cost portfolio that captures the momentum effect (WML) in stock returns.

4. Fama and French (2014a,b) (FF5)

This model is a five-factor model. The factors include the factors in the FF model and two zero-cost portfolios that capture the profitability (RMW) and investment growth (CMA) effects in stock returns.

5. CarhartA

The final model is a six-factor model, which includes all the factors in the FF5 model and the WML factor.

[14] Closed-end funds are not included in the formation of the factors or passive assets.

Table 1 reports summary statistics of the factors between January 1990 and December 2012. The summary statistics include the mean and standard deviation of monthly excess factor returns (%). The *t*-statistic examines the null hypothesis that the average excess factor returns equals zero.

Table 1 here

Table 1 shows that the WML factor has the highest mean excess return across all six factors at 0.835%. The average excess return on the WML factor is significantly positive. There is a strong momentum effect in U.K. stock returns over my sample period. Due to the magnitude of the average excess return on the WML factor compared to the other factors, this factor will play an important role in evaluating closed-end fund performance. The HML and CMA factors have significant positive average excess returns at the 10% significance level but the magnitude of the average excess returns is a lot lower than the WML factor. The average excess return on the market index is not more than two standard errors from zero. Both the SMB and RMW factors have average excess returns that are close to zero. The correlations (unreported) between the factors are in the main quite low. The largest correlations are between the HML and WML factors (-0.345), HML and RMW factors (-0.305), and HML and CMA factors (0.329).

C) Passive Portfolios

To evaluate how reliable the different factor models are to evaluate the performance of closed-end funds over my sample period, I examine how well the models are able to correctly assign zero performance to different groups of passive portfolios. I use three groups of ten portfolios of stocks sorted by size, book-to-market ratio (BM), and momentum characteristics as in Bansal, Dittmar and Lundblad (2005). The portfolios are value weighted buy and hold monthly returns. Details on the construction of the passive portfolios are included in the Appendix.

In unreported tests, I examine the average excess returns of the passive portfolios.[15] There is little size effect across the average excess returns of the ten size portfolios, which is consistent with the average excess returns on the SMB factor. The ten size portfolios have the narrowest spread in average excess returns. In contrast, there is a large spread in the average excess returns of the ten BM portfolios from 0.174% for decile 1 (Growth) and 1.009% for decile 10 (Value). The largest spread in average excess returns is for the ten momentum portfolios, which range between -1.147% (portfolio 2) and 0.791% (Winners). The two portfolios of the poorest past performing stocks have large negative average excess returns and the two portfolios with the best past performing stocks have large positive average excess returns.

IV Empirical Results

A) Tests of Linear Factor Models

I begin my empirical analysis by evaluating how reliable the different factor models are in assigning zero performance to the three groups of passive portfolios. Table 2 reports summary statistics of the tests of the five linear factor models. The table includes the Gibbons et al (1989) F test (GRS) of mean-variance efficiency, the average mispricing $|\alpha|$, the ratio of $|\alpha|/|r|$, the Sharpe ratio of the alphas ($SR(\alpha)$), and the *p* value of the GRS test. I do not report the individual alphas and *t*-statistics for the different groups of passive assets but these are available on request.

Table 2 here

[15] Results are available on request.

Table 2 shows that the null hypothesis of mean-variance efficiency can be rejected for every benchmark model. However it does depend upon the set of test assets used. The mean-variance efficiency of none of the benchmark models can be rejected using the BM portfolios. At the 5% significance level, only the Carhart and CarhartA models can be rejected using the size portfolios. The strongest rejection rates are in the ten momentum portfolios, where all the models are rejected. Likewise using all the test portfolios, the mean-variance efficiency of each factor model can be rejected.

The SR(α) measures in Table 2 show that there are large gains for the investor in deviating from the optimal weights of the benchmark models. Among the three sets of test assets, the gains are largest in the momentum portfolios and smallest in the size portfolios. Due to the larger number of assets, the Sharpe measures are highest using all test portfolios. Although there are large potential gains from the optimal orthogonal portfolios, these portfolios are subject to large long and short positions.

Comparing the performance of the models, the magnitude of average mispricing in Table 2 is similar across the models using the size and BM portfolios. However there is a much wider spread in average mispricing in the momentum portfolios. The Carhart and CarhartA models have substantially lower average mispricing compared to the CAPM, FF3, and FF5 models. This result is driven by the extreme Winners and Losers portfolios having large significant positive and negative alphas relative to the CAPM, FF, and FF5 models. These significant alphas are substantially reduced and often disappear when using the Carhart and CarhartA models.

The |α|/|r| ratios are large across all models in Table 2. The surprising result is for the size and BM portfolios where the lowest |α|/|r| ratio is 0.693 for the FF5 model using the BM portfolios. Although |α| is low in these portfolios, |r| is also low which leads to the high |α|/|r| ratios in the size and BM portfolios. The magnitude of the |α|/|r| ratios is similar across models. There is a much larger difference in the $|\alpha|/|r|$ ratios across models when using the momentum portfolios or all test portfolios. The Carhart and CarhartA models have considerably lower $|\alpha|/|r|$ ratios compared to the CAPM, FF, and FF5 models in these cases.

