PERSISTENCE IN PENSION ACCOUNT RETURNS: THE IMPACT OF SURVIVORSHIP AND THE REACTION OF ASSET FLOWS

by

David Hobson Myers

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Wayne Fuson

Wayne Ferson

Reading Committee:

Wayne Fuson

Wayne Ferson

Jeffrey Pontiff

Jeffrey Pontiff

Edward M. Rice

Edward Rice

Date July 26, 2001

University of Washington

Abstract

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Chairperson of the Supervisory Committee: Professor Wayne E. Ferson
Pigott-PACCAR Professor of Finance
Department of Finance and Business Economics

This paper is the first to examine the effects of survivorship on persistence in the performance of U.S. equity pension accounts. Evidence of predictability of returns is stronger with the total sample of accounts 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 accounts are terminated. Where other studies found predictability to be driven by the persistence of poor performers, we do not. We employ a time-varying conditional or dynamic alpha as our measure of past performance. We find the dynamic alpha predicts future returns across equity style groups, but not consistently within equity style groups. Given evidence of predictability, we examine the asset flow-performance relationship and find pension plan asset flows to equity accounts tend to follow three-year excess returns. We do not find a significant relationship between more sophisticated or risk-adjusted measures of performance and future asset flows. Since we do not study the hiring decision, pension plans may use sophisticated measures in the hiring decision, but not in the termination decision nor in determining intermediate asset flows. Asset flows follow performance more for small and large cap equity styles than for value or growth style accounts. Surviving accounts exhibit a stronger asset flow-performance relationship than the total sample.

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GLOSSARY

Asset flow is the movement of assets—stocks, bonds, cash—either among a single pension plan's investment accounts or between the plan and the accounts.

Alpha, α, is typically the symbol used to denote a risk-adjusted return. For example, Jensen's alpha is the risk-adjusted return from a single index market model.

Composite refers to the investment performance unit consisting of all the accounts under an investment manager's control. A composite may represent all accounts within a particular investment style.

Investment manager/advisor is an investment firm that oversees the separate account for a pension plan

Look-ahead bias is the bias in results due to requiring members of the sample to exist for a certain period of time.

Pension account in our study is a separate account with an investment advisor managing for a single pension plan sponsor. This is the basic unit of analysis in our study.

Pension plan is the total assets of a defined benefit pension scheme for a single organization or sponsor.

Plan sponsor is the organization that manages a pension plan for its employees and beneficiaries. The sponsor may be public or private organization.

Survivorship bias is the change in results due to examining a sample with only surviving accounts and not a sample of survivors and non-survivors over the period studied.

LIST OF ABBREVIATIONS

DB Defined benefit pension plan

DC Defined contribution pension plan

DOL Department of Labor

EG Earnings Growth

ERISA the Employee Retirement Income Security Act of 1974

IRS Internal Revenue Service

MO Market Oriented

PBGC Pension Benefit Guarantee Corporation

P&I *Pensions and Investments*

SC Small Capitalization

SEC Securities and Exchange Commission

VA Value

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DEDICATION

The author wishes to dedicate this dissertation to Heather H. Myers without whom this would not have been possible.

INTRODUCTION

In the context of U.S. equity pension accounts, we examine the relations between past and future performance and between past performance and asset flow. In particular, we explore the impact of survivorship on the predictability of future performance. The central issue is whether the past predicts the future. If future returns are predictable, then the second issue is can and do investors take advantage of this predictability with asset flows. We examine these two issues for separate account defined benefit pension plans. Defined benefit pension plans represent one of the largest pools of U.S. assets.

Recent research has found predictability in pension account equity returns; that is past performance predicts future performance. However, the results of previous research may be biased since only surviving accounts were studied. We study the effect of survivorship on measured predictability. For example, the pension plan sponsor may terminate poor performing accounts. These consistently poor performers would be one type of predictable behavior in the total sample, which are not observable in a survivor-only sample.

Many commercial data bases consist of only the surviving accounts. The use of surviving accounts takes all accounts existing at some date and examines their past return histories. Omitted from such a data set are those accounts that ceased to exist prior to the end date chosen. A bias will be created when there is a relationship between the measure under study and the survivorship criteria. If the survivorship criteria are related to performance and the persistence in performance, then the results of studies of predictability of pension account returns will be biased. We find that performance at the end of an account's life significantly deteriorates. Pension plans have to defend their performance and the performance of the managers hired. Poor performing managers are fired for continued poor performance.

We first establish the predictability of returns. We then study pension plans' asset flows for evidence of the plans taking advantage of the predictability in distributing their assets. If there is predictability, then asset flows should follow the past measures of performance, which predict future returns. We find evidence of asset flows following measures of two and three year lagged excess returns. We find no evidence that asset flows respond to more sophisticated measures of performance, such as dynamic alphas or other risk-adjusted measures of performance. The dynamic alphas are the measure of performance in which we find information that predicts the future returns. We believe the discrepancy between predictability and asset flow decisions to be explained by institutional features of the pension fund industry. Our results support the hypothesis that pension plans may use sophisticated measures of performance for the hiring decision, but use simpler excess return measures for asset flows after the relationship between the plan and the advisor has been established. This is consistent with pension plans employing consultants for the hiring process more often than for terminations or intermediate asset flow decisions.

The findings of persistence and the reaction of pension plan asset flows to performance have implications for investment manager behavior. In the literature on tournaments and incentives—Chevalier and Ellison (1996) and Brown, Harlow and Starks (1995), investment managers may change their risk behavior in reaction to incentives from tournaments that determine asset flows. Since our findings support differences in predictability and in the asset flow-performance among equity styles, future research may find that the strength of the reaction to performance in changing risk behavior is stronger for market-oriented and small cap investment managers than for value or growth managers.

The outline for the paper is as follows. First, there is a general introduction to pension funds and their regulatory environment. The discussion of pension funds focuses on their differences with mutual funds and the effects of pension funds' regulatory environment. Chapter two contains the results of our study of survivorship on persistence in performance. We find that measured predictability is stronger within the full data sample than in the survivor only sample. We also find the significance level in the total sample is stronger for small cap and market oriented equity styles than in the survivor sample. Chapter three concentrates on the relationship of asset flow to persistence. Asset flows tend to follow simple measures of past excess returns.

The appendices provide an opportunity to cover in more depth the models and econometrics we employ in the body of the paper than we would have covered if we had kept them in the body of the paper. Also, some of the appendices, if expanded upon further, could warrant being separate chapters. Appendix A examines other measures of past returns than the dynamic alpha as predictors of future returns. Appendix B expands the Brown et al (1992) model of survivorship bias on persistence by adding a nonperformance criterion to the model. Appendix C adds own lagged returns as a conditioning variable in the calculation of the dynamic alphas. Appendix D describes the econometric techniques employed to overcome errors-in-variables problems and the concerns of Stambaugh in predictive regressions.

CHAPTER 1: INSTITUTIONAL DYNAMICS OF PENSION FUNDS

As background to our study of pension account returns, we begin with a discussion of the regulatory environment in which pension plans exist. In this chapter, we discuss the environment for pension plans by highlighting their differences with mutual funds; especially, those differences that affect studies of persistence, survivorship and asset flow in relation to performance.

PENSION RULES & REGULATIONS

The best framework for understanding pension plans is to remember that pensions are a form of employee compensation. As a delayed payment, corporate pensions may help to bind the employee to the firm. The most important governmental bodies involved in regulating pension plans are the Internal Revenue Service (IRS) and the Department of Labor (DOL). Once a pension plan has decided to hire outside investment advisors the Securities & Exchange Commission (SEC) joins the oversight role. One major difference between mutual funds and pension accounts is most of the control and fiduciary responsibility of the assets remains with the pension plan and not the investment advisor.

Pension plans and their sponsors are subject to legal requirements that affect both the investment decisions as well as the accounting or asset flow decisions. For corporate pension plans, regulatory authority and guidelines are laid out in the Employee Retirement Income Security Act of 1974 (ERISA). ERISA specifies that pension plans are to be run solely for the benefit of participants and beneficiaries. The decisions made for the plan must be in accordance with what a prudent person would do. In fact, the case law and administrative rules have pushed the prudent person rule into what is now commonly accepted to be a "prudent expert rule." Anyone making an investment decision for the plan also becomes fiduciarily responsible. As a fiduciary, individuals become personally liable as well. Since the passage of ERISA, the pension industry has become filled with consultants, actuaries, lawyers, and investment advisory firms. All of them help spread the responsibility and liability. While there are pension plans, which run their investments in-house either in whole or part, this study focuses on those defined benefit plans who use outside investment advisors, equity managers in particular.

When ERISA was first enacted, many pension plans' portfolios were managed as balanced accounts by trust banks and insurance companies. The past twenty-seven years have seen a movement to diversification across asset classes and within asset classes as international investing, venture capital, equity and fixed income styles have expanded. The use of multiple investment managers for specialization has grown with the diversification. Lakonishok et al (1991) believe that specialization within asset classes, like equity, is to be expected in competitive industries. Specialization by equity style is a form of differentiation among competing advisors.

IRS Role in Pension Accounts

Because the contributions to pension plans are tax-exempt for the corporation, corporations have an incentive to provide their employees pensions as a form of delayed compensation. It also helps bond employees to the corporation given vesting and benefit schedules. The ability to maintain the tax-exempt status is dependent on funding levels as measured by accounting and actuarial measures. Pension plans can be, but it is unclear how often they are, penalized for being too overfunded or too underfunded by losing the tax-exempt status and the corporations' contributions are no longer deductible. The timing of asset flows is also important since contributions must be made before the tax returns are due.

The IRS, of course, has the ability to assess penalties beyond just the loss of tax-exempt status. Interest charges and excise taxes can be imposed if employers fail to make timely quarterly contributions or if the plans become too overfunded or underfunded. In contrast to mutual funds, which must pay out most of the income and capital gains earned during the year prior to year-end to remain tax-exempt, pension accounts have no requirement to pay out income as it is earned each year. Instead, pension assets become taxable when payments are made to the beneficiaries during retirement.

DEPARTMENT OF LABOR

The administrator or overseer of pension accounts is the Department of Labor (DOL). Through opinion letters, regulations, and administrative oversight, the DOL hopes to ensure that plans follow ERISA, such as ensuring that plans are funded, have stated objectives and follow the objectives, and are adequately diversified.

Corporate plans contribute to the Pension Benefits and Guarantee Corporation (PBGC), which acts as an insurance account for underfunded plans. As with any insurance plan, this may give pension plans more incentive to take on risk. Penalties and extra premiums to the PBGC can be assessed by the DOL against underfunded plans.

In addition to IRS and DOL sanctions, the implementation of FASB 87 also pushes corporations to maintain properly funded plans. FASB 87 puts pension liabilities directly onto corporate balance sheets. In studying the impact of FASB 87, Amir and Benartzi (1997) find that corporations use asset allocation to help smooth asset flows to their pension plans.

ROLE OF INVESTMENT ADVISORS

Gruber (1996) and Sirri and Tufano (1992) both mention reasons why mutual fund investors hire money managers—customer service, low transaction costs, diversification, and professional management (security selection). In addition to those advantages for hiring investment managers, pension plans can distribute the fiduciary liability through the hiring of investment managers and consultants. Unlike mutual fund investors, large pension plans with internal management can negotiate transaction costs. Pension plans also have the choice of internal management and index funds. In 1996, index funds account for over 20% of assets for the largest 200 accounts (*Pensions & Investments*, January 1997 survey results) while internal management represented 29%. As Gruber (1996) argues for mutual fund investors, index account managers still provide much of the customer service and diversification that pension plans desire. Pension plans also get fiduciary coverage.

When choosing an external investment management firm, pension plans may rely on consultants to assist them in the process. The consultant is another fiduciary and is a prudent expert. Consultants provide asset allocation advice and investment manager research. When an individual investor chooses a mutual fund, there is often one portfolio manager for that account and information is available through sources such as Weisenberger and Morningstar. When a pension plan hires an investment advisory firm, there may be different portfolio managers within a particular firm from which to choose. Consulting firms provide research of investment advisors that includes performance comparisons and information on the importance of different portfolio managers within a firm.

The costs of investment firm research differ between pension plans and mutual fund investors. Movement of accounts or funds among advisors by pension plans may be slowed by transaction costs. Search costs may include direct fees to a consultant. While mutual fund investors face front end or back end loads and capital gains tax costs when moving assets among funds, pension plans escape these costs. Pension plans transfer assets among investment advisory accounts by having the trustee banks reassign the assets. There is no need to liquidate equity positions in order to transfer funds to another investment advisor. When stocks are transferred, the responsibility for the performance of unwanted stocks in the portfolio accrue to the new investment advisor's account.

PENSION ACCOUNTS 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) totalled 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 all 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 have assets well over $100 billion. Large DB plans have the capacity to hire multiple investment management firms to run separate equity accounts. The hiring and firing of managers by a single plan creates many "dead" accounts and new accounts for our database. Each new manager hired creates a separate account to follow and each manager fired by a pension plan creates a dead account. Pension account deaths differ from mutual fund deaths because a pension account termination is the decision of one investor not many. Separate account data from pension plans therefore makes a fertile area for studying survivorship bias.

The life cycle for pension accounts differs from the life cycle of mutual funds. In the pension industry when a single plan sponsor terminates an account, the return history of the account ends. The account'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 account or merge it into another. Meanwhile, performance may 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 an account, the asset transfer can be made through its trustee bank without the need to liquidate holdings.

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 have been negative (net distributions to beneficiaries). Asset growth has come from market returns. In contrast, the mutual fund industry has been growing rapidly during this period. Net outflows also create a more fertile ground in the pension area for researching survivorship. As more assets flow out of pension accounts due to distributions there are likely to be more terminations of accounts.

CHAPTER 2: PREDICTABILITY AND SURVIVORSHIP IN PENSION ACCOUNT RETURNS

In this chapter, we examine two issues relating to persistence in the rate-of-return performance of U.S. equity pension accounts: 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 accounts for the period 1979 to 1996, we find that the significance of persistence is stronger in the total sample of accounts than previous studies have found using survivor only accounts. This lower level of significance in persistence with survivor only accounts 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 accounts. As previous pension studies measure persistence using only data on accounts 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 accounts, but not within style groupings[2]. We find that survivorship bias dampens the evidence of persistence within the small cap and value equity styles, but strengthens

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[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 account studies include Lakonishok et al (1991); Christopherson, Ferson and Glassman (1998); Brown, Draper and MacKenzie (1997); and Christopherson, Ferson and Turner (1999).

