

SURVIVORSHIP AND PREDICTABILITY IN
PENSION FUND RETURNS

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Abstract

This paper is the first to examine the effects of survivorship on persistence in the performance of U.S. equity pension funds. Evidence of predictability of returns is stronger with the total sample of funds than with the survivor only sample. The weaker result in the survivor only sample is consistent with the effects from a model where multiperiod performance evaluation determines whether funds are terminated. Where other studies found predictability results were driven by the persistence of poor performers, we do not. We employ a time-varying conditional or dynamic alpha as a measure of performance. We find the dynamic alpha predicts future returns across equity style groups, but not consistently within equity style groups.

INTRODUCTION

This paper examines two issues relating to persistence in the rate-of-return performance of U.S. equity pension funds: survivorship and equity style. Performance is said to persist if good (poor) relative returns in one period are followed by good (poor) returns in the succeeding period. Using a sample of 522 U.S. equity pension funds for the period 1979 to 1996, we find that the significance of persistence is stronger in the total sample of funds than previous studies have found using survivor only funds. This lower level of significance in persistence with survivor only funds is consistent with mutual fund studies such as Carhart (1997).¹ Examining survivor only samples creates a bias. This bias of survivorship can mask significant levels of persistence in the rate of return performance of pension funds. As previous pension studies measure persistence using only data on funds that survive their sample periods, previous evidence of persistence is likely to be understated.

We also examine persistence of returns within equity style groupings: Growth, Value, Small Capitalization and Market Oriented. Previous studies have focused on persistence across all equity funds, but not within style groupings². We find that survivorship bias dampens the evidence of persistence within the small cap and value equity styles, but strengthens evidence of persistence for market oriented style. Within some equity styles, the slope coefficient in a regression of future returns on past dynamic alphas is negative. The negative slope coefficient indicates that there are performance reversals within style groups. The negative slope

¹ Mutual fund survivorship bias studies include Brown, Goetzmann, Ibbotson and Ross, (1992); Brown et al (1997); Brown, Goetzmann, and Ross (1995); Elton, Gruber and Blake (1996); Carhart (1997); Hendricks, Patel, and Zeckhauser (1997); and Carpenter and Lynch (1999).

² Mutual fund persistence studies include Carhart (1997); Brown and Goetzmann (1995); Grinblatt and Titman (1992); and Kahn and Rudd (1995). Pension fund studies include Lakonishok et al (1991); Christopherson, Ferson and Glassman (1998); Brown, Draper and MacKenzie (1997); and Christopherson, Ferson and Turner (1999).

coefficients are mostly significant in the survivor only sample, not in the sample that includes funds that do not survive the full sample period. Reversals in performance in the survivor only data is consistent with spurious performance reversals induced under a multiperiod performance evaluation criteria for survival as discussed in the appendix of Brown, Goetzmann, Ingersoll and Ross (1992).

The impact of survivorship on pension funds has received little attention. One paper that looks at survivorship is Coggin and Trzcinka (1998) which uses a sample of pension fund composites to predict the termination of investment manager composites. Coggin and Trzcinka do not examine the survivorship bias on persistence. Composites include all funds managed by a single investment management firm in a particular equity style. The most recent published studies of persistence and pension funds are by Brown, Draper, and McKenzie (1997) for United Kingdom pension funds, and Christopherson et al (1998) and Christopherson, Ferson and Turner (1999) for U.S. funds. These studies find evidence of persistence and predictability, but none employs a database that includes non-surviving funds³.

Our analysis of the effects of survivorship on persistence is based on a model derived in Brown et al (1992). Survivorship bias may have different effects depending on whether termination is based on a single or multiple period evaluation. In the absence of persistence, but with differences in volatility, a single year evaluation can produce spurious performance persistence in the sample of survivors. Previous findings in mutual funds and our study do not find that

³ Other pension fund studies include Del Guercio (1996) and Lakonishok, et al (1991 and 1992), who examine some of the institutional peculiarities of pension funds—window dressing, agency relationships, and the effect of the prudent person rule. Del Guercio and Tkac (1998) examine the differences in the cash flow performance relationship between surviving pension and mutual funds. Coggin, Fabozzi, and Rahman (1993) examine timing and selectivity of pension funds. Ippolito and Turner (1987) study pension performance in light of turnover and fees. All of these studies use databases with survivorship bias.

survivorship bias generates spurious persistence as suggested by the Brown et al (1992) single period model of survivorship. In contrast, a multiperiod performance evaluation criterion for survival creates spurious performance reversals (BGIR). Poor performers in the first period must perform better in the second in order to survive. If there is persistence in performance, then the multiperiod criteria generates a survivorship bias that reduces the significance of persistence. We find lower levels of significance of predictability in our survival sample compared to our total sample. This finding is in keeping with the general perception that pension funds have long investment horizons.

We cannot explain our findings of persistence by the existence of poor performers who maintain their poor performance as other mutual and pension fund studies have found. When our data is split between positive and negative dynamic alphas, we do not reject the null of no persistence. This result is interesting because presumably we are adding back poor performers who have been fired. It might be expected that adding back dead poor performing funds to cause the heighten significance of persistence in the total sample.

The outline for this study is as follows: Section II discusses peculiarities of pension fund data. Section III examines the data employed for the study. Section IV introduces a model for survival based on Brown et al (1992). Section V introduces the methods for measuring returns and persistence. Section VI covers the results of style and survivorship on measures of persistence. Section VII summarizes the findings.

II. PENSION FUNDS AND DATA

In the period we examine, 1979-1996, pension plan assets represented one of the largest pools of assets in the United States. The assets of the largest 1000 plans, as reported in *Pensions and Investments* (P&I) were US\$3.4 trillion at the end of September 1996. Of this pool, we

examine defined benefit (DB) plans. P&I surveys indicate that DB plan assets for the largest 200 plans grew from half a trillion dollars in 1984 to \$2.1 trillion in 1996 and represent nearly two-thirds of pension dollars. Within the pension plan universe, DB plans are the largest by both aggregate size as well as individual size. The largest pension plans are well over \$100 billion. Large DB plans have the capacity to hire multiple investment management firms to run separate equity accounts or funds. The hiring and firing of managers by a single plan creates many “dead” funds and new funds for our database. Each new manager hired creates a separate account fund to follow and each manager fired by a pension plan creates a dead fund. Pension fund deaths, thus, differ from mutual fund deaths. Separate account data from pension plans makes for a fertile area for studying survivorship bias.

Dead funds are those funds that have dropped out of the database prior to the end of the sample period. A fund may leave the database for a variety of reasons. The fund may be terminated by the pension plan. The investment management firm may dissolve or merge. Fund structure may change, so that the fund no longer meets the criteria for inclusion in the Russell equity style data. The fund investment objective may change or the fund may change style. Not all of the reasons for fund death are performance related. Large pension plans invest with many investment managers across different asset classes and different equity styles creating multiple funds or accounts. So, switching among styles and/or changing asset allocations creates more dead funds to study.

The life cycle for pension funds is in contrast to the life cycle of mutual funds. In the pension industry when a single plan sponsor terminates a fund, the return history of the fund ends. The fund’s performance record ends. For a mutual fund, it might take time and the exit of many investors before an investment firm decides to close the fund or merge it into another. Meanwhile, performance may continue to deteriorate as equity assets must be sold to meet withdrawals, and more investors withdraw their money. In contrast, when a pension plan

employs or terminates a fund, the asset transfer can be made through its trustee bank without the need to liquidate holdings. The pension termination process could be much faster than in mutual funds. Poor performers would not be allowed to languish. If the persistence found in mutual fund studies were due to the continuation of poor performers, then in mutual funds the slower death process could maintain and enhance persistence, relative to pension funds.

The defined benefit pension business also differs from mutual funds. Since 1988 the net cash flow, contributions less distributions, from plan sponsors to pension plans has been negative (more distributions to beneficiaries). Asset growth has come from market returns. In contrast, the mutual fund industry has been growing rapidly during this period. The net outflows also create a more fertile ground in the pension area for researching survivorship.