The results in Table 2 suggest that, although the mean-variance efficiency of each model can be rejected, the Carhart and CarhartA models do a much better job in pricing the momentum portfolios compared to the CAPM, FF, and FF5 models. This finding is similar to Fama and French (2014b) who find that adding the momentum factor to their five-factor model leads to much better performance when the test assets are size/momentum portfolios but not for other sets of test assets. Given my focus on the persistence of closed-end fund performance, including the momentum factor is likely to be important (Carhart (1997)). As a result, I only use the CarhartA model for the remainder of the study.

B) Persistence Tests using Past Average or Market Adjusted Excess Returns

This subsection examines the persistence in closed-end fund performance using either average excess fund returns or market adjusted excess returns. Table 3 reports the out-of-sample performance of the Winners and Losers portfolios over different return horizons where the portfolios are formed using past average excess returns (panel A) or past average excess returns divided by residual volatility (panel B) during the past 12 months. The table includes the average excess returns (%), the Jensen performance (α, %) and *t*-statistic ($t(\alpha)$), the beta on the WML factor (β_{WML}) and corresponding *t*-statistic ($t(\beta_{WML})$).

Table 3 here

Panel A of Table 3 shows that there is persistence in the average excess returns up to 6 months after portfolio formation with the Winners portfolio having a higher average excess returns than the Losers portfolio. There is some evidence of reversals in average excess returns in the second and third years after portfolio formation. The factor betas on the WML factor explain this short-run persistence in average excess returns of the two portfolios. The WML portfolio has a significant positive beta on the WML factor over the first 3 months, months 4-6, and months 1-12 after portfolio formation. The Losers portfolio has a significant negative beta on the WML factor over the same horizons. These patterns in betas eliminate nearly all the persistence in average excess returns as reflected in the Jensen performance of the two portfolios. The Winners portfolio provides no significant positive Jensen performance over any horizon. The Losers portfolio has a significant positive Jensen performance at the 1-month and in the third year after portfolio formation.

When using the average excess return divided by residual volatility to rank funds in panel B of Table 3, the results are in the main similar to panel A. The Winners portfolio provides no significant Jensen performance at any horizon. The Winners portfolios has a significant positive beta on the WML factor during the first three months, months 4-6, and the first year after portfolio formation and the Losers portfolio has a significant negative beta on the WML factor. The Winners portfolio has a significant negative beta on the WML factor and the Losers portfolio has a significant positive beta on the WML factor in the second and third year after portfolio formation

Table 3 suggests that there is some short-run persistence in average excess returns between the Winners and Losers portfolios. However any short-run persistence in average excess returns can be explained by the factor loadings on the WML factor. There is no evidence of a significant positive Jensen performance by the Winners portfolio at any horizon after portfolio formation. Likewise, there is no evidence of any inferior Jensen performance by the Losers portfolio. The results suggest that when ranking funds by past average excess returns, that there is no persistence in closed-end fund performance. This result is similar to Carhart (1997) in open-end U.S. mutual funds.

I next examine whether there is any persistence in performance when funds are ranked on how well they perform relative to the market index. Table4 reports the out-of-sample performance of the Winners and Losers portfolios where the past performance of the fund is measured by the average market-adjusted excess returns divided by residual volatility during the prior 12 months (panel A) and prior 60 months (panel B).

Table 4 here

Panel A of Table 4 shows that there is some persistence in the average excess returns of the Winners and Losers portfolios in the second and third month, months 4-6 and 7-9, and in the first year after portfolio formation. However this turns to reversals in the second and third year after portfolio formation. Any persistence in the mean excess returns can be explained by the factor loadings on the WML factor as in Table 3. The Winners portfolio has no significant Jensen performance at any horizon after portfolio formation. In contrast, the Losers portfolio has a significant positive Jensen performance at the 1 month and in the third year after portfolio formation.

There is a dramatic change in performance when ranking funds by the average market-adjusted excess returns divided by residual volatility during the past 60 months in panel B of Table 4. There is now no persistence in the average excess returns between the Winners and Losers portfolios but reversals up to two years after portfolio formation. The reversals lead to significant value added by the Losers portfolio which provides a significant positive Jensen performance on all horizons up to one year after portfolio formation. The superior performance by the Losers portfolio stems from the high average excess returns and the negative beta on the WML factor. The Winners portfolio has a small insignificant Jensen performance across all horizons after portfolio formation. The Winners portfolio only has a significant positive beta on the WML factor during the first three months after portfolio formation.