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 coefficients are mostly significant in the survivor only sample, not in the sample that includes accounts that do not survive to the end of the 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 accounts has received little attention. One paper that looks at survivorship is Coggin and Trzcinka (1999), which uses a sample of pension account composites to predict the termination of investment manager composites. Coggin and Trzcinka do not examine the effect of survivorship bias on persistence. Composites include all accounts managed by a single investment management firm in a particular equity style. The most recent published studies of persistence and pension accounts are by Brown, Draper, and McKenzie (1997) for United Kingdom pension accounts, and Christopherson et al (1998) and Christopherson, Ferson and Turner (1999) for U.S. accounts. These studies find evidence of persistence and predictability, but none employs a database that includes non-surviving accounts[3].

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

[3] Other pension account studies include Del Guercio (1996) and Lakonishok, et al (1991 and 1992), who examine some of the institutional peculiarities of pension accounts—window dressing, agency relationships, and the effect of the prudent person rule. Del Guercio and Tkac (2000) 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 accounts. Ippolito and Turner (1987) study pension performance in light of turnover and fees. All of these studies use databases with survivorship bias.

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 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. Poor performers in the first period must perform better in the second period in order to survive and good performers do not have to perform as well to survive. The two-period survival generates more good-poor or poor-good performance, while poor-poor performers are terminated (see Appendix B for a more complete discussion of the model and an extension). 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 accounts have long investment horizons.

We cannot explain our findings of persistence by the high persistence of poor performers, as other mutual fund and pension account studies have found. When our data are 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 have been expected that adding back dead poor performing accounts causes heightened significance of persistence in the total sample.

We approach the study with the following steps: first, we examine the data employed for the study. Second, we introduce a model for survival based on Brown et al (1992). Third, we introduce the methods for measuring returns and persistence. Fourth, we cover the results of style and survivorship on measures of persistence. Finally, we summarize the findings.

DATA

For our study, we define "dead" accounts as those accounts that have dropped out of the database prior to the end of the sample period. An account may leave the database for a variety of reasons. The account may be terminated by the pension plan. The investment management firm may dissolve or merge. Account structure may change, so that the account no longer meets the criteria for inclusion in the equity style database. The account investment objective may change or the account may change style. Accounts not meeting the inclusion criteria are dropped from the database. Thus, not all of the reasons for account death are performance related. Large pension plans invest with many investment managers across different asset classes and different equity styles creating multiple accounts. Switching among styles or changing asset allocations creates more dead accounts to study.

Survivorship in our sample is related to the general pension industry in that accounts disappear from the data for many of the same reasons. First, poor performers may be fired. Second, investment professionals with very good performance may leave an investment firm to go out on their own causing old accounts to disappear and reappear as new accounts with the new firm. As with mutual funds, accounts may change investment style, thus disappearing as one style and reappearing as a new account in another style. For accounts that disappear from the data base for performance reasons, there will be an impact on conclusions about persistence.

UNIT OF ANALYSIS

Our study focuses on survivorship of separate accounts within the Frank Russell Company (Russell) database. As one of the largest consulting data bases and one used most often in published studies[4], we believe it is most indicative of pension account data. Separate pension accounts represent the assets of one plan sponsor with one investment management firm. The study of separate accounts provides insights into the plan-manager relationship as well as the actions of the investment advisor within the market. Separate account data provides more account deaths or disappearances than data based on composites, which are portfolios of similarly managed accounts by a single investment advisory firm. A composite disappears if there are no longer any accounts managed by an investment firm, if the firm changes ownership or if the firm ceases to exist. Over 40% of the accounts in our study die during the period from 1989 to 1996. In the Coggin and Trzcinka (1999) study of composites of pension accounts for investment firms from 1993 to 1996, less than 20% disappear. In the mutual fund area, Carhart (1997) finds fewer than 4% die each year.

Separate account data should weaken the asset flow-performance relationship since new accounts in our data cannot be tied to past performance in other accounts as would be true with composite data. Having accounts that have died may have the reverse effect. If accounts are terminated for poor performance, then there will be large percentage outflows from termination associated with poor performance. The inclusion of the terminated accounts will add back poor performers with a strong relation between performance and asset flow. Since Del Guercio and Tkac (2000) find the pension account relationship strongest in the bottom decile of performers losing money, our results may be stronger since we have terminated accounts. The ultimate asset outflow is termination.

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[4] Christopherson et al (1998) and Christopherson, Ferson, and Turner (1999) use a Russell database of representative accounts. Coggin, Fabozzi, and Rahman (1993) use a random sample of accounts data from Russell. Ferson and Khang (2000) use data from Callan and Russell.

SELECTION BIAS

All existing pension data sets are self-selected samples of the population, which raises issues of selection bias. Consultants create pension account return databases in order to advise their clients. Lakonishok et al. (1991) use data from SEI, a leading pension accounts' consultant. Christopherson et al (1998) use a Russell database of representative accounts. Coggin, Fabozzi, and Rahman (1993) use a random sample of surviving accounts data from Russell. Khang (1997) and Ferson and Khang (2000) employ Callan, a pension consultant, data for a study of conditional performance measures based on portfolio weights. Del Guercio and Tkac (2000) 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 accounts that existed and have dropped out (dead accounts) prior to December 1996. We do not have information on why these accounts 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 be included in a search. This may cause backfilling of data as managers submit accounts 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 accounts 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. As a test of the backfill bias, we removed the first three years, minimum amount of data to be added to the manager research data base, of data for each account from our sample and reran our results. Only the three-month horizon changed its level of significance away from the evidence of persistence. For look ahead bias and general survivorship bias, more horizons become less significant than for backfill.

Other selection issues include the choice by the manager or consultant of the accounts 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 accounts 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. Since we find a relation between larger accounts and asset flows, the $5 million criteria may strengthen our results compared to a complete universe of pension accounts. The difference in results due to size supports the hypothesis that larger pension plans employ more sophisticated measures of performance in their asset flow decisions.

EQUITY 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 account 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)[5]. The indices include a broad market index (Russell 1000™), a small cap index (Russell 2000™), and also style indices carved out of the Russell 1000™

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

(Russell Growth™ and Russell Value™ indices). For short-term cash, we employ the Salomon Brothers Treasury Bill 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 account managers categorize managers by investment styles. Pension consulting firms such as Russell, Callan, SEI, and Wilshire track account performance for their clients in manager universes. A universe is a group of similarly managed accounts, such as same style. Most often the data provider presents the styles. Or in some databases, investment managers declare their account styles. For Russell, an equity analyst must confirm the style database into which the account 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 in pension accounts are from a period of underperformance by small cap accounts. An account may perform well within in its style, but not well across all styles.

SUMMARY STATISTICS PENSION ACCOUNT DATA

Our database includes 737 different U.S. equity accounts over the period 1979 to 1996. The 737 accounts 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 (e.g., market oriented versus growth). Of the 737 accounts, 535 accounts have monthly data. We remove 13 mid cap accounts, because of the relatively short time horizon (only the last few years of our sample period) and the small sample size of mid cap accounts. The resulting database in the final sample is 522 accounts.

Within the 522 accounts, 227 accounts die before the end of December 1996 leaving 295 survivors. A snapshot of the number of accounts in the database at the end of years 1981, 1985, 1989, 1993, and 1996 is displayed in Figure 1. Survivors are accounts that exist at the end of the sample period. Dead accounts are simply those that do not exist in December 1996. There are fewer accounts in 1993 that die by the end of 1996 than in 1989 because the dead accounts are dying off faster than they are entering. No accounts 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 accounts outnumbered other styles until the 1990s. Small cap accounts in the 1990s are the most numerous. The distribution of accounts 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 accounts among the styles.

For our calculation of returns for groups of accounts, we employ equally weighted portfolios. This assumes that as money passes out of a dead account it is evenly divided among current existing accounts. 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 "follow the money" approach assumes that when an account dies the money is evenly divided among the existing funds, thus an equal weighting of the next period's accounts.

The returns from an equally weighted portfolio of all accounts for the period of examination, 1979-1996, are reported in Table 1. The average monthly return of an equally-weighted portfolio of accounts was 1.54% for survivors and 1.48% for dead accounts over the period from 1979-1996. The average account return beat all the indices over this period (see Table 12A). The best performing index was Russell Value™ at 1.37% per month over this period. Value and market-oriented 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 accounts contrasts to the period Lakonishok et al (1992) studied where the average account did not beat the S&P 500. We found that underperformance in Lakonishok et al is period specific. Christopherson et al (1998) attribute the underperformance to small cap accounts. The average pension account over our longer time period, even with possible poor performing dead accounts added back in, has not done as poorly against market indices. None of the differences between dead and surviving account 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 accounts 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 from requiring three years of returns before a new investment firm is placed in a manager search 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 accounts. 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 account's life to see if there is a performance drop. We find lower average returns in the average dying account'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 account samples. Dead accounts must be good performers at some point to compensate for the last year and to live as long as some dead accounts do. The dead accounts are not necessarily persistently poor performers.

MODELS OF SURVIVAL

Our hypotheses about the effects of survivorship bias on persistence are based on 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. An account survives if the return over two periods is positive, $x_1 + x_2 > 0$. Persistence is when one account outperforms another account over the two periods, $x_1 > y_1$ and $x_2 > y_2$. The two accounts are assumed to be independent and identically distributed with distributions symmetric about the origin. Based on the survival criteria, Brown et al show that $P[x_2>y_2 \mid x_1>y_1 \text{ and } c]=1/3<1/2$, where the survival criteria, c, is $\{x_1+x_2>0,\ y_1 + y_2 >0\}$. This model of survival is more likely to have performance reversals than persistence, as accounts must improve their second period performance to survive if the first period performance was poor. A more detailed model is presented in Appendix B. We find that the addition of a nonperformance related criterion might change the direction of the bias.

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. The implication of the hypothesis is that by moving from our total sample to the survivor only sample the evidence of persistence is dampened.

The model does not explicitly distinguish a correct return measure for evaluating performance for accounts. 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) employs a conditional Fama and French (1992) three factor model. Christopherson et al (1998) find persistence in pension accounts with a dynamic alpha from a conditional CAPM. Del Guercio and Tkac (2000) 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 Treasury Bill (RUSRMRF) for market excess return, and a term premium factor of Lehman Brothers Government-Corporate Bond Index less Salomon Treasury bill Index.

We follow Christopherson, Ferson and Glassman (1998) 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 account reporting or quarterly consultant performance reports. In the final chapter on asset flows and performance, we examine the relationship between shorter horizon returns and asset flows.

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 in previous studies, 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 for 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 accounts dead and survivors. Survivors are only those accounts that existed at the end of 1996, similar to the data in most previous studies. Dead accounts are those that exited the database prior to December 1996. ALL Styles 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.

DYNAMIC ALPHAS

Conditional performance models, such as Ferson and Schadt (1996), Christopherson et al (1998), Becker et al (1999), Farnsworth et al (1999), and Ferson and Harvey (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 accounts. In an extension of their work adding data from 1990 to 1996, Christopherson, Ferson and Turner (1999) 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.

$$\begin{aligned} r_{pt+1} &= a_{0p} + A_p' z_t + b_{0pb} r_{bt+1} + B_{pb}' z_t r_{bt+1} + u_{pt+1} \\ \beta_{pb}(Z_t) &= b_{0pb} + B_{pb}' z_t \\ z_t &= Z_t - E(Z) \\ \alpha^{4CD} &= a_{0p} + A_p' z_t \end{aligned} \qquad (1)$$

Where

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

z = a vector of the four demeaned lagged information variables—market 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 $(0,\ \sigma_p^2)$ for each portfolio or account, p. 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. The information variables may induce autocorrelation. This adds to the errors-in-variables problem in the dynamic alphas since they are estimated (see Appendix D for a further discussion). Christopherson et al conclude that pension accounts have non-zero significant dynamic alphas and that the dynamic alphas predict future returns.

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.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4CD} + u_{p(t,t+\tau)} \qquad (2)$$

for horizons, τ = 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 $(1-(\tau/t))$ where τ is the length of the lag and t is the length of the return horizon. The γ_1s (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 inverse of the standard error of 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. Further discussion on the use of generalized least squares can be found in Appendix D.

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

$$\chi_1^2 = \sum_i \sum_j \left(n_{ij} - n/4\right)^2 / n \qquad (3)$$
$$ij = WW, WL, LW, LL$$

where n_{ij} is the number of accounts in one of the four cells (WW, WL, LW, and LL) and n is the total number of accounts. 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 accounts 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. Given the number of accounts available in our sample period, we chose these periods to minimize the level of overlap and have avoided overlap in the evaluation or predictive stages. For chi-squared tests, we employ both a partial-look-ahead (PLA) bias methodology and a full- look-ahead bias (FLA) methodology from Carpenter and Lynch (1999). FLA ranks only those accounts that exist for both the ranking and evaluation periods, *n*. PLA ranks in the ranking stage those accounts that exist in the ranking stage, $n + d$, where d is the number of accounts that existed in the ranking stage, but die in the evaluation stage. PLA ranks in the evaluation stage those accounts 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.

RESULTS

In the first stage 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 no predictability in pension account 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_1s, 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 for the total sample and –24 to 86 basis points for the survivor sample. A one-percent increase in past dynamic alpha is equivalent to about a one-percent increase in future annual return for the total sample. The total sample provides stronger evidence against the null hypothesis of no predictability. The survivor sample has biased downwards the significance in predictability. Given that the total sample has more observations some of our results may be strengthened by the differences in the power of the two tests.

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 accounts within each of our four style groups. Within the four style breakdowns, there are 11 of 28 significant coefficients for the survivor sample. The significant γ_1s are mostly negative, indicating predictable performance reversals for accounts, within the value style and mostly positive within the market-oriented style group. In 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 reject the null for growth or value accounts in only two of fourteen periods for the total sample.