A. UNIT OF ANALYSIS

Our study uses separate accounts data from Frank Russell Company (Russell). Separate account pension funds represent the assets of one plan sponsor with one fund management firm. The study of separate account pension funds provides insights into the plan-manager relationship as well as the actions of the fund within the market. Separate account data provides more fund deaths or disappearances than data based on composites, which are portfolios of similarly managed funds by a single investment advisory firm. A composite disappears if there are no longer any funds that managed by an investment firm or the firm changes ownership or the firm ceases. Over 40% of the funds in our study die during the period from 1989 to 1996. In the Coggin and Trzcinka (1999) study of composite funds from 1993 to 1996, less than 20% disappear. In the mutual fund area, Carhart finds over 3% die each year.

B. SELECTION BIAS

All existing pension data sets are self-selected samples of the population, raising issues of selection bias. Consultants create pension fund return databases in order to advise their clients. Lakonishok et al. (1991) use data from SEI, a leading pension funds' consultant. Christopherson et al (1998) use a Russell database of representative funds. Coggin, Fabozzi, and Rahman (1993) use a random sample of surviving funds data from Russell. Khang (1997) employs Callan, a pension consultant, data for a study of conditional performance measures based on portfolio weights. Del Guercio and Tkac (1998) and Coggin and Trzcinka (1999) use composite data from Mobius, a purveyor of pension data. We employ a similar but larger Russell data set than Christopherson et al. Most importantly, we include 227 funds that existed and have dropped out (dead funds) prior to December 1996. We do not have information on why these funds were dropped.

Selection biases arise because a manager (or a pension plan) chooses to have their performance followed. Managers may send their data to a number of different consultants as a means of getting clients. Managers usually must have three to five years of performance to qualify for a search. This may cause backfilling of data as managers submit funds to be followed after the minimum period is survived. The backfilling of data is likely to cause the same types of bias as a look ahead bias—the bias created by requiring firms to last a certain amount of time such as 60 months in order to run particular regressions or calculate certain statistics. Since our dynamic alphas require five years of data to calculate, we also require funds to survive the same minimum amount of time. Thus, we do not expect backfill to bias our results beyond the look-ahead bias already created for calculating initial period alphas. These selection biases are typically not a problem in mutual fund research, but are evident in pension fund data.

Other selection issues include the choice by the manager or consultant of the funds to follow in the database. Managers or consultants may choose to follow only one representative account

or composite per investment style. There may be restrictions placed on funds by the pension plans that cause them to be unrepresentative of a manager's capability. Ethical investing is one type of restriction. Often, there is a size restriction on the databases. Russell's database includes only those equity accounts over \$5 million.

C. STYLES

Since we are concerned with the effects of equity style, we employ style indices. Given that we employ a Russell database and Russell clients compare their manager returns to Russell indices, it is appropriate to follow the same US equity indices to which Russell compares fund performance. The indices are the benchmarks from which clients base their decisions about hiring and firing and ensure that the managers are following the style of investment for which they were hired. Russell's US equity style categories include: market oriented (MO), growth (EG), value (VA), small capitalization (SC) and mid capitalization (MC)⁴. The indices include a broad market index (Russell 1000TM), a small cap index (Russell 2000TM), and also style indices carved out of the Russell 1000TM (Russell GrowthTM and Russell ValueTM indices). For short-term cash, we employ the Salomon Brothers Tbill Index and for longer-term bonds, the Lehman Brothers Government/Corporate Intermediate Bond Index. As a standard equity index, we also use the S&P 500 total return index.

Most recent studies of equity fund managers categorize managers by investment styles. Pension consulting firms such as Russell, Callan, SEI, and Wilshire track fund performance for their clients in manager universes. A universe is a group of similarly managed funds, such as same style. Most often the data provider presents the styles. Or in some databases, investment

⁴ Russell also includes sub styles for many of the funds. Given the use of styles by previous mutual fund and pension fund studies and the small number of observations for sub styles, our analysis is restricted to the four major styles—EG, MO, VA, and SC.

managers declare their fund styles. For Russell, the equity analyst must confirm the style database into which the fund will fall.

Style may have different impacts on persistence and survivorship. If different styles are shown to produce different mortality rates or are affected differently by market movements or conditioning variables, or if these styles have different excess return volatilities, then styles may affect survivorship and persistence. An example of the impact of style on performance is Christopherson et al's (1998) finding that Lakonishok et al's (1992) negative returns are from a period of underperformance by small cap funds. A fund may perform well within its style, but not well across all styles.

III. SUMMARY STATISTICS PENSION FUND DATA

Our database includes 737 different U.S. equity funds over the period 1979 to 1996. The 737 funds represent 333 investment management firms offering 511 different products, if divided by style, or 589 products if divided by sub style according to Russell style and sub style definitions. Of the 737 funds, 535 funds have monthly data. We remove 13 mid cap funds, because of the relatively short time horizon and the low number of funds resulting in the final sample of 522 funds.

Within the 522 funds, 227 funds die before the end of December 1996 leaving 295 survivors. A snapshot of the number of funds in the database at the end of years 1981, 1985, 1989, 1993, and 1996 is displayed in Figure 1. Survivors are funds that exist at the end of the sample period. Dead funds are simply those that do not exist in Dec. 1996. There are fewer funds in 1993 that die by the end of 1996 than in 1989 because the dead funds are dying off faster than they are entering. No funds in our data die before 1989. We do not have a completely

survivorship bias free data set. Our results may understate the effects from survivorship, but should point out the direction of the effect of survivorship.

Market oriented funds outnumbered other styles until the 1990s. Small cap funds in the 1990s are the most numerous. The distribution of funds among the four styles is fairly similar between the surviving and dead samples. Any impact by style on the persistence will be driven by the style returns and not by an imbalance in the number of funds among the styles.

For our calculation of returns for groups of funds, we employ equally weighted portfolios. This assumes that as money passes out of a dead fund it is evenly divided among current existing funds. This assumption is similar to the “follow the money approach” adopted in the mutual funds studies of Gruber (1996); Elton, Gruber, and Blake (1996); and Zheng (1999) to help minimize survivor bias on returns.

The returns from an equally weighted portfolio of all funds for the period of examination, 1979-1996, are reported in Table 1. The average monthly return of an equally weighted portfolio of funds was 1.54% for survivors and 1.48% for dead funds over the period from 1979-1996. The average return beat all the indices over this period (see Table 9A). The best performing index was Russell Value at 1.37% per month over this period. Value survivors are the worst surviving performers earning 1.46%. Market-oriented dead are the worst dead group at 1.39%. When style group portfolios of survivors are formed, all dead and surviving equity style portfolios beat the Russell Value Index over the period and the S&P 500 over the sample period. This outperformance by pension funds contrasts to the period Lakonishok et al (1992) studied where the average fund did not beat the S&P 500. We found that underperformance in Lakonishok et al is period specific. Christopherson et al (1998) attribute it to small cap funds. There is at least some indication that the average pension fund over our larger time period, even with possible poor performing dead funds added back in, has not done poorly against market

indices. None of the differences between dead and surviving fund average returns are significant. As would be expected survivors typically have higher average returns, though not significantly so. We examine the styles for differences in variance between dead and survivors. We find significant differences for each style group. For value and growth styles, survivors have higher variance. For small cap and market-oriented style groups, dead funds have higher variances. Survivorship and variance do not have a consistent relationship within the style groups as might be suggested by models of survivorship by Hendricks, Patel and Zechhauser (1995) or Brown et al (1992).

The possible selection bias, requiring three years of returns to be placed in a manager search, that is inherent in the creation of pension fund data leads us to examine the first 36 months of returns (see Table 2). We find that the returns in the first 36 months are higher than over the rest of the life of the funds. Christopherson et al found similar results using survivor only pension data. Because we require a 60-month period for calculating dynamic alphas, we do not expect the bias in selection to affect the persistence results.

We also examine the final 12 months of returns of a dying funds life to see if there is a performance drop. We find lower average returns in the average dying fund's last 12 months of life in the database. Other studies have found poor performers often drive the significant persistence results. While we find the lower performance in the last year, we found insignificant differences, in general, between survivors and the dead fund samples. Dead funds must be good performers at some point to compensate for the last year and to live as long as some dead funds do. The dead funds are not necessarily persistently poor performers.