Table 4 suggests that when the funds are evaluated relative to the market index over longer horizons, there are significant reversals in performance over the short-run of up to one year after portfolio formation but not over the longer run. Winning funds ranked relative to the market do not provide superior Jensen performance over any horizon after portfolio formation.

C) Persistence Tests on the Value Added by Funds

The past performance measures used in the previous subsection are based either on the past average excess returns or the past market-adjusted excess returns of the fund. To examine whether there is persistence in value added by the funds, I use the past Jensen performance. Empirical evidence from open-end mutual fund studies suggest that persistence may be stronger when ranking funds by alpha (see Carhart (1997), Elton, Gruber and Blake (2011) among others). Table 5 reports the out-of-sample performance of the Winners and Losers portfolios, where past performance is measured by the past Jensen performance divided by residual volatility.

Table 5 here

Table 5 shows that the pattern in average excess returns of the Winners and Losers portfolios differs from Tables 3 and 4. The average excess returns of the Losers portfolio tends to decline over the different holding horizons after portfolio formation and the average excess returns of the Winners portfolio tends to increase. The Losers portfolio has a significant positive Jensen performance performance over the first three months after portfolio formation and neutral performance over longer horizons. The Losers portfolio continues to have a significant negative beta on the WML factor at the first three months, months 4-6, and the first year after portfolio formation. The Winners portfolio has a small negative or positive beta on the WML factor but not statistically significant in contrast to the earlier tables. This result suggest that ranking funds by the past Jensen performance divided by residual volatility picks up different funds to include in the Winners portfolio compared to Tables 3 and 4. The Winners portfolio now provides significant positive Jensen performance at months 4-6 and 7-9 and during the first year after portfolio formation but not at the longer horizons.

Table 5 suggests that there is some persistence in value added by the best performing funds for periods up to one year after portfolio formation. At longer horizons, the Winners portfolio provides neutral performance. This result suggests that any persistence in value added by funds is temporary and short run. This result is similar to Carhart (1997). Table 5 also suggests that there is no persistence of funds which consistently destroy value to investors, which differs from open-end mutual funds (Carhart, Elton et al (2011,2012)).

The persistence in value added using closed-end fund stock returns would tend to contradict the performance theory of the discount where the ability of the fund manager is priced into stock returns (Gruber (1996), Berk and Stanton (2007)). According to the performance theory of the discount, any persistence in fund performance should be captured in the NAV excess returns. I repeat the persistence tests in Table 5 but this time use the NAV excess returns. Table 6 reports the out-of-sample performance of the Winners and Losers portfolios using NAV excess returns.

Table 6 here

Table 6 shows that there is significant persistence in performance using the NAV excess returns. There is persistence in the average excess returns where the Winners portfolio has a higher mean excess return than the Losers portfolio across all return horizons. The difference in mean excess returns is larger over the short return horizons. The Losers portfolio has a significant inferior performance at the 10% significance level at the 1-month and 4-6 months horizons but neutral performance beyond the 6-month horizon, which again suggests that there is little repeat inferior performance ability by U.K. equity closed-end funds. This result again differs from open-end mutual fund studies such as Carhart (1997) and Elton et al (2011,2012).

In contrast to the Losers portfolio, the Winners portfolio has a significant positive Jensen performance across all return horizons. The magnitude of the Jensen performance is similar across all return horizons. The Winners portfolio has a tiny beta on the WML factor, which is similar to the results for the stock returns. Although the statistical significance of the superior performance of the Winners portfolio is stronger in NAV excess returns compared to Table 5, the magnitude of the Jensen performance is less. This result is driven by the fact that the standard errors are lower in the performance tests using the NAV excess returns, which is due to the lower volatility in NAV returns compared to stock returns.

Table 6 suggests that there is persistence in the performance ability of U.K. equity closed-end funds. However, the magnitude of the persistence is lower than that observed in stock returns, which again contradicts the performance theory of the closed-end fund discount. My results differ from Bredin et al (2014). Bredin et al find evidence of persistence when measuring past performance using NAV returns. However this disappears when using past stock returns and evaluating performance relative to a global four-factor model. They find large significant positive alphas across all decile fund portfolios. The results of the two studies are not directly comparable for two reasons. First, Bredin et al combine both domestic and international equity funds (as well as specialist funds) in their sample. Second, Bredin et al evaluate performance using global factor models where I only use domestic linear factor models given my sample of domestic equity funds.

V. Conclusions

This paper examines the persistence in performance of U.K. closed-end funds with domestic equity objectives. A major focus in my study is whether there is any persistence in the value added by closed-end funds and whether any persistence is present in the short-run and long-run horizons. There are four main findings from my study.

First, I find that the Carhart and CarhartA models do the best job in pricing the passive portfolios over my sample period. The mean-variance efficiency of each factor model is rejected using all the test portfolios. The rejection is driven by the performance of the momentum portfolios. The Carhart and CarhartA models do a much better job in capturing the performance of the extreme Winners and Losers portfolios. This result is linked to Fama and French (2014b), who find that it is important to add the momentum factor to their five-factor model when pricing size/momentum sorted portfolios.