Having established stronger results in the total sample for predictability of pension account 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 in Table 5, 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 significant 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's two-period model of a multiperiod account review and termination process by pension plans. Accounts are likely to reverse poor performance from one period to the next to avoid being fired. The reversals in account 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 the multiperiod evaluation survivorship bias effect. For market oriented accounts, 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 across all equity style accounts, compared to within style groupings, we turn our attention to the distribution of the style groups within the rankings of all equity accounts. We want to find if the difference in predictability across styles versus within styles is driven by the dynamic alphas of the style accounts' 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 accounts are the majority of loser/losers. In period two, growth and value represent reversed patterns of winners and losers in the evaluation period. Growth accounts are mostly losers in the evaluation period (making up most of the LL and WL), while value accounts are mostly winners in the evaluation period (LW and WW). Using a strategy of investing in top dynamic alphas accounts results in concentrated portfolios of accounts with respect to style allocations, since certain periods are dominated by one equity style.

To test if the dominance in styles across periods is significant, we test the style group imbalances among quintile portfolios. We separate the accounts based on ranked dynamic alphas into quintiles and count the number of accounts in each style group in each quintile, n_{ij} with $n_{i.}$ as the row or style total and $n_{.j}$ is the column or quintile total.

$$\chi^2_{(r-1)(c-1)} = \sum_i \sum_j \left(n_{ij} - m_{ij}\right)^2 / m_{ij} \qquad (4)$$
$$m_{ij} = n_{i\bullet} n_{\bullet j} / n$$

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 accounts in each style by using m_{ij} as the conditional value for each cell. We plot the chi-squared probability in Figure 2 for each month.

The null hypothesis for the chi-squared test of styles across quintiles is that the distribution is random. We find that in most months since 1987, the chi-square test rejects the null hypothesis of equal proportions of accounts in each quintile portfolio for both the total sample and the survivor sample (see Figure 2). The earlier part of the sample, in which we do not reject the null, there may not be a sufficient number of accounts to be significant. We conclude that the distribution of the accounts 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 and 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 accounts each month on 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 accounts, not a very well diversified portfolio for pension plans. While a simple overweighting problem may arise from the imbalance among the number of accounts 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.

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 accounts 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 accounts and market oriented accounts.

STYLE ANALYSIS

We have found that persistence in performance is different among the four style groups and weaker than the overall result. To further analyze the different conclusions, we analyze the effect of employing excess returns over the average performance in each style category. To do this we first create equal-weighted portfolios for each of the four style groups. Returns for the four portfolios are calculated based on funds existing during each month, R^{EW}. The continuously compounded returns are then created for each of the horizons from one to thirty-six months. The hypothesis is that if style differences are driving the result across all funds, then by removing the average style performance we should find a lower level of significance. The removal of the average style performance should also have little impact on the style group results. We chose to use the equal weighted style portfolios instead of a benchmark index for each style group to avoid any benchmark biases or misspecifications. Our main interest is not whether style benchmarks are predictable, but whether the difference in our results between all funds and the style groups is due to behavior of the style groups. The average performance of each style group represents that behavior better than an index, especially if the managers are not tracking the index (see Tables 1 and 12).

Having created the equal-weighted style portfolios, we first test whether the style groups' returns are predictable (see Table 7). We find in most horizons the equal weighted style portfolio dynamic alphas do not predict future returns. The next step is to remove the style performance from the future returns for the accounts, $r^S = R_p - R^{EW}$. The second stage cross-sectional regressions are now future account excess return over the style portfolios (see Tables 8 and 9). The predictability found earlier in the long-term horizons is less significant for the overall sample, either for total or survivor samples. In the original regressions for the total sample the coefficients were significant for horizons from 3 to 36 months on future returns; now only horizons 3 to 12 months are significant. For the survivor only sample, the dynamic alphas predict reversals for future style excess returns for months one and three. While dynamic alphas predict future excess returns over the risk-free rate, dynamic alphas do not significantly predict excess returns over style average returns.

SENSITIVITY ANALYSIS

Other researchers have found that consistently poor performers generate the significance in persistence—Christopherson et al (1998) for pension accounts and Carhart (1997) for mutual funds. 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 10). If poor performers are the cause of the persistence results, then we should find significant slope coefficients within the negative dynamic alpha accounts and not the positive alpha accounts. 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. Persistently poor performers do not drive our results.[6]

In our results, we have talked about general survivorship bias and the impact on conclusions of predictability. There is a specific type of survivorship bias that we have not yet addressed. Look-ahead bias occurs when we require accounts to live a certain length of time so that we have a sufficient period of time to run our regressions. In this study we require all funds to have at least five years of data. For our three horizon future return regression on past five-year dynamic alphas, we require eight years of returns. To examine the look-ahead bias of the eight-year requirement we reexamine the shorter horizon regressions requiring all funds to exist for eight years. The look-ahead bias is similar to our overall survivorship bias in that the significance of the predictability decreases for both the total and survivor samples (see Table 11 versus Table 3).

[6] We also analyze the top third versus bottom third ranked accounts by dynamic alphas and again find that the bottom third (poor performers) does not significantly predict future returns.

CONCLUSIONS

We find that survivorship bias dampens evidence of predictability in returns across equity accounts. The evidence of predictability of past dynamic alpha on future return found in Christopherson, Ferson, and Glassman (1998) is stronger when we add nonsurviving accounts 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 account 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. Accounts 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 returns as the dependent variable for two of the four styles—small cap and value. We find significant persistence within small cap and market oriented accounts. We also find the allocation of accounts 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 criterion for investing, should (1) use dynamic alphas from all equity accounts 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 willingness to switch or time among the styles.

Table 1: Summary Statistics for Equal Weighted Portfolio of Accounts

The table shows the statistics—mean and standard deviation— for the monthly average returns of an equal weighted portfolio , R_{pt}, of all accounts existing at each month, t, for each category of surviving or dead accounts and by style. There are 522 accounts 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. The t and F statistics refer to differences between survivors and dead account portfolios for means and variances, respectively.

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

$$\alpha_0 = R_{pt} - R_{S\&P500,t}$$

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

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

The table shows the statistics—mean and standard deviation — for the monthly average returns of an equal weighted portfolio , R_{pt}, of all accounts existing at each month, t, for each category of surviving or dead accounts and by style. There are 522 accounts 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 accounts in each category.

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

$$\alpha_0 = R_{pt} - R_{S\&P500,t}$$

		Total		Survivors		Dead		Survivors -Dead
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
Age < 36 months	R_p	1.59%	4.30%	1.62%	4.38%	1.48%	4.21%	0.34
(Young)	α_0	0.23%	1.33%	0.26%	1.42%	0.14%	1.25%	0.93
Age > 35 months	R_p	1.43%	4.25%	1.45%	4.28%	1.41%	4.22%	0.08
(Old)	α_0	0.02%	1.14%	0.04%	1.12%	-0.01%	1.10%	0.47
More than 1 year	R_p	1.52%	4.27%	1.54%	4.34%	1.46%	4.26%	0.20
to live	α_0	0.16%	1.19%	0.18%	1.21%	0.14%	1.10%	0.37
Less than 1 year	R_p	1.02%	4.43%			1.02%	4.43%	
to live	α_0	-0.12%	1.40%			-0.12%	1.40%	
	Differences	t		t	prob>t	t		
Age (Young-Old)	$R_{pyoung}-R_{pold}$	0.38		0.39	0.35	0.16		
	$\alpha_{0,young}-\alpha_{0,old}$	1.70		1.71	0.04	1.29		
More vs. Less than 1 Year to live	$R_{pmore}-R_{pless}$	0.99				0.86		
	$\alpha_{0,more}-\alpha_{0less}$	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 accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. Annualized Mean γ_1 is calculated by divided the mean γ_1 by the length in years of the horizon. Horizon is in months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4CD} + u_{p(t,t+\tau)}$$

TOTAL	Horizon	Mean γ_1	t	prob>|t|	Number of months	Annualized Mean γ_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 accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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. Horizon is in months. Months refers to the number of cross-sectional regression months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4CD} + u_{p(t,t+\tau)}$$

		TOTAL			Annualized	Survivors			Annualized	
Horizon	Style	Mean γ_1	t	prob>|t|	Mean	Mean γ_1	t	prob>|t|	Mean	months
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	0.06	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_t, between the γ_1s 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 accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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 Ds. The standard errors and t statistics have been adjusted for τ-1 Newey-West lags. Horizon is in months. Number of months refers to the number of cross-sectional regression months.

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

$$D_{t,\tau} = \gamma^{T}_{1,t,\tau} - \gamma^{S}_{1,t,\tau}$$

Horizon	Mean D	s.e.	t	prob>|t|	Number of months
36	0.249	0.829	0.30	0.76	120
24	0.424	0.623	0.68	0.50	132
18	0.490	0.438	1.12	0.27	138
12	0.614	0.347	1.77	0.08	144
6	0.323	0.214	1.51	0.13	150
3	0.199	0.085	2.35	0.02	153
1	0.106	0.038	2.78	0.01	155

Horizon	Style	Mean D	s.e.	t	Prob>|t|	Number of months
36	EG	1.168	2.086	0.56	0.58	120
24	EG	1.097	0.632	1.74	0.08	132
18	EG	-0.119	0.619	-0.19	0.85	138
12	EG	0.317	0.454	0.70	0.49	144
6	EG	0.001	0.270	0.00	1.00	150
3	EG	0.101	0.155	0.65	0.51	153
1	EG	0.146	0.148	0.99	0.32	155
36	MO	-2.617	1.565	-1.67	0.10	120
24	MO	-2.492	1.205	-2.07	0.04	132
18	MO	-1.713	0.758	-2.26	0.03	138
12	MO	-0.735	0.427	-1.72	0.09	144
6	MO	-0.203	0.234	-0.87	0.39	150
3	MO	0.024	0.149	0.16	0.87	153
1	MO	0.047	0.058	0.81	0.42	155
36	SC	4.372	2.101	2.08	0.04	120
24	SC	3.240	1.808	1.79	0.08	132
18	SC	3.139	1.673	1.88	0.06	138
12	SC	3.169	0.924	3.43	0.00	144
6	SC	1.717	0.592	2.90	0.00	150
3	SC	1.020	0.307	3.32	0.00	153
1	SC	0.364	0.116	3.14	0.00	155
36	VA	0.086	1.519	0.06	0.96	120
24	VA	2.438	1.031	2.37	0.02	132
18	VA	2.767	1.042	2.65	0.01	138
12	VA	2.503	0.874	2.87	0.00	144
6	VA	1.547	0.618	2.50	0.01	150
3	VA	0.917	0.384	2.39	0.02	153
1	VA	0.211	0.178	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 accounts 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 accounts that exist for both the ranking and evaluation periods, *n*. Partial-look ahead (PLA) ranks in the ranking stage those accounts that exist in the ranking stage, *n+dead*, and ranks in the evaluation stage those accounts that exist in both, *n*.

$$\chi_1^2 = \sum_i \sum_j \left(n_{ij} - n/4\right)^2 / n$$

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

		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} for EW Style Portfolios

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 accounts existing for equal-weighted portfolios of style accounts—market oriented, value, growth and small cap styles as defined by Frank Russell Company. There are 522 (295 survivors) accounts 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_1s. The standard errors and t statistics have been adjusted for τ-1 Newey-West lags. Annualized Mean γ_1 is calculated by divided the mean γ_1 by the length in years of the horizon. Horizon is in months. Number of months refers to the number of cross-sectional regression months.

$$r^{EW}_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^{4CD}_{pt} + u_{p(t,t+\tau)}$$

	Mean γ_1	t	prob>|t|	Number of months	Horizon
TOTAL					
	6.32	0.45	0.65	120	36
	-2.22	-0.25	0.80	132	24
	0.54	0.10	0.92	138	18
	-0.84	-0.29	0.78	144	12
	-1.34	-0.56	0.57	150	6
	-1.10	-0.89	0.38	153	3
	-0.08	-0.18	0.86	155	1
SURVIVORS					
	8.91	0.68	0.50	120	36
	1.17	0.14	0.89	132	24
	3.13	0.52	0.60	138	18
	0.90	0.28	0.78	144	12
	0.54	0.40	0.69	150	6
	-0.12	-0.15	0.88	153	3
	0.02	0.06	0.95	155	1
DEAD					
	18.72	2.40	0.02	119	36
	7.26	1.42	0.16	131	24
	1.05	0.25	0.81	137	18
	-0.49	-0.18	0.85	143	12
	-1.38	-0.80	0.42	149	6
	-1.29	-1.06	0.29	152	3
	-0.09	-0.14	0.89	154	1

Table 8: Regressions of Future Returns on Past 5-Year α^{4CD} from Style Excess Returns

The table shows average γ_1 from a regression of future excess style returns over τ periods (1-36 months) over past 60 month dynamic alphas for accounts existing for at least 5 years. Style excess returns are return on the account minus the return on an equal weighted portfolio of similar style. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. Horizon is in months.

$$r^S = R_p - R^{EW}$$
$$r^S_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^{4CD}_{pt} + u_{p(t,t+\tau)}$$

Total					Survivors		
Mean γ_1	t	prob>|t|	obs.	horizon	Mean γ_1	t	prob>|t|
-0.03	-0.06	0.95	120	36	-0.19	-0.31	0.76
1.06	1.56	0.12	132	24	0.59	0.53	0.60
1.03	1.47	0.14	138	18	0.46	0.45	0.65
0.85	1.96	0.05	144	12	0.01	0.02	0.99
0.42	2.41	0.02	150	6	-0.17	-0.63	0.53
0.17	1.81	0.07	153	3	-0.23	-1.81	0.07
0.06	1.43	0.15	155	1	-0.10	-1.92	0.06

Table 9: Regressions of Future Returns on Past 5-Year α^{4CD} from Style Excess Returns for Style Groups

The table shows average γ_1 from a regression of future excess style returns over τ periods (1-36 months) over past 60 month dynamic alphas for accounts existing for at least 5 years. Style excess returns are return on the account minus the return on an equal weighted portfolio of similar style. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. Annualized Mean γ_1 is calculated by divided the mean γ_1 by the length in years of the horizon. Horizon is in months. Number of months refers to the number of cross-sectional regression months.