IV. MODELS OF SURVIVAL

Our hypotheses about the effects of survivorship bias on persistence are based a model of survival proposed by Brown et al (1992). In the model (presented in Brown et al's appendix), survival depends on a two-period performance evaluation. A fund survives if the return over two periods is positive, $x_1 + x_2 > 0$. Persistence is when one fund outperforms another fund over the two periods, $x_1 > y_1$ and $x_2 > y_2$. Based on the survival criteria, Brown et al show that $P[x_2 > y_2 / x_1 > y_1 \text{ and } c] < 1/2$, where the survival criteria, c , is $\{x_1 + x_2 > 0, y_1 + y_2 > 0\}$. The two funds are assumed to be independent and identically distributed with distributions symmetric about the origin. This model of survival is more likely to have performance reversals than persistence, as funds must improve their second period performance to survive if the first period performance was poor.

A model of multiperiod evaluation lends itself to the institutional structure of pension plans. Long horizons may be appropriate periods of evaluation for fiduciary and liability reasons. If pension plans are seen to fire managers too soon after hiring them, then the prudence of the hiring decision may come into question. Defined benefit pension plans have long horizon liabilities. To ensure pension plans are funded, the actuarial investment horizons typically match the long horizons of the liabilities. Our hypothesis is that the multiperiod model of performance evaluation is appropriate for pension plans. This hypothesis is taken to imply that by moving from our total sample to the survivor only sample the evidence of persistence is dampened.

The model does not explicitly appoint a correct return measure for evaluating performance. A number of return measures are suggested by existing literature. Gruber (1996) employs a four-factor model, finding that mutual fund investors' cash flows follow abnormal performance. Zheng (1999) employed the same four-factor model and a conditional version in early drafts of her paper. The *Journal of Finance* version of Zheng (1999) employs a conditional Fama-French three factor model. Christopherson et al find persistence in pension funds with a dynamic

alpha from a conditional CAPM. Del Guercio and Tkac (1999) report that pension cash flows follow performance with CAPM alpha. In hopes of controlling style differences, we employ a conditional four-factor model. For the four factors in our conditional model, we use combinations of the Russell indices. The factors are the differences between Russell Growth and Russell Value Indices (GRVA), Russell 2000 less Russell 1000 (SMLG) for small cap minus large, the Russell 1000 less the Salomon TBill (RUSRMRF) for market excess return, and a term premium factor of Lehman Brothers Bond Index less Salomon Tbill Index.

We follow Christopherson, Ferson and Glassman by calculating dynamic alphas using an initial period of at least 60 months. Other return periods may reflect actual pension plan termination behavior better. For example, pension plans review performance on a variety of period lengths. A minimum evaluation period on raw returns or excess over the market is one to three months given trustee bank and consultant performance reports. This shorter evaluation period corresponds to monthly fund reporting or quarterly consultant performance reports. In other work on asset flows and performance in Myers (2000), we examine the relationship between shorter horizon returns and asset flows. Termination is the ultimate asset outflow. Since this study is primarily interested in the impact of survivorship bias on predictability, we restrict our analysis to the five-year dynamic alphas found to have the greatest predictability by Christopherson et al.

V. METHODOLOGY

We have chosen a particular set of measures to study persistence based on previous studies. Since one of our objectives is to test the impact of non-survivors on the evidence for persistence, it is important to employ methodologies similar to previous studies. Christopherson et al and Christopherson, Ferson and Turner find that a conditional model with a dynamic alpha is the best predictor of future performance. For this reason, we follow their regression

methodology of future returns on past dynamic alphas. We also adopt a methodology that Carpenter and Lynch (1999) find to have the most power in finding persistence—a chi-squared test of a 2x2 contingency table (chi-squared). The chi-squared test is the most robust of their test statistics to data with a survivorship bias. We employ the chi-squared test both as a conservative measure of persistence and use the two-by-two contingency table to see the distribution of styles and their impact on relative persistence.

We employ the following categories for our analyses: total sample refers to all funds dead and survivors. Survivors are only those funds that existed at the end of 1996, similar to the data in most previous studies. Dead funds are those that exited the database prior to December 1996. ALL refers to all four equity styles—Growth (EG), Market-Oriented (MO), Small Cap (SC), and Value (VA)—grouped together whether part of survivors, dead, or total samples.

A. DYNAMIC ALPHAS, α^{4CD}

Conditional performance models, such as Ferson and Schadt (1996), Christopherson et al (1998) and Becker et al (1999), take into account changing public information, allowing for time varying alphas and betas. These studies show that conditional performance measures provide better models of manager behavior.

Christopherson et al (1998) found that the dynamic alpha was a better predictor of future returns than a fixed conditional alpha or other models in the period 1979-1990. The predictability they found is concentrated in poorer performing pension funds. In an extension of their work adding data from 1990 to 1996, Christopherson, Ferson and Turner also find some persistence in the top quintiles. To measure performance, we employ a four-factor model with time varying or dynamic alphas, α^{4CD} . This combines the conditional model of Christopherson et al and Christopherson, Ferson and Turner with the four-factor model of Gruber (1996) and

matches earlier versions of Zheng (1999). Our model is estimated using either 36 or 60 months of past returns.

$$\begin{aligned}
 r_{pt+1} &= a_{0p} + A'_p z_t + b_{0pb} r_{bt+1} + B'_{pb} z_t r_{bt+1} + u_{pt+1} \\
 \mathbf{b}_{pb}(Z_t) &= b_{0pb} + B'_{pb} z_t \\
 z_t &= Z_t - E(Z) \\
 \mathbf{a}^{4CD} &= a_{0p} + A'_p z_t
 \end{aligned} \tag{1}$$

Where

r_p = the return of the fund portfolio in excess of the risk-free rate

Z = a vector of the four demeaned lagged information variables—dividend yield, detrended bill rate (subtracting the 12 month moving average), January dummy, and term spread. Ferson, Sarkissian, and Simin (1999) find that it is useful to use demeaned lagged variables in conditional studies. We employ a rolling 60 month demeaned set of variables to match the rolling 60 month regressions.

r_b = vector of factor returns ($r_{mf} r_{GV} r_{SL} r_{Bf}$) with $r_{mf} = R_M - R_f$, $r_{GV} = R_G - R_V$, $r_{SL} = R_S - R_L$, and $r_{Bf} = R_B - R_f$

R_M = return of the S&P500 for 1 factor model and Russell 1000 for four factor model

R_f = return of US Treasury bills

R_S = return of the Russell 2000 (small cap index)

R_L = return of the Russell 1000 (large cap market index)

R_G = return of the Russell Growth Index

R_V = return of the Russell Value Index

R_B = return of the Lehman Brothers Government/Corporate Intermediate Bond Index

u_t = is the error term and is assumed to be distributed $(0, \mathbf{S}_p^2)$ for each portfolio or fund. There may be cross-sectional heteroskedasticity across portfolios.

The dynamic alphas, α^{4CD} , are time varying conditional alphas based on the current lagged information variables and the coefficients from the regression. Christopherson et al conclude that pension funds have non-zero significant dynamic alphas and that the dynamic alphas predict future returns.

B. PERFORMANCE PERSISTENCE METHODOLOGY

To study predictability in performance, we employ a cross-sectional regression technique similar to one used by Christopherson et al for the past 60 month dynamic alpha on future returns of 1, 3, 6, 12, 18, 24, and 36 months.

$$r_{p(t,t+\tau)} = \mathbf{g}_{0,t,t} + \mathbf{g}_{1,t,t} \mathbf{a}_{pt}^{4CD} + u_{p(t,t+\tau)} \quad (2)$$

for horizons, $\tau = 1, 3, 6, 12, 18, 24, 36$

Where Christopherson et al employed a one factor conditional model for calculating the dynamic alpha, we employ a four factor conditional model. The cross-sectional regression coefficients for each month are averaged over time similar to Fama and MacBeth (1973). For periods greater than 1 month, we employ Newey-West (1987a and b) weights to adjust the Fama-Macbeth (1973) t-statistics for the lags induced by the overlapping in time. The weights are $(1-(\mathbf{t}/t))$ where \mathbf{t} is the length of the lag and t is the length of the return horizon. The γ_1 s (in equation 2) measure the sensitivity of the future returns to the past dynamic alphas, α^{4CD} . We use a weighted-least squares approach for the cross-sectional regression (equation 2) where the weights are the residuals from equation one. The result is that we are employing an appraisal ratio, alpha divided by its standard error, based on Brown et al (1992) to compensate for

survivorship bias due to differences in volatility. If spurious persistence is created by differences in volatility, Brown et al show that the use of an appraisal ratio compensates for the bias.