Second, when sorting funds using the past one-year average excess returns or average market-adjusted excess returns, I find there is persistence in mean excess returns for periods up to six months after portfolio formation. However any persistence in mean excess returns disappears when evaluating performance relative to the CarhartA model. The factor loadings on the momentum factor capture this persistence. The Winners portfolio has a significant positive beta on the WML factor and the Losers portfolio has a significant negative beta. This result is similar to Carhart (1997).

Third, I find that there is some persistence in the value added by closed-end funds for one year after portfolio formation. The Winners portfolio delivers a significant positive alpha relative to the CarhartA model. However this persistence disappears over longer horizons.

There is no evidence of repeat underperformance by closed-end funds as the Losers portfolio has neutral performance. The lack of repeat inferior performance differs from open-end mutual fund studies such as Carhart (1997) and Elton et al (2011,2012).

Fourth, I find that there is significant persistence in performance ability when using the NAV excess returns of the funds. The Winners portfolio provides a significant positive performance across all return horizons. There is little evidence of repeat underperformance as the Losers portfolio has neutral performance over return horizons longer than 6-months. This again contrasts with what is observed in open-end mutual fund studies.

My results suggest that there is both persistence in value added and performance ability by U.K. equity closed-end funds. However the findings do not support the performance theory of the discount (Berk and Stanton (2007)) as there is persistence in the value added provided by funds and the magnitude of the superior performance by the Winners portfolio is larger in stock returns rather than in NAV returns. An interesting extension to this study would be to explore whether there is any persistence in the value added of international equity closed-end funds relative to global factor models. I leave an examination of this issue to future research.

Appendix

A) Sample of Closed-End Funds

I form my sample of closed-end funds by including all funds with a U.K. equity objective between 1990 and 2012. I include funds within the U.K. Growth, U.K. Growth and Income, U.K. Smaller Companies, and U.K. High Income sectors. I track the history of each fund throughout the sample period using the LSPD Names records. If a fund changes to a split capital fund or a secondary share, I exclude the fund from that point in the sample. Where a fund changes to an international equity sector or a specialist sector, I exclude the fund from that point in the sample. There are 223 funds within my sample period between 1990 and 2012 period.

B) Formation of Factors in the Linear Factor Models

Since the Jensen performance measure of closed-end funds are estimated over the prior 60 months, I construct the factors between January 1985 and December 2012. I construct the market index using a similar approach to Dimson and Marsh (2001). At the start of each year between 1985 and 2012,I construct a value weighted portfolio of all stocks on LSPD by their market value at the start of the year. I calculate buy and hold monthly returns during the next year. I exclude companies with a zero market value. I make a number of corrections and exclusions to the portfolio returns which I follow across forming the factors and the passive portfolios. Where a security has missing return observations during the year or month, I assign a zero return to the missing values as in Liu and Strong (2008). I correct for the delisting bias of Shumway (1997) by following the approach of Dimson, Nagel and Quigley (2003). A –100% return is assigned to the death event date on LSPD where the LSPD code indicates that the death is valueless. I exclude closed-end funds, foreign companies, and secondary shares using data from the LSPD archive file.

To form the SMB and HML factors I use a similar approach to Fama and French (2012). At the start of July each year between 1984 and 2012, all stocks on LSPD are ranked separately by their market value at the end of June and by their BM ratio from the prior calendar year. The BM ratio is calculated using the book value of equity at the fiscal year-end (WC03501) during the previous calendar year from Worldscope and the year-end market value. Two size groups (Small and Big) are formed using a breakpoint of 90% by aggregate market capitalization where the Small stocks are the companies with smallest 10% by market value and the Big stocks are the companies with the largest 90% by market value. Three BM groups (Growth, Neutral, and Value) are formed using break points of the 30^{th} and 70^{th} percentiles of the BM ratios of Big stocks. Six portfolios of securities are then constructed at the intersection of the size and BM groups (SG, SN, SV, BG, BN, BV). The monthly buy and hold return for the six portfolios are then calculated during the next 12 months. The initial weights are set equal to the market value weights at the end of June. Companies with a zero market value, and negative book values are excluded.

The SMB factor is the difference in the average return of the three small firm portfolios (SG, SN, SV) and the average return of the three large firm portfolios (BG, BN, BV). The HML factor is the average of HML_S and HML_B where HML_S is the difference in portfolio returns of SV and SG and HML_B is the difference in portfolio returns of BV and BG. The HML_S and HML_B zero-cost portfolios capture the value effect in Small stocks and Big stocks respectively.