$$r^S = R_p - R^{EW}$$

$$r^S_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^{4CD}_{pt} + u_{p(t,t+\tau)}$$

Style	Total Mean γ_1	t	prob>|t|	Number of months	Horizon	Survivors Mean γ_1	t	Prob>|t|
EG	-3.82	-2.21	0.03	120	36	-4.20	-1.49	0.14
EG	-2.59	-2.69	0.01	132	24	-3.20	-2.49	0.01
EG	-1.56	-1.84	0.07	138	18	-0.96	-0.91	0.37
EG	-0.54	-1.00	0.32	144	12	-0.58	-0.73	0.47
EG	-0.25	-0.94	0.35	150	6	-0.18	-0.48	0.63
EG	-0.16	-0.89	0.37	153	3	-0.25	-0.98	0.33
EG	-0.06	-0.87	0.39	155	1	-0.20	-1.15	0.25
MO	1.73	1.73	0.09	120	36	5.10	2.14	0.03
MO	0.86	1.34	0.18	132	24	3.73	2.28	0.02
MO	0.60	1.11	0.27	138	18	2.49	1.99	0.06
MO	0.38	0.88	0.38	144	12	1.19	1.42	0.16
MO	0.16	0.59	0.55	150	6	0.37	0.86	0.39
MO	0.04	0.25	0.80	153	3	0.01	0.06	0.96
MO	-0.01	-0.11	0.92	155	1	-0.04	-0.45	0.65
SC	0.51	0.40	0.69	120	36	-4.30	-1.47	0.14
SC	1.80	1.19	0.24	132	24	-1.70	-0.60	0.55
SC	1.79	1.37	0.17	138	18	-1.78	-0.74	0.46
SC	1.69	2.18	0.03	144	12	-1.81	-1.52	0.13
SC	0.95	2.52	0.01	150	6	-1.07	-1.85	0.07
SC	0.54	2.76	0.01	153	3	-0.62	-2.10	0.04
SC	0.16	1.87	0.06	155	1	-0.25	-1.79	0.08
VA	-2.96	-1.93	0.06	120	36	-2.43	-1.80	0.07
VA	-0.60	-0.44	0.66	132	24	-3.17	-2.65	0.01
VA	-0.39	-0.35	0.73	138	18	-3.18	-2.75	0.01
VA	-0.06	-0.08	0.94	144	12	-2.58	-3.09	0.00
VA	0.06	0.14	0.89	150	6	-1.64	-2.36	0.02
VA	-0.03	-0.12	0.91	153	3	-1.09	-2.22	0.03
VA	0.07	0.66	0.51	155	1	-0.20	-0.96	0.34

Table 10: 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) accounts 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_1s. The standard errors and t statistics have been adjusted for τ-1 Newey-West lags. Horizon is in months. Number of months refers to the number of cross-sectional regression months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4CD} + u_{p(t,t+\tau)}$$

NEGATIVE Alpha	Horizon	Mean γ_1	t	prob>|t|	Number 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
POSITVE 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 11: Regressions of Future Returns on Past 5-Year α^{4CD} for 8 year old accounts

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 accounts existing for at least 8 years. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. Horizon is in months. Number of months refers to the number of cross-sectional regression months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4CD} + u_{p(t,t+\tau)}$$

Total Horizon	Mean γ_1	t	prob>|t|	Number of months
24	2.42	2.82	0.01	120
18	1.82	2.03	0.05	120
12	0.93	1.65	0.10	120
6	0.42	1.58	0.12	120
3	0.15	0.85	0.40	120
1	0.06	0.85	0.40	120

Survivors Horizon	Mean γ_1	t	prob>|t|	Number of months
24	0.90	0.60	0.55	120
18	0.45	0.33	0.75	120
12	-0.56	-0.60	0.55	120
6	-0.50	-0.97	0.33	120
3	-0.42	-1.64	0.10	120
1	-0.15	-1.52	0.13	120

Table 12: Summary Statistics for Indices, Factors, and Account 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	ρ_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	ρ_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

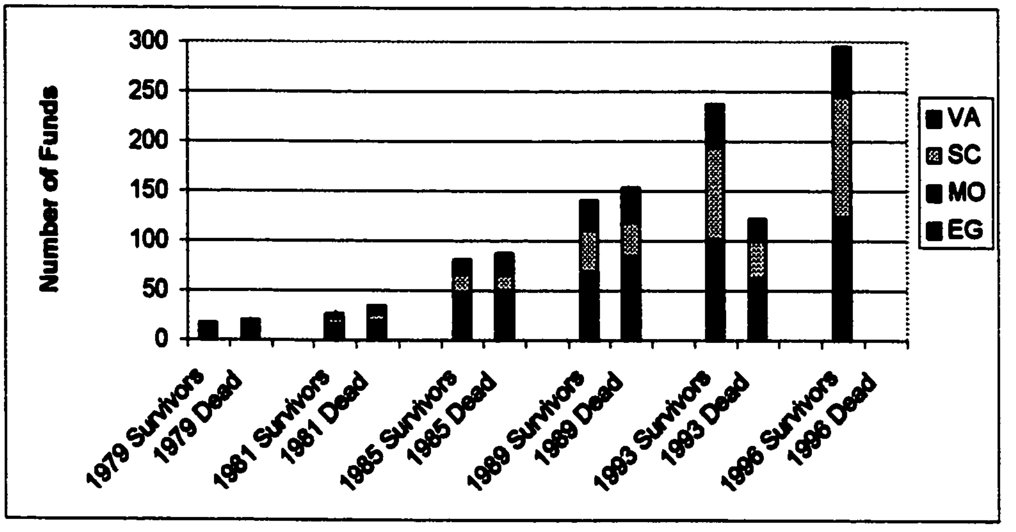

Figure 1: Existing Number of Accounts by Style and Survivorship

The number of accounts for each year shown represents the number in that category that existed at the end of the year. There are 522 accounts 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 accounts that entered the Russell data base after 1978 and did not exist in December 1996. In the graph, the number of Dead accounts is the number existing in that year and subsequently disappear before December 1996.

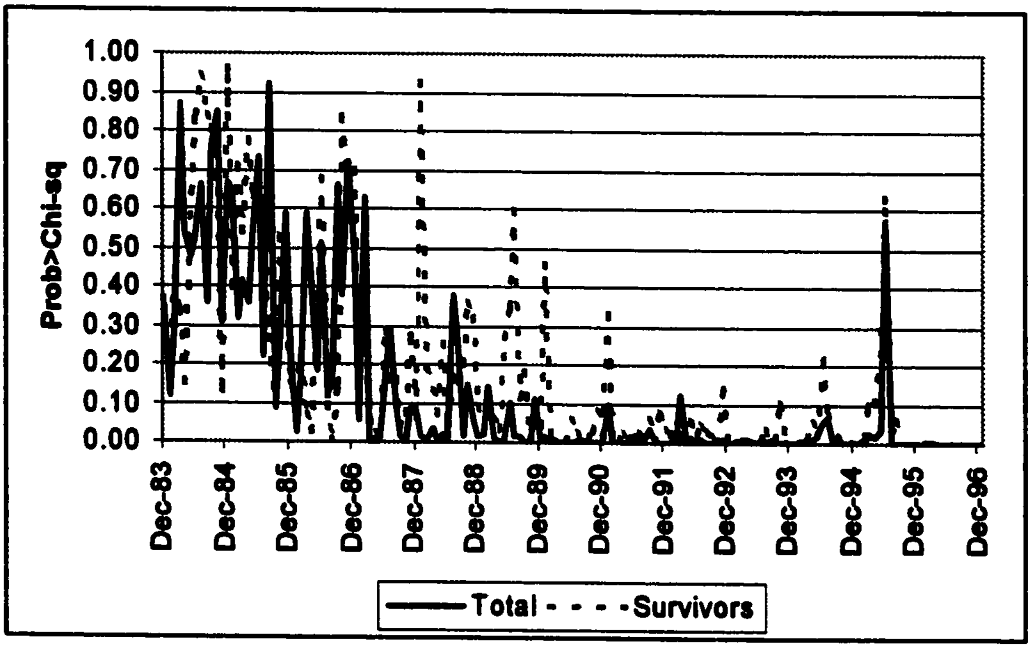

Figure 2: Chi-squared Probability for Test of 4x5 Contingency Table for Number of Accounts per Style per Quintile Portfolios based on Dynamic Alphas

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 conditonal 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 accounts) and the survivor only samples (295 accounts).

$$\chi^2_{(r-1)(c-1)} = \sum_i \sum_j \left(n_{ij} - m_{ij}\right)^2 / m_{ij}$$

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

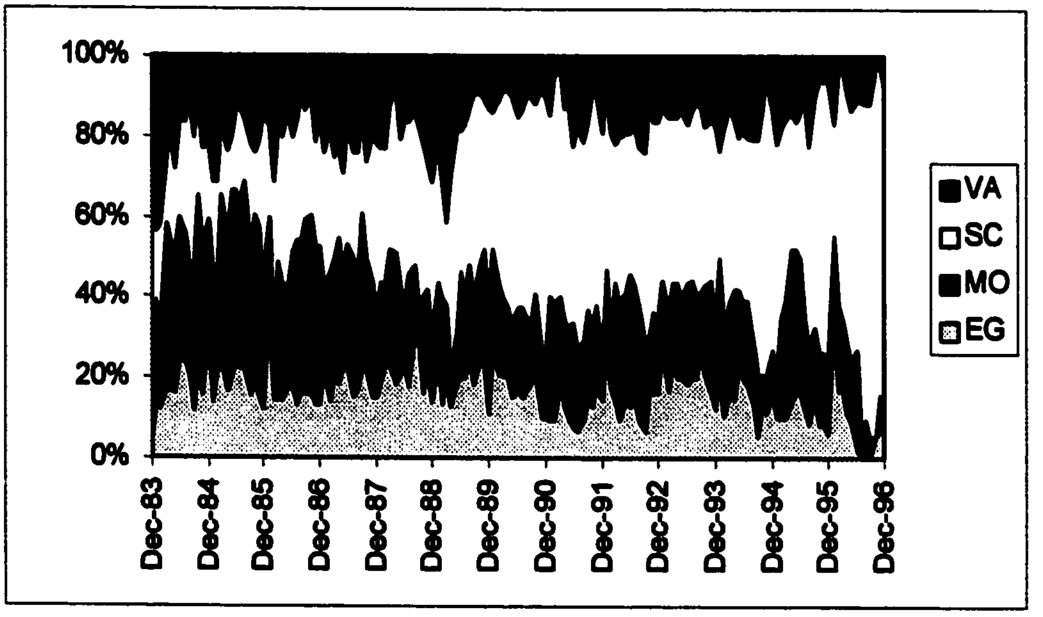

Figure 3: Style Allocation within the Top Quintile Portfolio based on Dynamic Alphas

The graph shows the percentage 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.

CHAPTER 3: ASSET FLOW AND PERFORMANCE

In the last chapter, we found that there is persistence in performance across all equity pension accounts and, in particular, small cap and market-oriented returns are predictable from dynamic alphas. This chapter addresses how pension accounts react to performance and persistence in performance with their money. The flow of assets from hiring, termination, reallocation, contributions and distributions among pension plans and their investment advisors we call asset flow. Asset flow is important for a number of reasons. First, asset flow is an implicit part of a manager's remuneration. Most managers are paid based on a percentage of assets under management. As assets grow—either through appreciation or new asset flows from the plan sponsor—the investment advisor earns more. As a consequence, investment advisors may react to the implicit incentives through risk changing behavior (Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997)). The alternative is that investment advisors do not react to asset flows as an implicit incentive. Second, asset flow impacts performance. Unexpected asset flows may affect the cash levels and market exposure of an account or an account may receive unwanted securities that must be sold to match their investment style. As mentioned in chapter one, however, some of these asset flows do not impact cash levels since assets such as securities may be transferred among managers. This chapter addresses whether pension plans' asset flows react to measures of performance. Since we found dynamic alphas significantly predicted performance for market oriented and small cap accounts, we use dynamic alphas as the primary measure of performance. We also consider other measures, including a conditional CAPM alpha, an alpha from CAPM, and three year lagged returns.

We examine the asset flow-performance relation for separate account equity accounts, to understand the relation between the investment manager for an existing account and the pension plan, via the implicit incentives that the asset flows represent. While performance for one client or composite may help an investment firm market to potential additional pension clients, we restrict our analysis to asset flows into and out of separate accounts. We use the term asset flows and not cash flows, since pension plans can transfer assets among accounts without having to liquidate to cash. This is in contrast to mutual fund investors who must liquidate holdings and transfer cash among accounts. The difference lies in the fact that pension plans own and maintain control over the assets in separate accounts.

Most of the asset flow performance literature relates to mutual funds[7]. Mutual fund studies find asset flow follows performance and may predict future performance. Gruber (1996) and Zheng (1999) find that mutual fund investors' asset flows predict future returns. For several reasons, pension plan asset flows may exhibit different results than for mutual funds. One argument is that pension accounts, with greater assets and resources at their disposal should be more successful than mutual fund investors in predicting performance, and should display this through their asset flows.

Another argument is the degrees of control pension plans have in terminating accounts. With separate accounts, a single investor or pension plan can terminate an account, unlike in a mutual fund. This difference between pension plans' separate accounts and mutual funds is similar to the difference in the unit of analysis between separate accounts and composites. One reason to study this difference is that if pension plan assets become more concentrated in defined contribution plans, and less in defined benefit plans, the more

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[7] Warther (1995), Ferson and Warther (1996) and Fant (1997) have carried out other work on flows for mutual funds, but on macro flows. Other papers in the area of asset flow and performance include Ippolito (1992), Rockinger (1995), Smith (1978), and Spitz (1970). Other mutual fund studies of asset flow include Sirri and Tufano (1998), Gruber (1996), Zheng (1999).

pension plan assets may act like mutual fund assets. It is important to understand the advantages and disadvantages of this trend for pension beneficiaries.