To get a snapshot of style breakdowns and persistence we use a two by two table of winners and losers and the associated chi-squared test (Carpenter and Lynch 1999). The chi-squared test statistic with one degree of freedom is

$$\begin{aligned}
 \chi^2 &= \sum_i \sum_j (n_{ij} - n/4)^2 / n \\
 ij &= WW, WL, LW, LL
 \end{aligned}
 \tag{3}$$

where n_{ij} is the number of funds in one of the four cells (WW, WL, LW, and LL) and n is the total number of funds. Chi-squared is based on contingency tables of winners and losers over two stages within one period. The initial stage is the ranking stage and the second stage is the evaluation stage. Winners (W) are above the median in performance and losers (L) are below the median. WW represents the number of funds that are winners in the ranking stage and winners in the evaluation stage, and WL represents winners in the ranking period and losers in the evaluation period. Persistent performance is WW or LL. Reversals are LW or WL. We examine two periods each with a ranking and evaluation stage. For 5 year dynamic alpha on 3 year return analysis, period one is a ranking stage of January 1983–December 1987 and an evaluation stage of January 1988–December 1990 and period two is a ranking stage of January 1988–December 1992 and an evaluation stage of January 1993–December 1995. For chi-squared tests, we employ a both a partial look ahead (PLA) bias methodology and a full look ahead bias (FLA) methodology from Carpenter and Lynch (1999). FLA ranks only on those funds that exist for both the ranking and evaluation periods, n . PLA ranks in the ranking stage those funds that exist in the ranking stage, $n + d$, where d is the number of funds that existed in the ranking stage, but die in the evaluation stage. PLA ranks in the evaluation stage those funds

that exist in both the ranking and evaluation stages, n . We do not find significant differences between the two tests with our data, but display them both.

VI. RESULTS

In the first step of our analysis, we test the null hypothesis of no predictability of future returns by past performance. We examine the regressions of future returns on past dynamic alphas using a cross-sectional regression of α^{4CD} s calculated from a four factor conditional model estimated over the previous 60 months of data (see Table 3). The slope coefficient, γ_1 , is averaged across periods and the Fama-Macbeth t-test for significance is adjusted using Newey-West lagged weights to account for overlapping periods. The null hypothesis is that there is no predictability in pension fund returns, that is the slope coefficient is not significantly different from zero. We find that in the survivor only sample only three of the seven γ_1 s, slope coefficient on the dynamic alphas, are significant at a 10% level for a two-tailed t-test. Significant positive slope coefficient implies that future returns are predictable from past dynamic alphas and persistent. The three significant periods in the survivor sample are the longest periods. This reconfirms the results of Christopherson et al that there is predictability of future returns from past dynamic alphas for longer return horizons. The total sample has significantly positive t-statistics for all but the one-month return period. When we calculate an annualized mean slope coefficient, by dividing by the horizon in terms of years, the range is now from 85 to 130 basis points. A one-percent increase in past dynamic alpha is equivalent to about a one-percent increase in future annual return. The total sample provides strong evidence against the null hypothesis of no predictability.

Having found predictability of future returns using past dynamic alphas across all styles, we turn to predictability within styles (see table 4). We run the same cross-sectional regression for each of the funds within each of our four style groups. Within the style breakdowns, there are few

significant γ_{1s} —only 11 of 28 significant coefficients for the survivor sample. The significant γ_{1s} are mostly negative, indicating predictable performance reversals for funds, within the value style and mostly positive within the market-oriented style group. When we move to the total sample most of the significance of the reversals disappear. In the total sample, we find significant positive slope coefficients for the market-oriented longer horizons and the small cap shorter horizons. Within styles, the evidence is not as strong for rejecting the null of no predictability as it was across all styles. We cannot reject the null for growth or value funds.

Having established stronger results in the total sample for predictability of pension fund returns, we now want to test whether there is a significant bias between the survivor sample and the total sample (see Table 5). The null hypothesis is that there is no bias between the surviving and total samples. To test this, we take the difference between the cross-sectional regression slope coefficients at each month, D_t . While the mean D_t is positive across all styles, it is only significant for 1, 3, and 12 months. Remember that it was in the shorter horizons that the total sample results were significant while the survivor sample were not. The survivorship bias in persistence is in shorter horizons. The results indicate that survivorship bias dampens the evidence of predictability in returns from the time varying alphas. This is consistent with the Brown et al model of a multiperiod fund review and termination process by pension plans. Funds are likely to reverse poor performance from one period to the next to avoid being fired. The reversals in fund performance dampen evidence of predictability and persistence, in a surviving sample, relative to what is found in the complete sample.

When we move to the within style analysis, the results vary by style. First, survivorship bias significantly decreases the slope coefficients—the γ_{1s} —for small cap and value styles. This result is similar to the dampening of predictability in examining across all equity styles and is consistent with multiperiod evaluation survivorship bias effect (Brown et al). For market oriented funds, however, the total sample has significantly lower γ_{1s} in four of the seven return

horizons. We caution pension plans that try to use past dynamic alphas to predict future returns within style groups. The results of predictability and survivorship bias can change the direction of the relationship between past dynamic alphas and future returns within equity styles.

Because of the difference in predictability for across all equity style funds, compared to within style groupings, we turn our attention to the distribution of the styles groups within the rankings of all equity funds. We want to find if the difference in predictability across styles versus within styles is driven by the dynamic alphas of the style funds grouping together. The first step is to take a snapshot of the style breakdowns using the chi-squared measures from a 2x2 contingency table of past 5 year dynamic alphas on 3 year future returns (see Table 6). Even though we have very few observations, we find significant differences in the style groupings that make up the winners and losers in certain periods. There are periods where the dynamic alphas for a particular style dominate the winners or losers. For period one, small cap funds are the majority of loser/losers. In period two, growth and value represent reversed patterns of winners and losers in the evaluation period. Growth funds are mostly losers in the evaluation period (making up most of the LL and WL), while value funds are mostly winners in the evaluation period (LW and WW). For the moment we raise a caution flag that using a strategy of investing in top dynamic alphas funds may result in highly concentrated portfolios of funds with respect to style allocations.

$$\mathbf{C}_{(r-1)(c-1)}^2 = \sum_i \sum_j (n_{ij} - m_{ij})^2 / m_{ij} \quad (4)$$

$$m_{ij} = n_{i\bullet} n_{\bullet j} / n$$

To better examine the significance of the changing style allocations, we test the style group imbalances among quintile portfolios. We rank the funds on dynamic alphas into quintiles and count the number of funds in each style group in each quintile, n_{ij} with $n_{i\bullet}$ as the row or style total and $n_{\bullet j}$ is the column or quintile total. We calculate a Pearson chi-square (equation 4) test

from the resulting 4x5 contingency table of the 4 style groups ranked into quintiles based on a ranking of dynamic alphas. The Pearson chi-squared has 12 degrees of freedom and takes into account the differences in row and column counts due to differences in the total number of funds in each style by using m_{ij} as the conditional value for each cell. We know there are differences in the number of funds per style grouping and this is why we adopt the Pearson chi-squared test. We plot the chi-squared probability in Figure 4 for each month.

The null hypothesis for the chi-squared test of styles across quintiles is that the distribution is random and the chi-squared is insignificant from zero. We find that in most months since 1987, the chi-square test rejects the null hypothesis of equal proportions of funds in each quintile portfolio for both the total sample and the survivor sample (see Figure 3). The earlier periods may not have a sufficient number of funds to be significant. We conclude that the distribution of the funds by styles across the dynamic alpha quintiles is not random. Style groupings are related to relative dynamic alpha equity performance. The four factor conditional model may not be adequately accounting for the style return differences. To glimpse inside the top quintile's (highest dynamic alphas) style allocations, we plot (see Figure 4) the allocations monthly within the top quintile portfolio. We find that there is a strong overweighting in small cap funds in the top quintile portfolio towards the end of the period examined. While a simple overweighting problem may arise from the imbalance among the number of funds among the four style groups, this cannot fully explain the rejection of the null by the Pearson chi-squared test. The Pearson chi-squared takes into account any imbalances among the style groups. Any rejection is a result of imbalances across the quintiles for each style.