I form the WML factor using a similar approach to Fama and French (2012). At the start of each month between January 1985 and December 2012, all stocks on LSPD are ranked separately by their market value at the end of the previous month and on the basis of their cumulative return from months –12 to –2. Two size groups (Small and Big) are formed as in the case of the size/BM portfolios. Three past return groups (Losers, Neutral, and

Winners) are formed using break points of the 30th and 60th percentiles of the past returns of Big stocks. Six portfolios of securities are then constructed at the intersection of the size and momentum groups (SL, SN, SW, BL, BN, BW). The value weighted return for the six portfolios are then calculated during the next month. Companies with a zero market value, and less than 12 return observations during the past year are excluded from the portfolios.

The WML factor is the average of WML_S and WML_B where WML_S is the difference in portfolio returns of SW and SL and WML_B is the difference in portfolio returns of BW and BL. The WML_S and WML_B zero-cost portfolios capture the momentum effect in Small stocks and Big stocks respectively.

To form the RMW and CMA factors, I use a similar approach to Fama and French (2014a,b). At the start of July each year between 1984 and 2012, I sort stocks separately by market value at the end of June and either by Operating Profitability (OP) or Investment Growth (Inv) from the prior calendar year. OP is defined as annual revenues (WC01001) minus cost of goods sold (WC01051), interest expense (WC01251), and selling, general, and administrative expenses (WC01101) divided by book equity (WC03501). Inv is defined as the annual change in total assets divided by lagged total assets (WC02999). Two size groups are formed as in the case of the size/BM portfolios. Three OP groups (Weak, Neutral, and Robust) are formed using break points of the 30th and 70th percentiles of the OP ratios of Big stocks and three Inv groups (Conservative, Neutral, and Aggressive) are formed using breakpoints of the 30th and 70th percentiles of the Inv ratios of Big stocks. Six portfolios are then formed of the intersection between the six size and OP groups (SW, SN, SR, BW, BN, BR) and the six size and Inv groups(SC, SN, SA, BC, BN, BA). The monthly buy and hold return for the two groups of six portfolios are then calculated during the next 12 months. The initial weights are set equal to the market value weights at the end of June. Companies with a zero market value, and zero or negative book values are excluded from the size/OP portfolios. Companies with zero total assets are excluded from the size/Inv portfolios.

The RMW factor is formed as the average of [(SR-SW)+(BR-BW)] and the CMA factor is formed as the average of [(SC-SA)+(BC-BA)]. Fama and French (2014a) also explore alternative ways of forming the factors and find that the performance of the factor models is robust to how the factors are formed.

C) Passive Portfolios

I form three groups of passive portfolios based on size, BM ratio, and momentum following Bansal et al (2005). For the 10 size portfolios, I use a similar approach to Dimson and Marsh (2001). At the start of January each year between 1990 and 2012, all stocks on LSPD are ranked by their market value at the end of December and grouped into 10 portfolios. Decile 1 is the smallest 1%, decile 2 is the next 2%, decile 3 is the next 7%, and then deciles 4 to 9 are the next 10% bandings, and decile 10 contains stocks greater than 70%. Monthly buy and hold returns for each portfolio is calculated during the next 12 months, where the initial weights are given by the market values at the end of the previous year. I exclude companies with zero market value.

I form the 10 BM portfolios, at the end of June each year between 1989 and 2012. All stocks are ranked by their BM ratio from the previous calendar year. The BM ratio is defined as in the case of the size/BM portfolios. I form 10 portfolios of stocks on the basis of their BM ratios, with an equal number of stocks in each portfolio as an approximation. Monthly buy and hold returns for each portfolio is calculated during the next 12 months, where the initial weights are given by the market values at the end of June. I exclude companies with zero market value and negative book values.

I form the ten momentum portfolios each month between January 1990 and December 2012. All stocks are ranked on the basis of their cumulative return during months t-12 to t-2 and grouped into ten portfolios. All portfolios contain an equal number of stocks as an approximation. I then calculate the value weighted buy and hold return during the next month using market values at the end of the previous month. I exclude companies with zero market values and less than 12 past return observations.

Table 1 Summary Statistics of Factors

	Mean	Standard Deviation	*t*-statistic
Market	0.281	4.014	1.165
SMB	-0.073	3.316	-0.364
HML	0.29	2.745	1.758[2]
WML	0.835	3.758	3.691[1]
RMW	-0.077	2.18	-0.584
CMA	0.239	2.125	1.869[2]

[1] Significant at 5%
[2] Significant at 10%

The table reports summary statistics of the excess returns of the factors in the linear factor models between January 1990 and December 2012. The summary statistics include the mean, and standard deviation of the factor excess returns (%) and the *t*-statistic of the null hypothesis that the average factor excess returns equals zero. The factors include the excess returns on the U.K. market index, and zero-cost portfolios of the size (SMB), value/growth (HML), momentum (WML), operating profitability (RMW), and investment growth (CMA) effects in U.K. stock returns.