There are two main hypotheses that we test with respect to the asset flow performance relation for pension plans. The first hypothesis is that pension plans' asset flows follow dynamic alphas. Our alternative hypothesis is that pension plans follow other measures of performance in determining asset flows. We find that pension plans' asset flows do follow performance. Good performance is rewarded with more assets and poor performance is penalized with withdrawals. We find that asset flows to separate pension accounts do not follow sophisticated measures of performance such as dynamic alphas. We find that three-year simple excess returns are highly correlated with future one-year asset flows. These results hold for the total sample, we find the results are more significant if terminated funds are excluded from the total sample. This indicates that studies may overstate the response of flows to past performance if they employ survivor-only samples and indicates that the asset flow relation is different between surviving and terminated accounts.

The second hypothesis is that pension plans' assets follow performance more for those equity styles that have more predictable future returns. In the previous chapter, dynamic alphas for small cap and market oriented accounts were better predictors of future returns than for value and growth accounts. We find that pension plans follow past performance with their assets for small cap and market oriented accounts more than for value or growth accounts. However, they seem to respond to simple excess returns and not dynamic alphas nor other risk-adjusted measures of performance.

Our results differ from previous studies in several interesting ways. Del Guercio and Tkac (2000) find pension plans' flows follow risk-adjusted measures of performance, where we find that the simple measures of excess returns are more relevant. We believe the results differ due to the unit of analysis. Combined with their findings, our results suggest a refined insight into the flow-performance relation for pension funds. Del Guercio and

Tkac study investment firm composite returns, whereas we study separate accounts. The unit of analysis has three important effects. Composites give weight to new account flows, while separate accounts do not measure these flows. Thus, new account asset flows based on previous returns for other clients will be a major component of the Del Guercio and Tkac results, but not in our results. Composites give more weight to larger account flows. Separate accounts allow us to differentiate between the actions of smaller account sizes and larger account sizes. Finally, separate accounts give more emphasis to terminated account flows in a normalized asset flow measure. This is because the only one hundred percent flow related to performance is the outflow since we do not have the one hundred percent inflow for new accounts.

For new accounts entering a composite the hiring decisions are influenced by sophisticated measures as Del Guercio and Tkac find. This is consistent with the use of a consultant for a hiring search, the employment of performance universes and more sophisticated measures of performance by consultants. The incremental asset flow, as we find, is driven more by simple excess returns[8]. There is no contradiction if the influence of consultants and sophisticated measures is for the hiring decision. Consultants often are hired in the search for new investment advisors. Rarely, if ever, are consultants retained for only firings. A full retainer relationship may cover both hiring and firing, but many consulting contracts are only for hiring or manager searches. The conclusion is that the flow-performance relation is consistent with the assumption that relatively sophisticated measures are used by consultants for the hiring decision and less sophisticated measures are used by pension plans for interim asset flows and firings.

[8] In addition to the unit of analysis difference, our data runs from 1979 to 1996 for the separate accounts while Del Guercio and Tkac's data is for 1985-1994.

The remainder of the chapter is as follows: an outline of the data employed in the analysis, a review of the models for performance returns and asset flows, an outline of the performance asset flow relationship hypotheses, the results, and a summary of the findings.

Pension Account Asset Flow Characteristics

Asset flows between pension accounts and investment managers can be broken down into three categories. First, there are flows due to the contributions or disbursements by the plan sponsor for payment to the beneficiaries. Second, there is the reallocation of accounts among managers in different asset classes (or styles) for rebalancing to asset allocation policy weights. This second type is driven by different returns in different asset classes or among managers. For our study, we remove the impact of returns from asset flows. Finally, there are asset flows to better expected performing managers either incrementally or through firing old and hiring new managers. It is in the third type of flow that we are most interested. The available data make it difficult to differentiate among the three types of asset flows. However, for aggregate flows and for a small subset of our data, we disaggregate two of the three types of flows. We are able to distinguish net contributions and rebalancing flows from performance related flows.

Our main hypotheses rely on our expectation of a positive relation between performance and the third component of asset flows—better performers should garner more assets and poorer performers should lose assets. For rebalancing and net contributions, we expect a negative relation with performance. As performance improves, a pension plan may reduce the weighting to that account to reallocate to accounts or asset classes that have underperformed, in order to maintain investment policy weights. Similarly, strong performance by a pension plan's accounts will reduce the need for the plan sponsor to make positive net contributions.

On the aggregate level corporate plan sponsors have been negative net contributors to the plans since 1988. Given that our results show a positive asset flow-performance relation, the positive asset flow-performance relation must outweigh the negative effects from rebalancing and net contributions flows.

DATA

We employ a data set of separate equity accounts that existed between 1979 and 1996 provided by Frank Russell Company (Russell). Accounts must have at least $5 million in assets to be included in the Russell data base. The exclusion of very small pension accounts may strengthen bias towards results supporting the hypothesis that larger accounts use more sophisticated performance measures. The return data base includes 737 different accounts over the period 1979 to 1996. The account must have monthly returns and quarterly asset values. Of the 737 accounts, 535 accounts have monthly return data. The 737 accounts represent 333 different 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. Requiring both returns and quarterly market values we have 350 accounts: 204 surviving accounts and 146 dead accounts for the four major style groupings. Survivors exist at December 1996 end; dead accounts are terminated before December 1996. No accounts drop out of this data base prior to 1987. While there may be a survivorship bias in the first half of the data, it is not evident or significant when we compare two sub-samples of the data from the beginning and ending parts of the study period. The equity style breakdown is earnings growth accounts include 37 survivors and 27 dead accounts; market-oriented accounts, 57 and 55; small cap, 73 and 32; and value, 37 and 32.

There is a potential selection bias by choosing accounts with both market values and monthly returns, instead of quarterly returns. Of the accounts with only quarterly returns, the average age of both survivors and dead is at least ten months older for the quarterly funds. The breakdown among account types is relatively stable between the two samples—58% surviving accounts in the monthly and quarterly sample versus 60% in the quarterly only or larger sample. Given that our results of asset flow and three year lagged returns are stronger with survivors only, the bias from our selection criteria may lead us to understate these results since there is a slight underweighting of the surviving accounts.

PENSION GROWTH DATA

We first examine macro-level pension asset flows, since overall asset flow includes contributions and distributions from pension plans. *Pensions and Investment* conducts an annual survey of pension accounts. The survey is published each January covering data for the largest 1000 pension accounts as of the previous September 30. The top 1000 plans had 500 billion dollars in 1981 and over 3.39 trillion dollars by 1996. Most of the growth over the period in defined benefit pension assets has come through investment returns and not through contributions from pension plans. Defined benefit plan contributions have lagged behind benefit payments since 1988 (see Figure 4). Net asset flow (contributions minus benefits) ranged from 1.7% of total assets to -1.7% over the period (or 2% to -2.3% relative to the previous period's total assets).

ACTUAL ASSET FLOW VERSUS IMPLIED ASSET FLOW DATA

For some Russell data, actual portfolio asset flows are available. These asset flows include payment of fees (other fees, advisory fee and trustee fees), transfer of accounts among pension account's portfolios, and contributions and distributions from the account. These data are available for only the period 1987 to 1996. We have over 3800 asset flows (see Table 13). As with the aggregate pension industry data, most of the monies for our accounts are flowing out—either transfers out of equity accounts to other asset class accounts or distributions to the pension plan. The average distribution is twice the size of the average contribution, though there are more instances of contributions. The average transfer out of equity accounts, $6.2 million, is more than the average transfer in, $3.3 million.

The Russell data confirm the trend seen in the pension industry data. Total distributions (flows out) are greater over the period 1987-1996 than contributions (flows in)—$1,078 million versus $900 million. When one examines transfers among portfolios, asset flows out of equity portfolios swamps asset flows into those portfolios—$9.2 billion of transfers out versus $4 billion of transfers in. These transfers represent both transfers among equity portfolios as well as transfers to other asset classes.

DATA STATISTICS

The market value of the accounts under review at December end 1982 is over $5 billion and rose to over $40 billion at the end of 1996. Market oriented and small capitalization accounts are the two largest style groups. Value and growth accounts are roughly the same size at the end of the period at over $6 billion each for between 69 and 59 accounts, respectively. The smallest in average size are the value accounts at $89 million. Market oriented accounts average over $277 million (see Table 14).

Performance-driven flows are combined with rebalancing and net-contribution flows for each separate account, since we cannot separate them. For our analysis of asset flow, we employ two measures. Both measures are of an individual separate account aggregate asset flow. The first measure is dollar value asset flows, $c_1 = (V_1 - V_0R_1)$, where V_1 is end of the period account value, V_0 is beginning of the period account value, and R_1 is one plus the return on the account for the period. Positive values represent asset inflow to an account and negative values represent asset outflow. The second measure is the normalized asset flow, c_3, where $c_3 = c_1/V_0$. The normalized measure places more weight on smaller-sized accounts compared to the dollar value measures.

Both measures assume that the asset flows occur at the end of each period. An alternative is to assume end of period asset flows. We also calculate end of period asset flows for the dollar and normalized measures, c_2 and c_4, respectively. The results do not differ much using these measures.

Below, we find some interesting differences along these dimensions. Normalized asset flows by quarter vary more across dead accounts than across surviving accounts (see Table 15). The middle two quarters of the year are the worst for dead accounts, both exhibiting negative flows on the dollar measure, c_1, but not on the normalized measure, c_3. For the total sample and survivor sample, the average flows per quarter are $3.5 million to $5.8 million and $4.7 million to $9.5 million, respectively. When we examine asset flow by style (see Table 16), we see that market-oriented accounts and small cap accounts had the highest average flows and were the most volatile. The value accounts had the lowest level of average flows and their flows were the least volatile. While the aggregate pension data was shrinking during 1985-1996, the Russell data base was growing. The overall introduction of new accounts makes the average asset flow for all four equity styles positive.

MODELS OF EXCESS RETURN

PERFORMANCE MEASURES

To measure performance or excess returns, we employ three different measures. The first measure of past performance is dynamic alpha. This is motivated by the conclusions from the last chapter and by work by Zheng (1999). Christopherson et al (1998) also 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. In the previous chapter, we reconfirm and strengthen their findings of the predictability by adding back dead accounts. Zheng (1999) found in mutual funds that there was a significant relationship between dynamic alphas and asset flows. To measure performance, we employ the same four-factor model with time varying or dynamic alphas, α^{4CD}, as we did in the previous chapter.

$$
\begin{aligned}
& r_{pt+1} = a_{0p} + A_p' z_t + b_{0pb} r_{bt+1} + B_{pb}' z_t r_{bt+1} + u_{pt+1} \\
& \beta_{pb}(Z_t) = b_{0pb} + B_{pb}' z_t \\
& z_t = Z_t - E(Z) \\
& \alpha^{4CD} = a_{0p} + A_p' z_t
\end{aligned}
\tag{5}
$$

Where

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

z = a vector of the four demeaned lagged information variables—market dividend yield, detrended bill rate, January dummy, and term spread. Ferson, Sarkissian, and Simin (2001) find that it is useful to use demeaned lagged variables in conditional studies. It is also important to demean the instrumental variables over past data relative to the regression. 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, σ_p^2)* for each portfolio or account, *p*.

The second measure of performance is CAPM or Jensen's alpha. The information variables in the dynamic alpha case are a constant and the market is the only factor—equation (5) simplifies to equation (6).

$$r_{pt+1} = a_{0p} + b_{0pb} r_{bt+1} + u_{pt+1}$$
$$\alpha^{CAPM} = a_{0p} \qquad (6)$$

We also include the excess return over the SP500. Del Guercio and Tkac (2000) found that pension accounts employed risk-adjusted measures of performance while mutual funds employed simple excess return measures when deciding asset flows. We measure the excess return for two periods—two and three-year returns (see equation 7).

$$\alpha_{it}^{0} = R_{it} - R_{mt} \qquad (7)$$

Where

R_{it} = return of the account

R_{mt} = return of the S&P500

RESULTS

ASSET FLOW AND PERFORMANCE MEASURES

We first test the main hypothesis that pension plans' asset flows follow past performance. The first step in our analysis is to split our universe of accounts into deciles based on past excess return measures. Following Gruber (1996), we employ the Spearman rank correlation. For each of the different performance measures—dynamic alpha, Jensen's alpha and the two and three year excess returns, the ranking on the performance measure is then used in a Spearman rank test against the two asset flow measures, dollar asset flows, c_1, and percent of total assets, c_3 (see Table 17). The previous quarter's performance measure rank is compared with the next years' asset flow.

Using the normalized asset flow measure, c_3, there is no significant relation between past performance and future asset flows into or out of an account. The Spearman rank correlations range from a low of 0.14 for the dynamic alpha to 0.48 for the two year excess return. For the four performance measures on future dollar flows, c_1, the Spearman rank correlations are much higher. The correlations range from 0.54 for dynamic alpha on future two-year dollar asset flow to 0.88 for three year excess return on future dollar flows. Using deciles requires a correlation of at least 0.648 to be significant at the five percent level according to tables from Snedecor and Cochran (1967).

From the Spearman test, we accept the null hypothesis that pension plans' asset flows do not follow dynamic alphas. We reject the null for three-year excess returns. We find pension plan dollars significantly follow past three-year excess returns (see Figure 5). It is this "unsophisticated" return measure that is most strongly related to future asset flows. It may very well be that when a plan sponsor hires a new manager that they employ more sophisticated measures, as recommended by pension consultants, but when a plan sponsor makes incremental changes to an existing account, the plan sponsor uses the less sophisticated measure. Consultants are often hired for investment manager searches only. The difference in results between the two measures of asset flows, c_1 and c_3, is an indication that larger separate accounts follow past performance with their asset flows more than smaller accounts. The dollar flow measure gives more weight to larger accounts than the normalized flow measure. Composite studies would also miss the distinction between the actions of the small and large accounts.