To confirm the imbalance is across quintiles (equivalently within styles), we break the four by five tables of quintiles by styles into the separate rows and columns to examine within and across styles or across and within quintiles for the total sample. In the total sample, we reject random distribution of the styles across quintiles in 61% of the months for the Pearson Chi-

squares at a 10% level. Across quintiles (or within each style group), Small Cap funds reject random distribution across the quintiles in 66% of the months, Market Oriented, 41%, and Value and Growth only 19% and 14%, respectively. When the analysis is switched to look within quintiles or across styles, the rejection rates of random distribution within quintiles are more uniform ranging from 41 to 66%. The result appears to be driven by the small cap funds and market oriented funds.

To highlight the effect of style differences in persistence on a strategy based on persistence across styles, we plot the monthly asset allocation (see Figure 3) of the following strategy. First, rank the funds each month on their past dynamic alphas into equally weighted quintile portfolios. Next invest in the top or best performing quintile portfolio and reallocate each month. The resulting allocation by the end of the sample period is almost entirely in small cap funds, not a very well diversified portfolio for pension plans.

A. ROBUSTNESS OR SENSITIVITY ANALYSIS

We run a series of tests to compare our results with previous studies. Since we employ a dynamic alpha from a four factor conditional model, we rerun our results (see table 7) with a dynamic alpha from a conditional CAPM and an alpha from a CAPM. This is similar to Christopherson et al and Christopherson, Ferson and Turner. We find that the dynamic alpha predicts future returns better than the CAPM alpha. We reconfirm our survivorship bias results, survivorship dampens evidence in persistence across styles.

Other researchers have found that consistently poor performers generate the significance in persistence (Christopherson et al). To test this phenomenon, we split the model's dynamic alphas into positive and negative groups to see if the poor performers are driving the persistence results (see table 8). If poor performers are the cause of the persistence results, then we should find significant slope coefficients within the negative dynamic alpha funds and not the positive

alpha funds. Once the data has been split between positive and negative dynamic alphas our results are no longer significant. Neither positive nor negative dynamic alphas alone are sufficient to create significant persistence results. By not finding significant slope coefficients within the negative dynamic alpha group, we cannot say that persistently poor performers drive our results.

VII. CONCLUSIONS

We find that survivorship bias dampens evidence of predictability in returns across equity funds. The evidence of predictability of past dynamic alpha on future return found in Christopherson, Ferson, and Glassman (1998) is stronger when we add nonsurviving funds to the analysis. The dampening of the significance of predictability by survivorship bias is implied by a multiperiod performance evaluation by pension plans, as modeled by Brown et al (1992). Performance reversals are a result of multiperiod performance evaluation criterion that allows poor performers to reverse their poor performance and survive. Based on this result, future research attempting to predict fund or manager survival should consider employing a multiperiod performance evaluation model. Two possible reasons for the use of a multiperiod evaluation by pension plans include the importance of non-performance-related criteria driving the hiring and firing decisions and also long investment horizons for pension plans. Funds may be able to survive longer with poor performance if they provide other valuable services.

When we break down the analysis to style groupings we continue to find that survivorship bias lowers the value of the coefficient on past dynamic alphas in a regression with future return as the dependent variable for two of the four styles—small cap and value. We find significant persistence within small cap and market oriented funds. We also find the allocation of funds by style is not random across winners or losers or across quintiles based on dynamic alpha rankings. We conclude that pension plans, if considering past performance as a criteria for

investing, should (1) use dynamic alphas from all equity funds for determining relative performance and (2) realize that there may be less style diversification as a result. If the intent is to predict future returns, then using a dynamic alpha as a predictor appears to imply a willingness to switch or time among the styles.

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Table 1: Summary Statistics for Equal Weighted Portfolio of Funds

The table shows the statistics—mean and standard deviation—for the monthly average returns of an equal weighted portfolio, R_{pt} , of all funds existing at each month, t for each category of surviving or dead funds and by style. There are 522 funds from Frank Russell Company data with monthly returns that existed between January 1979-December 1996. Styles are defined by Frank Russell Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. Style indexes include Russell 1000, Russell 2000, and Russell Value and Russell Growth. The t and F statistics refer to differences between survivors and dead fund portfolios for means and variances, respectively.

$$R_{pt} = \frac{1}{N_t} \sum_{i=1}^{N_t} R_{it}, i = \text{funds } 1 \text{ to } N_t$$

$$a_0 = R_{pt} - R_{S\&P500,t}$$

Style	Variable	Group	Mean	SD	t	Prob> t	F	Prob>F'
ALL Styles	α_0	Total	0.16%	1.18%	Test for means		Test for variance	
	R_p	Total	1.52%	4.27%			s	
ALL Styles	α_0	Survivors	0.18%	1.21%	0.65	0.52	1.18	0.22
		Dead	0.11%	1.11%				
ALL Styles	R_p	Survivors	1.54%	4.34%	0.14	0.89	1.07	0.63
		Dead	1.48%	4.20%				
EG	α_0	Survivors	0.20%	1.57%	0.75	0.46	1.35	0.03
		Dead	0.09%	1.35%				
EG	R_p	Survivors	1.56%	4.83%	0.20	0.84	1.10	0.48
		Dead	1.47%	4.61%				
MO	α_0	Survivors	0.10%	0.75%	0.62	0.54	1.40	0.01
		Dead	0.05%	0.89%				
MO	R_p	Survivors	1.46%	4.05%	0.18	0.85	1.16	0.29
		Dead	1.39%	3.77%				
SC	α_0	Survivors	0.30%	2.27%	-0.01	1.00	1.34	0.03
		Dead	0.30%	2.62%				
SC	R_p	Survivors	1.66%	4.97%	0.04	0.97	1.17	0.25
		Dead	1.64%	5.38%				
VA	α_0	Survivors	0.10%	1.23%	0.17	0.87	1.41	0.01
		Dead	0.08%	1.03%				
VA	R_p	Survivors	1.46%	3.79%	0.01	0.99	1.03	0.81
		Dead	1.45%	3.85%				

Table 2: Differences in Returns based on Age and Last Year of Fund Life

The table shows the statistics—mean and standard deviation — for the monthly average returns of an equal weighted portfolio, R_{pt} , of all funds existing at each month, t for each category of surviving or dead funds and by style. There are 522 funds from Frank Russell Company data with monthly returns that existed between January 1979-December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. Style indexes include Russell 1000, Russell 2000, and Russell Value and Russell Growth. T-tests are for both across groups Survivors and Dead and across categories young and old or last year or more of life and have been adjusted for differences in the number of funds in each category.

$$R_{pt} = \frac{1}{N_t} \sum_{i=1}^{N_t} R_{it}, i = \text{funds } 1 \text{ to } N_t$$

$$a_0 = R_{pt} - R_{S\&P500,t}$$

		Total		Survivors		Dead		Survivors-Dead
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
Age < 36 months (Young)	R_p	1.59%	4.30%	1.62%	4.38%	1.48%	4.21%	0.34
	α_0	0.23%	1.33%	0.26%	1.42%	0.14%	1.25%	0.93
Age > 35 months (Old)	R_p	1.43%	4.25%	1.45%	4.28%	1.41%	4.22%	0.08
	α_0	0.02%	1.14%	0.04%	1.12%	-0.01%	1.10%	0.47
More than 1 year to live	R_p	1.52%	4.27%	1.54%	4.34%	1.46%	4.26%	0.20
	α_0	0.16%	1.19%	0.18%	1.21%	0.14%	1.10%	0.37
Less than 1 year to live	R_p	1.02%	4.43%			1.02%	4.43%	
	α_0	-0.12%	1.40%			-0.12%	1.40%	
	Differences	t		t	prob>t	T		
Age (Young-Old)	$R_{p\text{young}} - R_{p\text{old}}$	0.38		0.39	0.35	0.16		
	$\alpha_{0,\text{young}} - \alpha_{0,\text{old}}$	1.70		1.71	0.04	1.29		
More vs. Less than 1 Year to live	$R_{p\text{more}} - R_{p\text{less}}$	0.99				0.86		
	$\alpha_{0,\text{more}} - \alpha_{0,\text{less}}$	1.85				1.74		