Table 2 Summary Statistics of Tests of Linear Factor Models

Panel A					
Size	GRS	|α|	|α|/|r|	SR(α)	*p*(GRS)
CAPM	1.552	0.104	0.896	0.243	0.121
FF	1.659	0.108	0.931	0.253	0.09
Carhart	2.14	0.117	1.012	0.299	0.022
FF5	1.704	0.104	0.899	0.259	0.08
CarhartA	2.225	0.12	1.036	0.308	0.017
Panel B					
BM	GRS	|α|	|α|/|r|	SR(α)	*p*(GRS)
CAPM	1.217	0.173	0.868	0.215	0.28
FF	1.08	0.145	0.73	0.204	0.377
Carhart	1.048	0.146	0.733	0.209	0.404
FF5	0.976	0.138	0.693	0.196	0.465
CarhartA	0.937	0.139	0.7	0.2	0.499
Panel C					
Momentum	GRS	|α|	|α|/|r|	SR(α)	*p*(GRS)
CAPM	3.1	0.575	1.094	0.343	0.001
FF	3.403	0.624	1.187	0.362	0
Carhart	2.059	0.246	0.469	0.294	0.028
FF5	3.271	0.596	1.133	0.358	0.001
CarhartA	2.058	0.233	0.443	0.296	0.028
Panel D					
All	GRS	|α|	|α|/|r|	SR(α)	*p*(GRS)
CAPM	1.934	0.284	1.019	0.488	0.004
FF	1.924	0.292	1.049	0.491	0.004
Carhart	1.537	0.17	0.61	0.457	0.042
FF5	1.893	0.279	1.003	0.491	0.005
CarhartA	1.587	0.164	0.589	0.469	0.032

[1] Significant at 5%
[2] Significant at 10%

The table reports the summary statistics of the mean-variance efficiency tests of Gibbons et al (1989) on five linear factor models between January 1990 and December 2012. The tests are run on four groups of passive assets, which are 10 size portfolios (panel A), 10 book-to-market (BM) portfolios (panel B), and ten momentum portfolios (panel C), and 30 size/BM/momentum portfolios (All, panel D) The table includes the Gibbons et al F test (GRS), the average absolute value of the alpha (|α|), the ratio of the average absolute alpha to the average absolute deviation in mean excess returns from the average mean excess returns across the portfolios (|α|/|r|), the Sharpe ratio of the alphas (SR(α)), and the *p* value of the GRS test (*p*(GRS)).

Table 3 Persistence Tests Using Past Average Excess Returns

Panel A									
Mean	1	2	3	4-6	7-9	10-12	1-12	13-24	25-36
Losers									
Average	0.39	0.25	0.15	0.06	0.35	0.43	0.2	0.54	0.69
α	0.44	0.32	0.2	-0.09	0.12	0.02	0.07	0.14	0.34
t(α)	1.66[2]	1.25	0.82	-0.44	0.68	0.08	0.42	0.92	1.87[2]
β_{WML}	-0.4	-0.41	-0.39	-0.2	-0.08	0.05	-0.16	0.06	0.06
$t(\beta_{WML})$	-4.25[1]	-4.52[1]	-4.51[1]	-2.75[1]	-1.41	0.79	-2.63[1]	1.3	1.53
Winners									
Average	0.6	0.65	0.66	0.61	0.42	0.43	0.48	0.36	0.35
α	0.13	0.19	0.21	0.2	0.02	-0.01	0.11	-0.01	-0.02
t(α)	0.75	1.11	1.24	1.25	0.14	-0.04	0.74	-0.11	-0.18
β_{WML}	0.26	0.24	0.23	0.15	0.09	0.02	0.12	-0.06	-0.04
$t(\beta_{WML})$	4.46[1]	4.12[1]	3.99[1]	2.62[1]	1.53	0.43	2.38[1]	-1.27	-1.2
Panel B									
Mean/σ	1	2	3	4-6	7-9	10-12	1-12	13-24	25-36
Losers									
Average	0.41	0.21	0.12	0.1	0.37	0.5	0.23	0.5	0.62
α	0.4	0.19	0.09	-0.09	0.14	0.1	0.07	0.07	0.25
t(α)	1.7[2]	0.88	0.42	-0.45	0.86	0.59	0.44	0.56	1.59
β_{WML}	-0.31	-0.31	-0.3	-0.16	-0.09	0.02	-0.13	0.07	0.09
$t(\beta_{WML})$	-4.29[1]	-4.52[1]	-4.34[1]	-2.37[1]	-1.69[2]	0.3	-2.41[1]	1.73[2]	2.15[1]
Winners									
Average	0.46	0.52	0.54	0.56	0.43	0.38	0.42	0.39	0.33
α	0.07	0.13	0.16	0.19	0.07	-0.01	0.09	0.04	-0.05
t(α)	0.46	0.93	1.18	1.43	0.52	-0.05	0.81	0.3	-0.4
β_{WML}	0.18	0.17	0.16	0.11	0.06	-0.02	0.08	-0.08	-0.06
$t(\beta_{WML})$	4.04[1]	4.03[1]	3.7[1]	2.23[1]	1.19	-0.35	1.82[2]	-1.87[2]	-1.96[1]