ASSET FLOWS AND STYLE GROUP PERFORMANCE

In the chapter on persistence, we found differences across equity styles in the persistence in performance. If pension plans are aware of these differences, they may act accordingly with their asset flows. The next step in our analysis is to examine the asset flow-performance relation within equity styles. We expect the relation to be stronger for small cap and market oriented styles than for value and growth styles. Money should follow good performance and flee poor performance only if the performance measure is a predictor of future performance. Since we have found that money follows three-year excess returns, we test the four equity style asset flows on the three-year return measure (see Table 18). Other measures of performance did not exhibit a significant relation within styles. As with the total equity universe of accounts, the relationship between excess return and asset flow is stronger with the dollar measure, c_1, than with the normalized measure, c_3. For growth accounts the Spearman correlation is –0.36 for c_3. For market-oriented accounts and small cap the correlations are above 0.60 for past three year excess return on future one year normalized asset flow, c_3. Using past return on dollar flows, c_1, the correlation is 0.855 (see also Figure 6). The correlations are not significant for value and growth accounts, but the dollar asset flow to past performance correlations are significant for the small cap and market oriented accounts.

We find that pension plans' asset flows are more sensitive to past performance for small cap and market-oriented styles. However, the past performance measure is the three-year excess returns, not the dynamic alphas. Our results show that pension plans are not as sensitive to past performance for value and growth accounts. Historically, this result may make sense, pension plans moved initially from core equity accounts (market oriented) to value and growth for diversification, and to small cap for extra return. In the early part of our sample, core equity accounts or market-oriented accounts make up the majority of accounts. By the end of the sample period, pension plans have diversified across the four styles. Pension plans may be more sensitive to small cap account performance with their asset flows, because they view the style as being more performance driven. Value versus growth may be viewed more as hedges against which style is in favor. Also, pension plans may believe that small cap and market oriented returns are more predictable than value and growth, as was shown in the previous chapter.

PERFORMANCE AND TERMINATION

We now move to examine the ultimate outflow—termination—and survivorship bias. In our separate account data we have argued that one difference between composite data versus separate account data is the weight placed on new accounts in composite data and dead accounts in separate account data. Composite data can capture large inflows from new accounts based on past composite performance, where separate accounts have no past history for initial flows. On the other end of an account's life, we can study terminations. Separate account terminations represent a 100% outflow, versus only a portion of a composite.

By studying separate accounts and their asset flows, we can better examine the asset flows performance relationship at fund termination and how the terminated accounts affect the overall results—survivorship bias. We do so by excluding dead or terminated accounts from the analysis. The hypothesis is that the inclusion of dead accounts affects the performance relation to the normalized asset flow measure, c_3, more than the dollar asset flow, c_1. Termination of an account is a 100% outflow for any sized account, so that small dead accounts have the same impact as large dead accounts and the normalized measure is more sensitive to small accounts. The study of separate accounts and termination should highlight the difference between small and large accounts and between separate account and composite data.

When the dead accounts are excluded, the correlation between asset flows and past performance is strengthened (see Figure 7). For the past two year excess return measure the Spearman rank correlation rises from 0.66 (see Table 17) to 0.98 in the survivors only samples (see Table 19). There is no change in the three-year excess return correlation with future asset flow, c_1. For the normalized asset flow measure, c_3, the correlations rise, when dead accounts are excluded, for both simple excess return measures. For dead accounts the correlations are low. For accounts that will be fired or leave the database there is little correlation between their performance and their asset flow. This is surprising in that we expect the large outflow as they depart to be tied to performance.

As was seen in the chapter on persistence, performance in the last year of life is significantly lower than the rest of the accounts life (see Table 2). The large outflows are not enough to sway the interim asset flow-performance relationship for other parts of an account's life. Overall, the effect of the addition of the dead accounts is to dampen the asset flow-past excess return relationship. The survivorship bias strengthens the normalized asset flow-performance relationship more than the dollar asset flow-performance correlation. The terminated accounts affect the normalized relationship more because termination is a 100% outflow event. The dollar size of the termination is dependent on the size of the account.

CONCLUSIONS

In the previous chapter, we found that there was predictability in future returns from past dynamic alphas. In this chapter, we find that pension plans do not take advantage of this predictability with their asset flows. Instead of following past dynamic alphas, we find that the dollar asset flows follow simple excess returns over the S&P500 for separate account pension funds. This is in contrast to the results from studies employing composite data that show pension plans follow risk-adjusted measures of performance such as Jensen's alpha. We do not find a strong relationship between more sophisticated measures of performance and future asset flows.

Pension plans do not take advantage of the predictability in future returns from dynamic alphas for incremental flows. We believe the discrepancy between predictability and asset flow decisions to be institutional. Institutionally, our results support the hypothesis that pension plans may use sophisticated measures of performance for the hiring decision, but use simpler excess return measures for asset flows after the relationship between the plan and the advisor has been established.

As with predictability in returns, we find that the relation to past performance is significant for small cap and market oriented accounts. Pension plans respond to past performance with future asset flows for small cap and market oriented accounts, but not for value or growth accounts. This implies that past performance and the incentives to manipulate it are much more important for investment managers overseeing small cap and market oriented accounts for pension plans. Further, we find that the results are not only sensitive to equity style, but also to survivorship. Surviving accounts exhibit a stronger asset flow-performance relationship than the total sample. The addition of terminated funds weakens the overall result. This result is similar to the result of poor performers not driving the persistence result. If terminated accounts with long life spans are added back, then they will have periods of good performance prior to the periods of poor performance that caused their termination.

Our results are stronger when the dollar measure of asset flow is employed than with a percentage or normalized asset flow measure. The implication is the asset flow performance relation is stronger for larger account sizes than for smaller. Asset flow studies of composite data would also be tilted to larger account sizes. Our results employing separate accounts differentiate between small and large accounts especially when comparing the differences in results between dollar and normalized asset flows. This is not possible with composite data.

Table 13: Actual Asset Flows of Equity Portfolios

The table shows actual asset flows by type from Frank Russell Company. An asset flow represents any transaction into or out of a separate account. Asset flows are identified by type. Flows in and out are flows from the sponsor to the separate account (contributions and distributions). Transfers in and out are flows among existing accounts for a single sponsor.

Type of Asset Flow	Obs.	Mean	Std. Dev.
Advisory Fees	608	$ 128,831	$ 140,424
Flow In	262	3,438,188	11,813,320
Flow Out	149	7,238,619	21,997,557
Other Fees	165	270	9,779
Trustee Fees	44	7,612	2,938
Transfer Flow In	1202	3,360,183	15,286,433
Transfer Flow Out	1487	6,206,761	20,656,204

Table 14: Equity Style Market Values

The table shows the average of each account's average quarterly market values and standard deviation from each account's quarterly average market values by equity style for 350 accounts existing between January 1979 and December 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. Standard deviations are based on the means of the portfolios in that style. The cash flow measure is c_t, end of quarter assumption, $c_t = (V_t - V_0R_t)$.

	Total Sample Mean	Standard Deviation	Survivors Acct.s	Mean	Standard Deviation
ALL	$194,787,651	$457,597,713	204	$252,219,069	$553,438,978
EG	173,795,940	445,921,086	37	245,492,419	566,815,519
MO	277,402,300	565,072,874	57	423,502,402	749,502,263
SC	152,593,705	205,839,098	73	171,586,281	211,107,681
VA	89,634,783	133,334,914	37	114,875,871	167,401,782
			Dead Acct.s	Mean	Standard Deviation
ALL			146		
EG			27	$ 71,766,334	$109,817,830
MO			55	128,645,832	183,331,231
SC			32	109,094,582	189,334,192
VA			32	60,449,774	69,386,036

Table 15: Implied Cash Flows by Quarter

The table shows two measures of implied asset flows. Dollar asset flow measures are $c_1 = (V_1 - V_0R_1)$. Normalized asset flows are $c_3 = (V_1 - V_0R_1)/V_0$. Data represent 350 accounts from the Frank Russell Company database of equity accounts for the period 1979-1996. Survivors exist in December 1996.

Variable	# of Obs.	Total Sample Mean	Standard Deviation
	QTR=1		
C1	2714	3,592,314	57,909,478
C3	2714	6.6%	31.5%
	QTR=2		
C1	2715	4,077,895	70,748,505
C3	2715	3.8%	32.7%
	QTR=3		
C1	2767	5,780,511	91,188,234
C3	2767	5.5%	87.0%
	QTR=4		
C1	2821	3,583,190	53,706,455
C3	2821	4.7%	22.2%

Variable	Survivors Mean	Standard Deviation	Dead Mean	Standard Deviation
C1	5,062,587	62,294,616	1,336,798	50,391,823
C3	8.2%	29.8%	4.3%	33.9%
C1	6,704,054	78,127,176	(41,473)	57,083,990
C3	4.9%	31.9%	2.0%	33.9%
C1	9,523,506	107,507,235	(265,594)	54,994,217
C3	5.3%	22.8%	5.8%	137.8%
C1	4,764,673	59,895,500	1,596,458	41,207,866
C3	4.4%	21.7%	5.3%	23.1%

Table 16: Asset Flow By Style

The table shows the mean and standard deviations for quarter implied asset flows as measured by $c1=V_1-V_0R_1$ by equity style group. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value.

Asset Flows by Style, C1

	Mean	S.D.
EG	2,845,702	11,657,057
MO	9,080,887	32,822,852
SC	7,133,612	16,933,797
VAL	1,094,510	3,096,210

Table 17: Annual Asset Flow on Previous Measures of Return

Table shows decile rankings on past measures of return (dynamic alpha, CAPM alpha, 3 year return and 2 year return) and average annual asset flow for each decile. There are 350 accounts in the Frank Russell database from 1979-1996. Asset flow measures are average annual implied asset flows for dollar values, c_1 and normalized asset flows, c_3. Spearman is the Spearman rank correlation coefficient of past decile ranks of returns on future average annual asset flow. ** Significant at 1% and * Significant at 5% (Snedecor and Cochran (p. 195)).

Rank on Dynamic Alpha Decile	C1	C3	Rank on CAPM Alpha	C1	C3
1	1,850,994	10.7%	1	(7,597,892)	11.0%
2	6,639,167	23.2%	2	(4,008,330)	3.5%
3	(654,339)	2.0%	3	17,183,879	26.9%
4	(2,797)	3.1%	4	(1,891,162)	2.9%
5	218,425	5.3%	5	11,094,324	7.0%
6	5,057,085	10.1%	6	(2,646,165)	5.2%
7	3,951,797	6.8%	7	3,537,129	4.6%
8	18,439,383	18.1%	8	7,091,489	8.2%
9	3,769,840	9.0%	9	8,070,178	17.8%
10	22,008,417	16.8%	10	27,820,911	17.0%
Spearman	0.54	0.14	Spearman	0.60	0.26

Rank on 3 year Return	C1	C3	Rank on 2 year return	C1	C3
1	(13,792,262)	3.9%	1	(14,342,000)	2.8%
2	1,271,817	8.8%	2	1,142,524	20.5%
3	2,320,698	11.0%	3	(65,862)	8.0%
4	(2,285,039)	21.7%	4	(3,923,871)	6.6%
5	4,504,687	6.5%	5	5,425,873	6.9%
6	4,173,108	5.3%	6	13,152,403	7.2%
7	6,166,544	12.3%	7	3,788,650	10.0%
8	2,474,981	7.0%	8	(6,093,464)	14.7%
9	14,413,257	12.0%	9	21,313,788	12.0%
10	32,193,061	13.8%	10	32,029,346	14.8%
Spearman	0.88**	0.42	Spearman	0.66*	0.48

Table 18: Annual Asset Flow on Previous 3-Year Returns by Style

Table shows decile rankings on past measures of return (dynamic alpha, CAPM alpha, 3 year return and 2 year return) and average annual asset flow for each decile. There are 350 accounts in the Frank Russell database from 1979-1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. Asset flow measures are average annual implied asset flows for dollar values, c_1 and normalized asset flows, c_3. Spearman is the Spearman rank correlation coefficient of past decile ranks of returns on future average annual asset flow. ** Significant at 1% and * Significant at 5% (Snedecor and Cochran (p. 195)).

Rank by 3yr Return	EG # of obs.	EG C1	EG C3	MO # of obs.	MO C1	MO C3
1	34	(6,994,409)	4.2%	50	(33,123,321)	3.3%
2	46	(6,368,782)	5.5%	68	(16,513,814)	7.7%
3	43	9,828,399	6.6%	89	1,697,557	9.1%
4	50	7,288,359	3.7%	77	(7,231,955)	2.0%
5	45	10,649,906	16.0%	77	10,388,216	1.6%
6	52	746,186	-4.0%	92	19,704,705	7.2%
7	49	(8,371,182)	2.1%	87	10,672,580	8.9%
8	51	(3,650,645)	1.8%	89	24,395,592	10.0%
9	47	9,376,940	6.9%	88	5,630,546	9.5%
10	42	25,175,464	-1.1%	79	24,699,966	18.2%
Spearman		0.37	-0.358		0.855**	0.661*

Rank by 3yr Return	SC # of obs.	SC C1	SC C3	VA # of obs.	VA C1	VA C3
1	51	(12,256,557)	11.9%	38	(2,352,803)	0.8%
2	66	(889,002)	9.3%	40	777,942	7.0%
3	65	(735,417)	8.5%	54	(9,191,352)	0.8%
4	72	(5,852,196)	6.6%	59	(539,578)	3.8%
5	73	(2,235,097)	11.3%	58	5,045,528	11.6%
6	70	17,309,916	82.3%	60	(9,507,393)	4.7%
7	71	16,771,769	17.5%	59	(4,165,657)	3.8%
8	74	9,087,297	24.0%	53	(11,026,010)	6.4%
9	73	42,340,482	15.6%	60	9,312,266	12.2%
10	66	57,831,067	21.6%	53	1,212,860	5.7%
Spearman		0.855**	0.648		0.152	0.467

Table 19: Annual Asset Flow on Previous 2 & 3-Year Returns by Survivorship

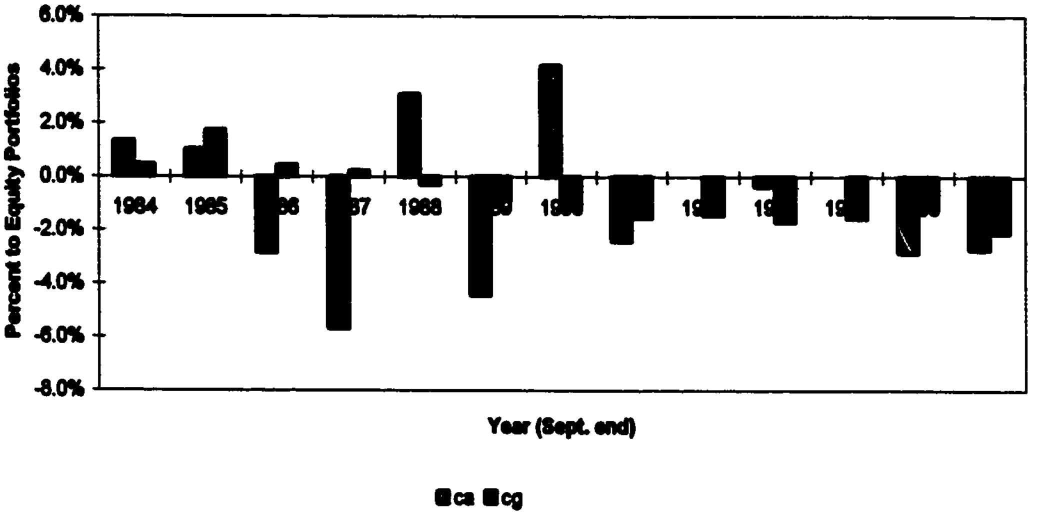
Table shows decile rankings on past measures of return (dynamic alpha, CAPM alpha, 3 year return and 2 year return) and average annual asset flow for each decile. There are 350 accounts in the Frank Russell database from 1979-1996. Survivors exist in December 1996. Asset flow measures are average annual implied asset flows for dollar values, c and normalized asset flows, c_s. Spearman is the Spearman rank correlation coefficient of past decile ranks of returns on future average annual asset flow. ** Significant at 1% and * Significant at 5% (Snedecor and Cochran (p. 195)).