Table 3: Regressions of Future Returns on Past 5-Year α^{4CD}

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month dynamic alphas for funds existing for at least 5 years. There are 522 (295 survivors) funds in the data base from Frank Russell Company in the period January 1979-December 1996. Survivors existed at the end of December 1996. The t statistics are the Fama-MacBeth t-statistics based on the time series average of the γ_1 s. The standard errors and t statistics have been adjusted for $\tau-1$ Newey-West lags. Annualized Mean γ_1 is calculated by divided the mean γ_1 by the length in years of the horizon.

$$r_{p(t,t+t)} = \mathbf{g}_{0,t,t} + \mathbf{g}_{1,t,t} \mathbf{a}_{pt}^{4CD} + u_{p(t,t+t)}$$

TOTAL	Horizon	Mean \mathbf{g}_1	t	prob> t	Number of months	Annualized Mean \mathbf{g}_1
	36	2.84	4.04	0.00	120	0.95
	24	2.15	2.88	0.00	132	1.07
	18	1.73	2.41	0.02	138	1.15
	12	1.30	3.08	0.00	144	1.30
	6	0.61	3.66	0.00	150	1.23
	3	0.21	1.88	0.06	153	0.85
	1	0.09	1.59	0.11	155	1.03
SURVIVOR						
	36	2.59	2.78	0.01	120	0.86
	24	1.72	1.68	0.10	132	0.86
	18	1.24	1.64	0.10	138	0.82
	12	0.68	1.46	0.15	144	0.68
	6	0.29	1.30	0.20	150	0.58
	3	0.01	0.10	0.92	153	0.06
	1	-0.02	-0.30	0.76	155	-0.24

Table 4: Regressions of Future Returns on Past 5-Year α^{4CD} for Style Groups

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month dynamic alphas for funds existing for at least 5 years. There are 522 (295 survivors) funds in the data base from Frank Russell Company in the period January 1979-December 1996. Survivors existed at the end of December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. The t statistics are the Fama-MacBeth t-statistics based on the time series average of the γ_1 s. The standard errors and t statistics have been adjusted for $\tau-1$ Newey-West lags.

$$r_{p(t,t+\tau)} = \mathbf{g}_{0,t,t} + \mathbf{g}_{1,t,t} \mathbf{a}_{pt}^{4CD} + u_{p(t,t+\tau)}$$

Horizon	Style	TOTAL			Annualize	Survivors			Annualize	months
		Mean \mathbf{g}_1	t	prob> t	Mean	Mean \mathbf{g}_1	t	prob> t	Mean	
36	EG	-2.892	-1.54	0.13	-0.96	-4.060	-1.35	0.18	-1.35	120
24	EG	-2.236	-2.35	0.02	-1.12	-3.333	-2.63	0.01	-1.67	132
18	EG	-1.289	-1.46	0.15	-0.86	-1.171	-1.10	0.27	-0.78	138
12	EG	-0.295	-0.58	0.56	-0.29	-0.612	-0.79	0.43	-0.61	144
6	EG	-0.165	-0.66	0.51	-0.33	-0.166	-0.44	0.66	-0.33	150
3	EG	-0.115	-0.72	0.47	-0.46	-0.217	-0.95	0.34	-0.87	153
1	EG	-0.036	-0.53	0.60	-0.43	-0.182	-1.11	0.27	-2.19	155
36	MO	2.274	2.97	0.00	0.76	4.891	2.27	0.03	1.63	120
24	MO	1.339	2.68	0.01	0.67	3.831	2.69	0.01	1.92	132
18	MO	0.877	2.34	0.02	0.58	2.590	2.61	0.01	1.73	138
12	MO	0.473	1.48	0.14	0.47	1.207	1.97	0.05	1.21	144
6	MO	0.133	0.57	0.57	0.27	0.336	0.98	0.33	0.67	150
3	MO	0.002	0.01	0.99	0.01	-0.022	-0.10	0.92	-0.09	153
1	MO	-0.005	-0.09	0.93	-0.06	-0.052	-0.59	0.56	-0.62	155
36	SC	0.632	0.49	0.63	0.21	-3.740	-1.37	0.17	-1.25	120
24	SC	1.340	0.90	0.37	0.67	-1.900	-0.75	0.46	-0.95	132
18	SC	1.424	1.13	0.26	0.95	-1.714	-0.80	0.43	-1.14	138
12	SC	1.428	1.91	0.06	1.43	-1.742	-1.54	0.13	-1.74	144
6	SC	0.826	2.25	0.03	1.65	-0.892	-1.59	0.11	-1.78	150
3	SC	0.513	2.79	0.01	2.05	-0.507	-1.71	0.09	-2.03	153
1	SC	0.153	1.92	0.06	1.84	-0.210	-1.55	0.12	-2.52	155
36	VA	-2.318	-2.04	0.04	-0.77	-2.404	-1.63	0.11	-0.80	120
24	VA	-0.637	-0.59	0.56	-0.32	-3.075	-2.59	0.01	-1.54	132
18	VA	-0.393	-0.43	0.67	-0.26	-3.160	-2.67	0.01	-2.11	138
12	VA	0.015	0.02	0.98	0.01	-2.489	-2.85	0.01	-2.49	144
6	VA	0.096	0.23	0.82	0.19	-1.451	-2.07	0.04	-2.90	150
3	VA	-0.022	-0.10	0.92	-0.09	-0.939	-2.05	0.04	-3.76	153
1	VA	0.057	0.62	0.54	0.69	-0.154	-0.79	0.43	-1.84	155

Table 5: Differences in Total Sample and Survivor Sample Regression Coefficients, γ_1

The table shows the difference, D_p , between the γ_1 s from the total and survivor sample cross-sectional regressions of future returns over τ periods (1-36 months) over past 60 month dynamic alphas for funds existing for at least 5 years. There are 522 (295 survivors) funds in the data base from Frank Russell Company in the period January 1979-December 1996. Survivors existed at the end of December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. The t statistics are the Fama-MacBeth t-statistics based on the time series average of the γ_1 s. The standard errors and t statistics have been adjusted for τ -1 Newey-West lags.

$$r_{p(t,t+t)} = \mathbf{g}_{0,t,t} + \mathbf{g}_{1,t,t} \mathbf{a}_{pt}^{ACD} + u_{p(t,t+t)}$$

$$D_{t,t} = \mathbf{g}_{1,t,t} - \mathbf{g}_{1,t,t}$$

Horizon	Mean D	t	prob> t	months
36	0.249	0.30	0.76	120
24	0.424	0.68	0.50	132
18	0.490	1.12	0.27	138
12	0.614	1.77	0.08	144
6	0.323	1.51	0.13	150
3	0.199	2.35	0.02	153
1	0.106	2.78	0.01	155

Horizon	Style	Mean D	t	prob> t	Months
36	EG	1.168	0.56	0.58	120
24	EG	1.097	1.74	0.09	132
18	EG	-0.119	-0.19	0.85	138
12	EG	0.317	0.70	0.49	144
6	EG	0.001	0.00	1.00	150
3	EG	0.101	0.65	0.51	153
1	EG	0.146	0.99	0.32	155
36	MO	-2.617	-1.67	0.10	120
24	MO	-2.492	-2.07	0.04	132
18	MO	-1.713	-2.26	0.03	138
12	MO	-0.735	-1.72	0.09	144
6	MO	-0.203	-0.87	0.39	150
3	MO	0.024	0.16	0.87	153
1	MO	0.047	0.81	0.42	155
36	SC	4.372	2.08	0.04	120
24	SC	3.240	1.79	0.08	132
18	SC	3.139	1.88	0.06	138
12	SC	3.169	3.43	0.00	144
6	SC	1.717	2.90	0.00	150
3	SC	1.020	3.32	0.00	153
1	SC	0.364	3.14	0.00	155
36	VA	0.086	0.06	0.96	120
24	VA	2.438	2.37	0.02	132
18	VA	2.767	2.65	0.01	138
12	VA	2.503	2.87	0.00	144
6	VA	1.547	2.50	0.01	150
3	VA	0.917	2.39	0.02	153
1	VA	0.211	1.19	0.24	155