[1] Significant at 5%
[2] Significant at 10%

The table reports the out-of-sample performance between January 1990 and December 2012 of two equal weighted portfolios of closed-end funds formed on the basis of past performance. The portfolios are formed each month from the top quartile and bottom quartile of funds where funds are ranked by their average excess return (Mean) during the prior 12 months (panel A) and their average excess return divided by residual volatility (Mean/σ) during the prior 12 months (panel B). The table reports the performance of the portfolios for each of the first three months (1,2,3), the second, third, and fourth quarters (4-6,7-9,10-12), and the first, second, and third years (1-12,13-24,25-36) after portfolio formation. The table includes the average excess return (%), Jensen performance (α) relative to the CarhartA model, *t*-statistic of α (*t*(α)), the portfolio beta with respect to the WML factor (β_{WMl}) and corresponding *t*-statistic ($t(\beta_{WML})$). The *t*-statistics are corrected for the effects of heteroskedasticity using the method of White (1980).

Table 4 Persistence Tests Using Past Average Market-Adjusted Excess Returns

Panel A									
Market/σ_{12}	1	2	3	4-6	7-9	10-12	1-12	13-24	25-36
Losers									
Average	0.48	0.28	0.18	0.1	0.34	0.42	0.21	0.53	0.74
α	0.54	0.34	0.22	-0.06	0.15	0.05	0.1	0.13	0.39
$t(\alpha)$	2.35[1]	1.53	1.01	-0.29	1	0.3	0.66	0.98	1.76[2]
β_{WML}	-0.39	-0.39	-0.38	-0.21	-0.13	-0.01	-0.18	0.05	0.05
$t(\beta_{WML})$	-5.22[1]	-5.28[1]	-5.1[1]	-3.25[1]	-2.62[1]	-0.25	-3.42[1]	1.16	1.16
Winners									
Average	0.51	0.57	0.61	0.6	0.46	0.42	0.47	0.35	0.29
α	0.08	0.13	0.18	0.18	0.07	0.01	0.11	-0.01	-0.07
$t(\alpha)$	0.51	0.84	1.22	1.4	0.51	0.11	0.93	-0.06	-0.66
β_{WML}	0.23	0.24	0.23	0.15	0.09	0	0.11	-0.07	-0.06
$t(\beta_{WML})$	4.51[1]	4.68[1]	4.59[1]	2.96[1]	1.83[2]	0.04	2.56[1]	-1.63	-1.89[2]
Panel B									
Market/σ_{60}	1	2	3	4-6	7-9	10-12	1-12	13-24	25-36
Losers									
Average	0.76	0.6	0.58	0.46	0.59	0.71	0.53	0.59	0.37
α	0.73	0.57	0.54	0.28	0.36	0.34	0.38	0.21	0.03
$t(\alpha)$	3.48[1]	2.86[1]	2.87[1]	1.71[2]	2.22[1]	1.99[1]	2.5[1]	1.61	0.29
β_{WML}	-0.28	-0.27	-0.27	-0.13	-0.06	0	-0.12	0.02	-0.04
$t(\beta_{WML})$	-3.79[1]	-3.85[1]	-3.83[1]	-2.59[1]	-1.31	-0.01	-2.41[1]	0.59	-0.94
Winners									
Average	0.34	0.31	0.3	0.31	0.24	0.32	0.25	0.29	0.39
α	-0.03	-0.06	-0.07	-0.04	-0.07	-0.06	-0.05	-0.06	0.03
$t(\alpha)$	-0.23	-0.5	-0.59	-0.34	-0.51	-0.45	-0.42	-0.59	0.23
β_{WML}	0.1	0.1	0.09	0	-0.07	-0.1	-0.02	-0.1	-0.04
$t(\beta_{WML})$	2.68[1]	2.56[1]	2.3[1]	-0.06	-1.54	-2.15[1]	-0.47	-3.28[1]	-1.17

[1] Significant at 5%
[2] Significant at 10%

The table reports the out-of-sample performance between January 1990 and December 2012 of two equal weighted portfolios of closed-end funds formed on the basis of past performance. The portfolios are formed each month from the top quartile and bottom quartile of funds where funds are ranked by their average market-adjusted excess return divided by residual volatility (Market/σ_{12}) during the prior 12 months (panel A) and their average market-adjusted excess return divided by residual volatility (Market/σ_{60})during the prior 60 months (panel B). The table reports the performance of the portfolios for each of the first three months (1,2,3), the second, third, and fourth quarters (4-6,7-9,10-12), and the first, second, and third years (1-12,13-24,25-36) after portfolio formation. The table includes the average excess return (%), Jensen performance (α) relative to the CarhartA model, *t*-statistic of α ($t(\alpha)$), the portfolio beta with respect to the WML factor (β_{WMl}) and corresponding *t*-statistic ($t(\beta_{WML})$). The *t*-statistics are corrected for the effects of heteroskedasticity using the method of White (1980).