Ranking on 36 month Returns

Deciles	C1 Survivors	C1 Dead	C3 Survivors	C3 Dead
1	(21,256,155)	(5,333,932)	4.5%	2.3%
2	(1,581,463)	(6,842,415)	11.3%	7.9%
3	3,772,124	19,477,736	10.2%	57.9%
4	2,835,750	(4,383,783)	4.7%	4.0%
5	10,569,860	(3,153,714)	9.6%	1.4%
6	829,272	(3,356,908)	7.9%	4.0%
7	7,799,787	(4,351,245)	12.3%	5.5%
8	27,949,486	290,503	12.8%	5.2%
9	23,080,084	(21,762,306)	16.3%	1.9%
10	31,563,520	31,979,534	12.9%	16.0%
Spearman	0.88**	0.32	0.78*	0.01

Ranking on 24 month Returns

Deciles	C1 Survivors	C1 Dead	C3 Survivors	C3 Dead
1	(18,162,203)	(5,180,195)	5.0%	-1.8%
2	(10,569,520)	26,922,519	3.3%	56.7%
3	2,466,868	(8,174,956)	6.9%	4.8%
4	3,245,733	(8,624,051)	8.3%	4.1%
5	7,043,998	(5,205,728)	5.9%	1.8%
6	12,435,173	(92,434)	8.7%	5.4%
7	10,683,131	3,579,284	12.9%	15.7%
8	15,258,736	(12,212,432)	20.6%	4.9%
9	35,990,677	(19,797,229)	16.0%	2.5%
10	29,501,278	34,210,105	14.7%	13.3%
Spearman	0.98**	(0.08)	0.90**	0.24



c_{a1}=($w_{E1}V_1$ -$w_{E0}R_{E1}V_0$)/ V_1

R=1+r, and R_E is Russell 1000

w_E = weight in equity

V_1 = Market Value at time one

c_g = (Contributions-Distributions)/V_1

Figure 4: Percent Asset flow to Equity Accounts from Growth and Reallocation

The graph is for c_a, asset flow percent change to equity due to a reallocation between stocks and bonds, given the *Pension and Investment*'s September year end data for largest 200 corporate pension accounts asset allocation. C_g is the growth in overall pension assets.

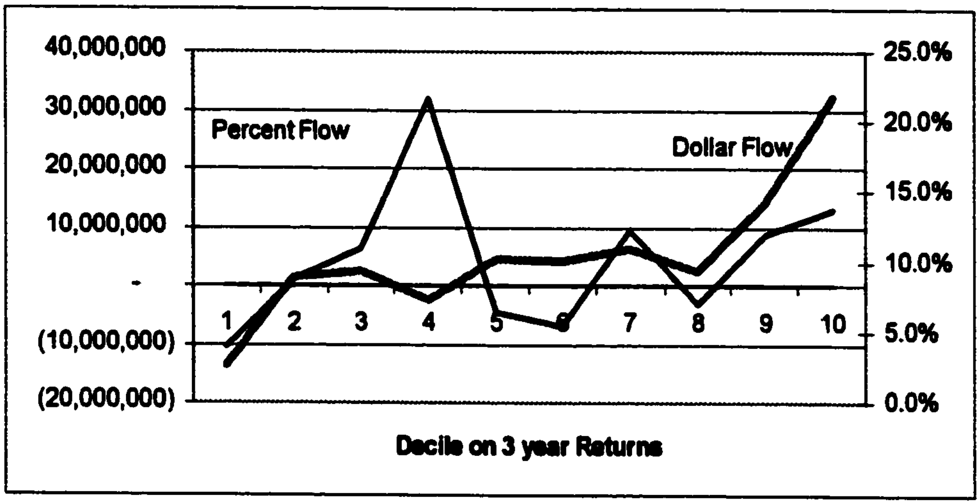


Figure 5: Past 3-Year Return Decile Portfolios and Average Annual Asset Flows

The graph shows the future annual average asset flow based on decile portfolios formed by ranking previous 3 year returns. Asset flow measures are average annual implied asset flows for dollar values, c_1 and normalized asset flows, c_3.

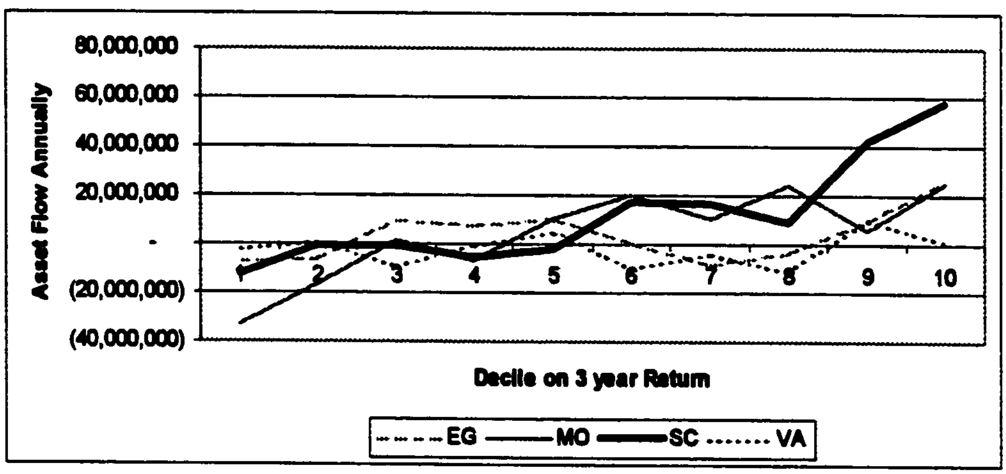


Figure 6: Asset Flow to Decile Portfolios Ranked on Past 3-Year Returns by Equity Style Group

The graph is for c_1 asset flow to decile ranked portfolios on past 3 year returns for survivors and dead accounts. There are 350 accounts in the Russell data between 1979 and 1996. Styles are defined by Frank Russell Company Company—EG=Earnings Growth, MO=Market Oriented, SC=Small Cap, and VA=Value. $C_t = V_t - V_0 R_t$.

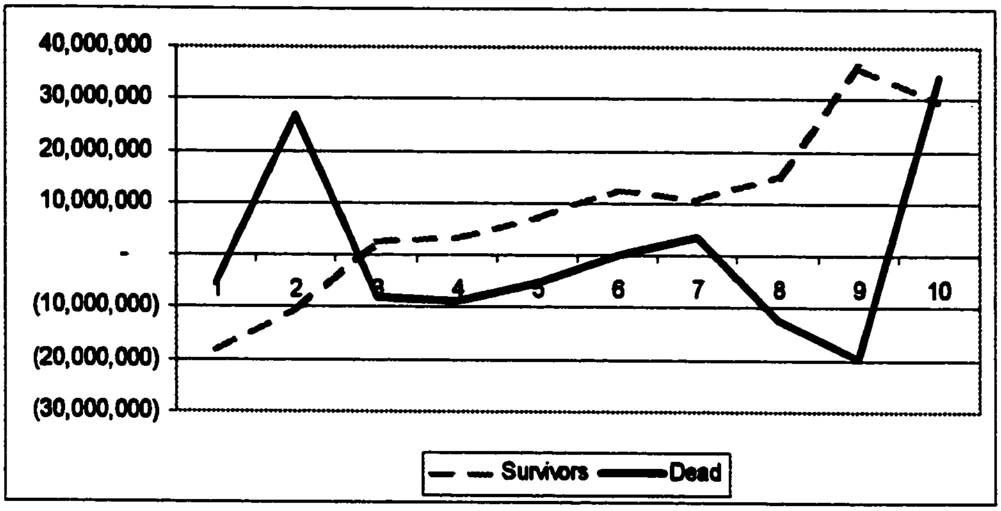


Figure 7: Asset Flow to Decile Portfolios Ranked on Past 3-Year Returns by Survivorship

The graph is for c_l, asset flow to decile ranked portfolios on past 3 year returns for survivors and dead accounts. There are 204 surviving accounts and 146 dead accounts between 1979 and 1996. Dead accounts are those accounts that do not exist in December 1996. $C_l = V_l - V_0 R_l$.

REFERENCES

Amir, Eli and Shlomo Benartzi, 1997, "The Determinants of Pension Asset Allocation in Light of Statement of Financial Accounting Standard No. 87," Working Paper

Becker, Connie, Wayne Ferson, David Myers & Michael Schill, 1999, "Conditional Market Timing with Benchmark Investors," *Journal of Financial Economics*, Vol. 52, No. 1, April 1999, pp. 119-148

Brown, Gavin, Paul Draper, and Eddie McKenzie, 1997, "Consistency of UK Pension Account Investment Performance," *Journal of Business Finance and Accounting*, March, 24 (2), 155-178

Brown, Keith, W.V. Harlow and Laura Starks, 1996, "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual fund Industry", *Journal of Finance*, March, vol. LI No. 1,

Brown, Stephen and William N. Goetzmann, 1995, "Performance Persistence" *Journal of Finance*, Vol. L No. 2

Brown, Stephen J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1997, "Rejoinder: The J-shape of performance persistence given survivorship bias," *The Review of Economics and Statistics*, Vol. LXXIX, No. 2, May, 167-170

Brown, Stephen, William Goetzmann, Roger Ibbotson and Stephen Ross, 1992, "Survivorship Bias in Performance Studies," *Review of Financial Studies*, 5, 553-580

Brown, Stephen, William Goetzmann, and Stephen Ross, 1995, "Survival", *Journal of Finance*, Vol. L No. 3, July, 853-873

Carhart, Mark, 1997, "On Persistence in Mutual fund Performance", *Journal of Finance*, March, vol. LII no. 1

Carpenter, Jennifer N. and Anthony W. Lynch, 1999, "Survivorship Bias and Attrition Effects in Measures of Performance Persistence," forthcoming *Journal of Financial Economics*

Chevalier, Judith and Glenn Ellison, 1997, "Risk Taking by Mutual funds as a Response to Incentives", *Journal of Political Economy*, vol. 105, no. 6, pp. 1167-1200

Christopherson, Jon, Wayne Ferson, and Debra Glassman, 1998, "Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance," *The Review of Financial Studies*, Spring, Vol. 11, No.1, pp. 111-142.

Christopherson, Jon A, Wayne E. Ferson, and Andrew L. Turner, 1999, "Performance Evaluation Using Dynamic Alphas and Betas: Conditional Performance Evaluation and Prediction," Working Paper Frank Russell Company

Cochrane, John H., 2001, *Asset Pricing*, Princeton University Press

Coggin, T. Daniel, Frank J. Fabozzi, and Shafiqur Rahman, 1993, "The Investment Performance of U.S. Equity Pension Account Managers: An Empirical Investigation," *Journal of Finance*, Vol. XLVIII, No.3, 1039-1055.

Coggin, T. Daniel and Charles A. Trzcinka, 1999, "The Performance of Institutional US Equity Portfolio Managers," Working Paper, SUNY Buffalo

Del Guercio, Diane, 1996, "The Distorting Effect of the Prudent Man Laws on Institutional Equity Investments", *Journal of Financial Economics* 40, 31-62

Del Guercio, Diane and Paula A. Tkac, 2000, "The Determinants of the Flow of Accounts of Managed Portfolios: Mutual funds versus Pension Accounts", Working Paper University of Oregon

Elton, Edwin J., Martin J. Gruber and Christopher R. Blake, 1996, "Survivorship Bias and Mutual fund Performance", *The Review of Financial Studies*, Winter vol. 9, No. 4, 1097-1120

Fama, Eugene and Kenneth French, 1992, " The Cross-Section of Expected Stock Returns", *Journal of Finance*, Vol. XLVII, No. 2

Fama, Eugene F., and James MacBeth, 1973, "Risk, Return and Equilibrium: Empirical Tests," *Journal of Political Economy*, 607-36

Fant, L. Franklin, "Investment Behavior of Mutual fund Investors: The Evidence from Aggregate Account Flows and the Supply of Equity Securities", Working Paper University of New Hampshire, July 1997.