Table 6: Contingency Table of Past 5 year α^{4CD} and Future 3-Year Returns

The table shows the Carpenter and Lynch chi-squared test for a 2x2 matrix of past winners and losers on future winners and losers. Winners (losers) are above (below) the median based on 5 year conditional 4 factor model alphas and the evaluation period is based on 36 monthly raw returns. There are 522 funds in the data base from Frank Russell Company in the period January 1979-December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. The style breakdowns are based on overall equity median for the rankings. period one is a ranking stage of January 1983–December 1987 and an evaluation stage of January 1988–December 1990 and period two is a ranking stage of January 1988–December 1992 and an evaluation stage of January 1993–December 1995. Full-look ahead (FLA) ranks only on those funds that exist for both the ranking and evaluation periods, n . Partial-look ahead ranks in the ranking stage those funds that exist in the ranking stage, $n+dead$, and ranks in the evaluation stage those funds that exist in both, n .

$$c_1^2 = \sum_i \sum_j (n_{ij} - n/4)^2 / n$$

$$ij = WW, WL, LW, LL$$

		LL	WL	LW	WW	n	Chi-sq	Chi Prob
FLA	Period 1							
	All Styles	19	14	14	19	66	0.38	0.54
	EG	1	1	3	6	11	1.52	0.22
	MO	4	6	6	10	26	0.73	0.39
	SC	10	2	2	1	15	3.52	0.06
	VA	4	5	3	2	14	0.36	0.55
	Period 2							
	All Styles	35	30	31	36	132	0.20	0.66
	EG	12	9	3	1	25	3.15	0.08
	MO	13	5	15	8	41	1.53	0.22
	SC	9	12	7	10	38	0.34	0.56
	VA	1	4	6	17	28	5.21	0.02
PLA	Period 1							
	All Styles	20	13	14	19	66	0.56	0.45
	EG	1	1	3	6	11	1.52	0.22
	MO	5	5	6	10	26	0.65	0.42
	SC	10	2	2	1	15	3.52	0.06
	VA	4	5	3	2	14	0.36	0.55
	Period 2							
	All Styles	31	35	28	38	132	0.44	0.51
	EG	12	9	3	1	25	3.15	0.08
	MO	10	9	13	9	41	0.26	0.61
	SC	9	12	7	10	38	0.34	0.56
	VA	0	5	5	18	28	6.36	0.01

Table 7: Regressions of Future Returns on Past 5-Year α^{4CD}

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month CAPM dynamic alphas and CAPM alphas for funds existing for at least 5 years. There are 522 (295 survivors) funds in the data base from Frank Russell Company in the period January 1979-December 1996. Survivors existed at the end of December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. The t statistics are the Fama-MacBeth t-statistics based on the time series average of the γ_1 s. The standard errors and t statistics have been adjusted for $\tau-1$ Newey-West lags.

$$r_{p(t,t+\tau)} = \mathbf{g}_{0,t,\tau} + \mathbf{g}_{1,t,\tau} \mathbf{a}_{pt}^{CCAPM} + u_{p(t,t+\tau)}$$

$$r_{p(t,t+\tau)} = \mathbf{g}_{0,t,\tau} + \mathbf{g}_{1,t,\tau} \mathbf{a}_{pt}^{CAPM} + u_{p(t,t+\tau)}$$

CCAPM					
Total		Horizon, τ	Survivors		
t	prob> t 		t	prob> t 	
2.06	0.04	36	1.87	0.06	
2.85	0.01	24	2.18	0.03	
2.03	0.04	18	1.53	0.13	
2.56	0.01	12	1.53	0.13	
0.88	0.38	6	-0.09	0.93	
0.99	0.32	3	-0.02	0.98	
1.91	0.06	1	0.96	0.34	
CAPM					
-0.56	0.58	36	-1.70	0.09	
-0.20	0.84	24	-1.28	0.20	
0.12	0.90	18	-0.80	0.42	
0.72	0.48	12	-0.50	0.62	
0.08	0.94	6	-1.03	0.31	
-0.12	0.90	3	-0.99	0.32	
0.11	0.91	1	-0.51	0.61	

Table 8: Regressions of Future Returns on Past 5-Year Positive or Negative α^{4CD}

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month four factor dynamic alphas. Regressions were split in two between those with positive and negative dynamic alphas. There are 522 (295 survivors) funds in the data base from Frank Russell Company in the period January 1979-December 1996. Survivors existed at the end of December 1996. The t statistics are the Fama-MacBeth t-statistics based on the time series average of the γ_1 s. The standard errors and t statistics have been adjusted for $\tau-1$ Newey-West lags.

$$r_{p(t,t+t)} = \mathbf{g}_{0,t,t} + \mathbf{g}_{1,t,t} \mathbf{a}_{pt}^{4CD} + u_{p(t,t+t)}$$

					Number
NEGATIVE Alpha	Horizon	Mean \mathbf{g}_1	t	prob> t	of months
TOTAL	36	4.92	1.11	0.27	120
	24	2.56	1.25	0.21	132
	18	0.44	0.53	0.60	138
	12	0.74	0.71	0.48	144
	6	0.10	0.33	0.74	150
	3	0.07	0.43	0.67	153
	1	-0.17	-1.36	0.18	155
SURVIVOR	36	-3.22	-1.55	0.12	119
	24	-1.54	-0.87	0.38	132
	18	0.12	0.18	0.86	138
	12	-0.53	-1.24	0.22	144
	6	-0.57	-2.22	0.03	150
	3	1.94	0.80	0.43	153
	1	-0.49	-2.05	0.04	155
POSITIVE alpha					
TOTAL	36	0.24	0.44	0.66	120
	24	0.03	0.05	0.96	132
	18	0.61	1.34	0.18	138
	12	0.84	2.14	0.03	144
	6	0.06	0.21	0.84	150
	3	-0.02	-0.19	0.85	153
	1	-0.04	-0.52	0.60	155
SURVIVOR	36	0.26	0.41	0.68	120
	24	-9.24	-1.03	0.31	132
	18	0.97	1.67	0.10	138
	12	2.19	1.90	0.06	144
	6	-1.32	-1.04	0.30	150
	3	0.58	1.19	0.24	153
	1	0.07	0.32	0.75	155

Table 9: Summary Statistics for Indices, Factors, and Fund Returns

The data are monthly from January 1979-December 1996. The units are decimal fraction per month. Mean is the sample mean. Std. Dev. is the sample standard deviation. Skewness and Kurtosis are the third and fourth moments. ρ_1 is the first order autocorrelation. Frank Russell Company provided Index data. The factors are SMLG=R2000-R1000, GRVA=Russell Growth-Russell Value, RUSRMRF=R1000-Salomon Brothers Tbill, and BdCa= Lehman Brothers Govt & Corp. Bond - Salomon Brothers Tbill. Information Variables—January Dummy, Detrended Tbill Yield, Dividend Yield and Term Premium—are presented as less their means over the period 1979-1996.

A. Indices

Return	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	ρ_1
Russell 1000	0.0135	0.0425	-0.2169	0.1294	-0.6859	3.8878	0.0084
Russell 2000	0.0136	0.0542	-0.3062	0.1437	-1.2052	5.4099	0.1712
Russell Growth	0.0133	0.0474	-0.2323	0.1434	-0.5565	3.1288	0.0344
Russell Value	0.0137	0.0397	-0.2016	0.1367	-0.6793	4.0634	-0.0136
Salomon Brothers Tbill	0.0062	0.0025	0.0023	0.0125	0.6627	-0.0381	0.9881
Lehman Brothers Govt & Corp. Bond	0.0081	0.0151	-0.0462	0.0898	0.6719	4.9928	0.2075
S&P 500	0.0136	0.0419	-0.2154	0.1347	-0.6421	3.9720	-0.0158

Correlation Coefficients	Russell 1000	Russell 2000	Russell Growth	Russell Value	Salomon Brothers Tbill	Lehman Brothers Govt & Corp.	S&P 500
Russell 1000	1.00						
Russell 2000	0.88	1.00					
Russell Growth	0.98	0.87	1.00				
Russell Value	0.97	0.85	0.90	1.00			
Salomon Brothers Tbill	-0.05	-0.05	-0.05	-0.05	1.00		
Lehman Brothers Govt & Corp.	0.32	0.19	0.28	0.35	0.11	1.00	
S&P 500	1.00	0.85	0.97	0.97	-0.05	0.32	1.00