Table 5 Persistence in Value Added by Closed-End Funds

α/σ	1	2	3	4-6	7-9	10-12	1-12	13-24	25-36
Losers									
Average	0.66	0.52	0.48	0.4	0.38	0.56	0.39	0.54	0.40
α	0.57	0.43	0.37	0.14	0.1	0.16	0.18	0.15	0.06
$t(\alpha)$	2.76[1]	2.28[1]	2.12[1]	0.99	0.68	1.07	1.33	1.3	0.54
β_{WML}	-0.23	-0.21	-0.2	-0.09	-0.04	0	-0.08	0.01	-0.01
$t(\beta_{WML})$	-3.15[1]	-3.29[1]	-3.35[1]	-2.15[1]	-1	-0.03	-1.96[1]	0.27	-0.4
Winners									
Average	0.42	0.44	0.47	0.55	0.54	0.64	0.5	0.6	0.56
α	0.15	0.17	0.2	0.29	0.23	0.21	0.24	0.14	0.1
$t(\alpha)$	1.12	1.29	1.56	2.2[1]	1.73[2]	1.6	1.9[2]	0.97	0.66
β_{WML}	-0.04	-0.03	-0.03	-0.08	-0.03	0	-0.04	0.03	0.03
$t(\beta_{WML})$	-1	-0.9	-0.9	-1.9[2]	-0.61	-0.04	-0.91	0.47	0.5

[1] Significant at 5%
[2] Significant at 10%

The table reports the out-of-sample performance between January 1990 and December 2012 of two equal weighted portfolios of closed-end funds formed on the basis of past performance. The portfolios are formed each month from the top quartile and bottom quartile of funds where funds are ranked by their Jensen performance divided by residual volatility (α/σ) during the prior 60 months. The table reports the performance of the portfolios for each of the first three months (1,2,3), the second, third, and fourth quarters (4-6,7-9,10-12), and the first, second, and third years (1-12,13-24,25-36) after portfolio formation. The table includes the average excess return (%), Jensen performance (α) relative to the CarhartA model, *t*-statistic of α ($t(\alpha)$), the portfolio beta with respect to the WML factor (β_{WMl}) and corresponding *t*-statistic ($t(\beta_{WML})$). The *t*-statistics are corrected for the effects of heteroskedasticity using the method of White (1980).

Table 6 Persistence in Performance Ability of Closed-End Funds

	1	2	3	4,6	7,9	10,12	1,12	13,24	25,36
Losers -									
Average	0	0.02	0.04	0.07	0.21	0.36	0.11	0.33	0.25
α	-0.18	-0.16	-0.15	-0.18	-0.04	0.02	-0.1	0	-0.06
t(α)	-1.71[2]	-1.57	-1.48	-1.83[2]	-0.52	0.27	-1.18	-0.04	-0.8
Mom	-0.08	-0.08	-0.08	-0.05	-0.02	0	-0.04	0.02	-0.01
t(Mom)	-2.45[1]	-2.53[1]	-2.59[1]	-1.96[1]	-1.11	-0.01	-1.74[2]	0.79	-0.4
Winners -									
Average	0.36	0.36	0.36	0.4	0.43	0.53	0.38	0.52	0.5
α	0.14	0.14	0.14	0.15	0.18	0.16	0.16	0.14	0.15
t(α)	1.9[2]	1.97[1]	2.04[1]	2.27[1]	2.66[1]	2.42[1]	2.43[1]	2.04[1]	2.08[1]
Mom	-0.04	-0.04	-0.04	-0.05	-0.05	-0.02	-0.04	0	0
t(Mom)	-1.61	-1.82[2]	-2.03[1]	-2.68[1]	-2.59[1]	-1.25	-2.26[1]	0.28	0.24

[1] Significant at 5%
[2] Significant at 10%

The table reports the out-of-sample performance between January 1990 and December 2012 of two equal weighted portfolios of closed-end funds formed on the basis of past performance using NAV excess returns. The portfolios are formed each month from the top quartile and bottom quartile of funds where funds are ranked by their Jensen performance divided by residual volatility (α/σ) during the prior 60 months. The table reports the performance of the portfolios for each of the first three months (1,2,3), the second, third, and fourth quarters (4-6,7-9,10-12), and the first, second, and third years (1-12,13-24,25-36) after portfolio formation. The table includes the average excess return (%), Jensen performance (α) relative to the CarhartA model, *t*-statistic of α ($t(\alpha)$), the portfolio beta with respect to the WML factor (β_{WMl}) and corresponding *t*-statistic ($t(\beta_{WML})$). The *t*-statistics are corrected for the effects of heteroskedasticity using the method of White (1980).

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