B. Factors

Return	Mean	Std Dev	Minimum	Maximum	Skewness	Kurtosis	r_1
SMLG	0.0001	0.0263	-0.0892	0.0935	0.1038	0.7426	0.1354
GRVA	-0.0004	0.0205	-0.0683	0.0575	-0.2274	0.7055	0.1222
RUSRMRF	0.0074	0.0427	-0.2219	0.1248	-0.7129	3.7531	0.0170
BDCA	0.0019	0.0150	-0.0568	0.0791	0.2809	4.4144	0.2030

Correlations
Coefficients

	SMLG	GRVA	RUSRMRF	BDCA
SMLG	1.00			
GRVA	0.15	1.00		
RUSRMRF	0.20	0.39	1.00	
BDCA	-0.12	-0.03	0.33	1.00

C. Information Variables

	Std Dev	Minimum	Maximum	Skewness	Kurtosis	r_1
Term Spread	0.0098	-0.0312	0.0173	-0.8209	0.3292	0.9560
Dividend Yield	0.0106	-0.0165	0.0272	0.6261	-0.6452	0.9887
January Dummy	0.2770	-0.0833	0.9167	3.0362	7.2861	-0.0886
Tbill Yield	0.0141	-0.0416	0.0442	0.0649	1.0177	0.8564

Correlation
Coefficients

	Term Spread	Dividend Yield	January Dummy	Tbill Yield
Term Spread	1.00			
Dividend Yield	-0.45	1.00		
January Dummy	-0.04	0.03	1.00	
Tbill Yield	-0.57	-0.02	-0.01	1.00

Figure 1: Existing Number of Funds by Style and Survivorship

The number of funds for each year shown represents the number in that category that existed at the end of the year. There are 522 funds in the data base from Frank Russell Company in the period January 1979-December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. Survivors existed at the end of December 1996. Dead are funds that entered the Russell data base after and did not exist in December 1996. In the graph, the number of Dead funds is the number existing in that year and subsequently disappear before December 1996.

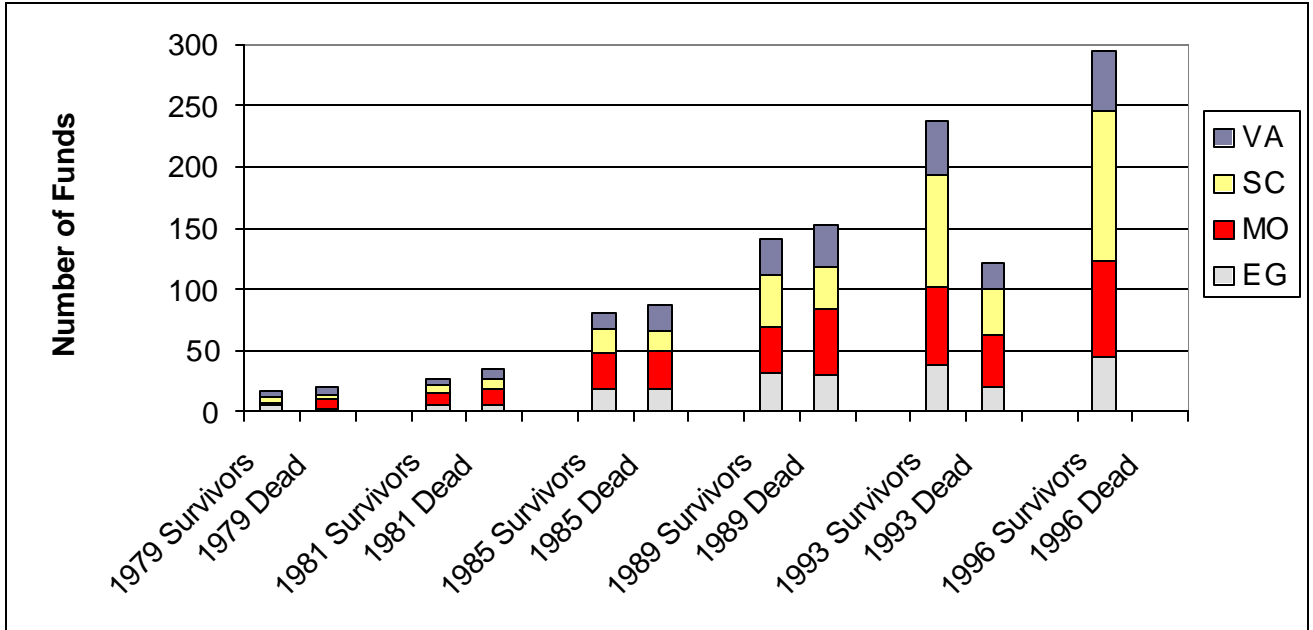


Figure 2: Chi-squared Probability for Test of 4x5 Contingency Table for Number of Funds per Style per Quintile Portfolios based on Dynamic Alphas

The graph shows the probability of being greater than chi-squared from chi-squared tests for a 4x5 contingency table of the four equity styles—EG, MO, SC, VA—and five quintile portfolios ranked on past dynamic alpha. The dynamic alphas are calculated from a four factor conditional model over 60 months. The data covers 1979-1996 and is from Frank Russell Company. There are 12 degrees of freedom for the chi-squared test. The graph contains plots of the total sample (522 funds) and the survivor only samples (295 funds).

$$C_{(r-1)(c-1)}^2 = \sum_i \sum_j (n_{ij} - m_{ij})^2 / m_{ij}$$

$$m_{ij} = n_{i\bullet} n_{\bullet j} / n$$

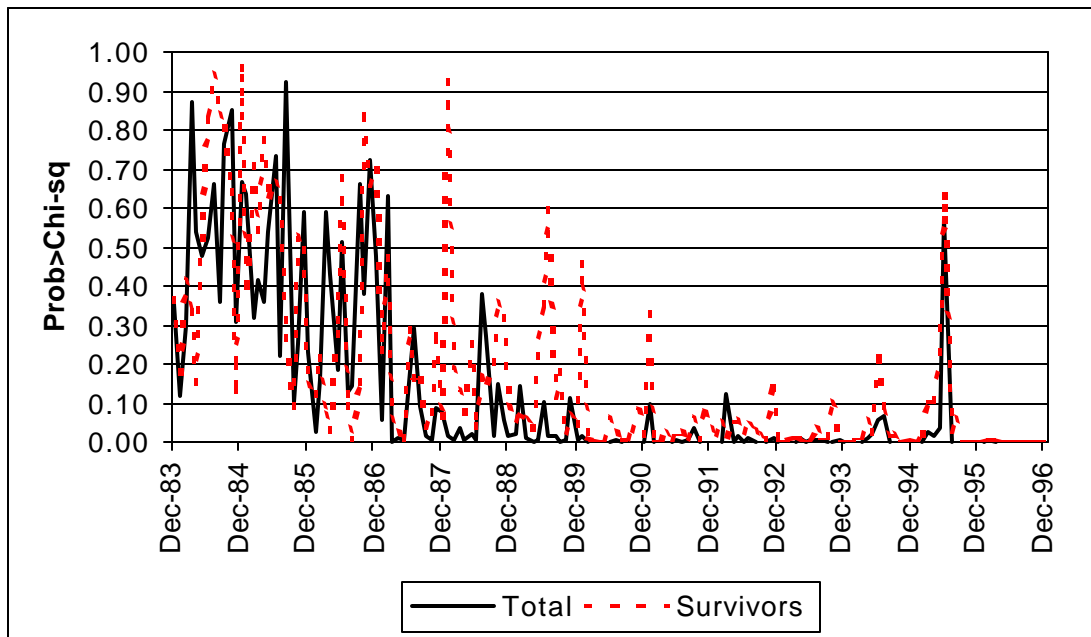


Figure 3: Style Allocation within the Top Quintile Portfolio based on Dynamic Alphas

The graph shows the allocation of the four equity styles—EG, MO, SC, VA—within the top quintile portfolio ranked monthly on past dynamic alphas. Dynamic alphas are calculated from a four factor conditional model using 60 months of data. Allocations are based on equal weighting of the funds or the graph shows the percentage of funds from each style represented in the top quintile (highest dynamic alphas) each month from December 1983 to December 1996.