Farnsworth, Heber, Wayne Ferson, David Jackson, and Steven Todd, 1999, "Performance Evaluation with Stochastic Discount Factors," working paper, University of Washington

Ferson, Wayne E. and Campbell R. Harvey, 1999, "Conditioning Variables and the Cross-Section of Stock Returns," *Journal of Finance*, Vol. LIV, No. 4, pp. 1325-1360

Ferson, Wayne and Kenneth Khang, 2000, "Conditional Performance Measurement using Portfolio Weights: Evidence for Pension Funds," University of Washington

Ferson, Wayne, Sergei Sarkissian, and Tim Simin, 1999, "Spurious Regressions in Financial Economics," working paper, University of Washington

Ferson, Wayne and Rudi Schadt, 1996, "Measuring Account Strategy and Performance in Changing Economic Conditions," *Journal of Finance*, 51(2), 425-61

Ferson, Wayne and Vincent A. Warther, 1996, "Evaluating Account Performance in a Dynamic Market", *Financial Analysts Journal*, Nov/Dec

Grinblatt, Mark, and Sheridan Titman, 1992, "The Persistence of Mutual fund Performance, " *Journal of Finance*, Vol. XLVII, No. 5, 1977-1984

Gruber, Martin J., 1996, "Another Puzzle: The Growth in Actively Managed Mutual funds," *Journal of Finance*, July, Vol. LI, No. 3

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1997, "The J-shape of performance persistence given survivorship bias," *The Review of Economics and Statistics*, May, Vol. LXXIX, Number 2, 161-166

Ippolito, R.A., 1992, "Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual fund Industry," *Journal of Law and Economics*, vol. XXXV, April, 45-70

Ippolito, R., and J. Turner, 1987, "Turnover, Fees, and Pension Plan Performance, *Financial Analysts Journal* 31, 16-26.

Kahn, Ronald N. and Andrew Rudd, 1995, "Does Historical Performance Predict Future Performance?," *Financial Analysts Journal*, November-December, 43-52

Kandel, Shmuel and Robert F. Stambaugh, 1995, "Portfolio Inefficiency and the Cross-section of Expected Returns," *Journal of Finance*, Vol. L, No. 1, March, 157-184

Khang, Kenneth, 1997, "Performance Measurement using Portfolio Weights and Conditioning Information: An Examination of Pension Account Equity Manager Performance," Dissertation, University of Washington

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992, "The Structure and Performance of the Money Management Industry," *Brookings Papers: Microeconomics*, 339-391

Lakonishok, Joseph, Andrei Shleifer, Richard Thaler, and Robert W. Vishny, 1991, "Window Dressing by Pension Account Managers," *American Economic Review, Papers and Proceedings* 81, May, 227-231 (Working Paper 310)

Newey, Whitney K. and Kenneth D. West, 1987, "Hypothesis Testing with Efficient Method of Moments Estimation," *International Economic Review*, vol. 28, no. 3, October, 777-787

Newey, Whitney K. and Kenneth D. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, vol. 55, no. 3, May, 703-708

Rockinger, Michael, 1995, "Determinants of Capital Flows to Mutual funds," Working Paper, HEC

Roll, Richard and Stephen Ross, 1994, "On the cross-sectional relation between expected returns and betas," *Journal of Finance*, March, Vol. 49, Issue 1, pp. 101-122

Shanken, Jay, 1992, "On the Estimation of beta-pricing models," *Review of Financial Studies* Volume 5, number 1, pp. 1-33

Sirri, Erik and Peter Tufano, 1992, "Buying and Selling Mutual funds: Flows, Performance, Fees, and Services", Working Paper, Harvard Business School

Smith, K.V., 1978, "Is Account Growth Related to Account Performance?" *Journal of Portfolio Management*, Spring, 49-54

Snedecor, George W. and William G. Cochran, (1967) *Statistical Methods*, Iowa State University Press, 6th edition

Spitz, A.E., 1970, "Mutual fund Performance and Cash Inflow," *Applied Economics* 2: 141-145

Stambaugh, Robert F., 1999, "Predictive Regressions," Working Paper, University of Pennsylvania, May

Torous, Walter and Shu Yan, 1999, "Predictive Regressions Revisited", UCLA Working Paper #2-00, December

Warther, Vincent A., 1995, "Aggregate mutual fund flows and security returns", *Journal of Financial Economics*, 39, 209-235

Zheng, Lu, 1999, "Is Money Smart? A Study of Mutual fund Investors' Account Selection Ability," *Journal of Finance*, June, vol. 54 No. 3, 901-934

APPENDIX A: OTHER MEASURES OF ALPHA FOR PERSISTENCE

In chapter two, we employ a dynamic alpha based on a four factor conditional asset pricing model to predict future returns. Here, we present the results from other measures of performance to predict future return. We choose three other measures that correspond to other major work in the pension account research area. First, we employ an alpha from a market model or CAPM. Second, we employ a dynamic alpha from a conditional CAPM. This second measure is the dynamic alpha that Christopherson, Ferson, and Glassman (1998) found to be the best predictor of future returns. The third measure we employ is an excess return over the S&P 500 for three years. Of the three measures, we find that the dynamic alpha predicts future returns the best. We reconfirm our survivorship bias results, survivorship dampens evidence in persistence across styles.

PERFORMANCE MEASURES

The first measure of return we employ is the dynamic alpha from a conditional CAPM. This dynamic alpha is based on Christopherson et al (1998). The main difference between the model present here and the one employed earlier is in the beta vector (see equation 8). The four factor conditional model was based on the sensitivity to four factors—small versus large cap returns, growth minus value, short versus long term bonds, and market excess returns. The one factor or conditional CAPM model (CCAPM) employs only the market excess returns. The conditional or informational variables are the same as before.

$$
\begin{aligned}
r_{pt+1} &= a_{0p} + A_p' z_t + b_{0pb} r_{bt+1} + B_{pb}' z_t r_{bt+1} + u_{pt+1} \\
\beta_{pb}(Z_t) &= b_{0pb} + B_{pb}' z_t \\
z_t &= Z_t - E(Z) \\
\alpha^{CCAPM} &= a_{0p} + A_p' z_t
\end{aligned}
\tag{8}
$$

Where

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

z = a vector of the four demeaned lagged information variables—market dividend yield, detrended bill rate (subtracting the 12 month moving average), January dummy, and term spread.

r_b = excess return of the market, r_{mf}, with $r_{mf} = R_M - R_f$

R_M = return of the S&P500

R_f = return of US Treasury bills

u_t = is the error term and is assumed to be distributed $(0, \sigma_p^2)$ for each portfolio or account, p. There may be cross-sectional heteroskedasticity across portfolios.

The second measure of performance is CAPM or Jensen's alpha. The information variables are the null set—equation 8 simplifies to equation 9.

$$
\begin{aligned}
r_{pt+1} &= a_{0p} + b_{0pb} r_{bt+1} + u_{pt+1} \\
\alpha^{CAPM} &= a_{0p}
\end{aligned}
\tag{9}
$$

The third measure of return employed is three-year excess returns over the S&P 500 index.

$$\alpha_{pt}^{0} = R_{pt} - R_{Mt} \tag{10}$$

R_M = return of the S&P500.

We measure the significance of predictability by measuring the significance of γ_1. The appropriate measure of alpha is substituted into equation 11. Consistent with our earlier work, we employ a weighted least squares approach using the appraisal ratio and employ Newey-West lag weights for the overlapping data to adjust the standard errors in the Fama-MacBeth t-statistics.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt} + u_{p(t,t+\tau)} \qquad (11)$$

RESULTS

When the dynamic alpha from the one-factor CCAPM is used to predict future returns (see Table 20), the total sample's γ_1 is significant in all horizons. For the survivor sample, only the longer horizons, 1 year and up, are significant. The total sample results are more significant and generally more positive than the survivor only sample. For the unconditional CAPM, none of the total nor survivor γ_1's are significant. The direction of the survivor bias is still negative; survivor γ_1's are less positive or more negative than the total sample's γ_1. For the regressions of future returns on past three-year excess returns (see Table 21), only one result is significant for either the total or survivor sample. In general past three-year excess returns do not predict future returns. As with the other measures, the direction of the survivor bias is the same between the total and surviving samples. Using the total sample gives larger γ_1s. These results reconfirm the findings by Christopherson et al (1998) and our results. Dynamic alphas are better predictors of future returns than other measures of past performance and predictability is more significant with the total sample than the survivor only.

When we move to the style breakdown—value, growth, market oriented and small cap—analysis, our one and four factor dynamic alpha results are similar (see Table 22 and Table 4). Value accounts have significant reversals in performance for the survivors.

Market oriented accounts show more significant and larger coefficients for the surviving sample than total sample. Small cap accounts total sample has significant coefficients for all but the three-year future return horizon. The usage of the one factor dynamic alpha provides approximately the same conclusions as our four factor dynamic alpha model.

For the analysis of style breakdowns with the CAPM alpha (see Table 23), the results are not significant except for the value accounts total sample. Not only are the coefficients significant for all horizons, but they are strongly negatively significant. Value accounts that survive reverse performance between the past CAPM alpha and future excess returns. This significant reversal of performance is also found in both the surviving and total samples regressions on past three-year excess returns for value accounts (see Table 24).

CONCLUSIONS

In general, we have found that the result of using different performance measures confirms the result of Christopherson et al (1998). Dynamic or conditional alphas are better predictors of future excess returns than unconditional measures of performance. The survivor bias across all measures for pension accounts typically understates the level and significance of predictability. The major exception to this is when style groups are employed. In some cases, the bias is reversed (value and market oriented accounts). Within style groups, small cap accounts have the most significance for the dynamic alpha as a predictor.

Table 20: Regressions of Future Returns on Past 5-Year α[1]

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month Conditional CAPM dynamic alphas (CCAPM) and CAPM alphas for accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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_1s. The standard errors and t statistics have been adjusted for τ-1 Newey-West lags. T-S is the total sample mean γ_1s less the survivor sample. Horizon is in months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{CCAPM} + u_{p(t,t+\tau)}$$

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{CAPM} + u_{p(t,t+\tau)}$$

CAPM TOTAL					CAPM Survivors			
Mean γ_1	t	prob>|t|	obs	Horizon	Mean γ_1	t	prob>|t|	T-S
-1.38	-0.30	0.77	120	36	-4.28	-0.85	0.40	2.90
1.51	0.51	0.61	132	24	-0.04	-0.01	0.99	1.55
1.52	0.66	0.51	138	18	0.38	0.17	0.86	1.14
1.50	1.14	0.26	144	12	0.62	0.56	0.58	0.88
0.42	0.60	0.55	150	6	-0.27	-0.42	0.67	0.69
0.22	0.53	0.60	153	3	-0.10	-0.25	0.80	0.32
0.12	0.75	0.46	155	1	0.01	0.04	0.97	0.11
CCAPM TOTAL					CCAPM Survivors			
3.35	2.22	0.03	120	36	4.14	1.40	0.16	-0.79
3.23	2.90	0.00	132	24	3.16	2.26	0.03	0.07
2.53	2.43	0.02	138	18	2.01	2.38	0.02	0.52
1.93	2.86	0.00	144	12	1.40	2.74	0.01	0.53
0.75	2.04	0.04	150	6	0.22	0.57	0.57	0.53
0.41	2.01	0.05	153	3	0.13	0.55	0.59	0.28
0.21	2.58	0.01	155	1	0.12	1.21	0.23	0.09

Table 21: Regressions of Future Returns on Past 3-Year α^0

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 36 month excess returns over the S&P 500 for accounts existing for at least 3 years. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. T-S is the total sample mean γ_1s less the survivor sample. Horizon is in months.

$$\alpha^0_{pt} = R_{pt} - R_{mt}$$

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^0_{pt} + u_{p(t,t+\tau)}$$

TOTAL					Survivors			
Mean γ_1	t	prob>|t|	obs	horizon	Mean γ_1	t	prob>|t|	T-S
0.05	1.01	0.31	120	36	0.01	0.16	0.88	0.048
0.04	1.57	0.12	132	24	0.02	0.79	0.43	0.019
0.02	1.23	0.22	138	18	0.01	0.54	0.59	0.011
0.03	1.65	0.10	144	12	0.02	0.97	0.33	0.008
0.01	1.00	0.32	150	6	0.01	0.63	0.53	0.004
0.01	0.82	0.41	153	3	0.01	0.72	0.47	0.000
0.00	1.00	0.32	155	1	0.00	0.93	0.35	0.000

Table 22: Regressions of Future Returns on Past 5-Year α^{1CD} 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 Conditional CAPM dynamic alphas (CCAPM) for accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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. T-S is the total sample mean γ_1s less the survivor sample. Horizon is in months.

$$r_{pt} = \alpha^1_{pt} + \beta_{p,t} r_{mt} + e_{pt}$$

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^1_{pt} + u_{p(t,t+\tau)}$$

CCAPM
TOTAL

Style	Mean γ_1	t	Prob>|t|	Obs	Horizon	Survivors Mean γ_1	t	Prob>|t|	T-S
EG	-0.28	-0.12	0.91	120	36	-2.86	-1.47	0.14	2.58
EG	0.26	0.18	0.86	132	24	-2.70	-1.89	0.06	2.96
EG	0.64	0.46	0.64	138	18	-0.96	-1.04	0.30	1.60
EG	0.72	0.89	0.37	144	12	-0.51	-0.61	0.54	1.23
EG	0.24	0.57	0.57	150	6	-0.42	-0.65	0.52	0.67
EG	0.17	0.72	0.47	153	3	-0.12	-0.45	0.65	0.29
EG	0.04	0.37	0.71	155	1	-0.06	-0.42	0.68	0.10
MO	2.51	2.16	0.03	120	36	5.70	1.72	0.09	-3.18
MO	1.90	2.46	0.02	132	24	4.20	1.94	0.05	-2.29
MO	1.33	1.80	0.07	138	18	2.53	1.98	0.05	-1.19
MO	0.87	1.24	0.22	144	12	1.66	1.77	0.08	-0.79
MO	0.34	0.80	0.43	150	6	0.26	0.40	0.69	0.08
MO	0.20	0.94	0.35	153	3	0.01	0.03	0.97	0.18
MO	0.11	1.33	0.18	155	1	0.04	0.33	0.74	0.07
SC	1.74	0.87	0.39	120	36	-1.46	-0.47	0.64	3.20
SC	2.63	1.77	0.08	132	24	0.76	0.28	0.78	1.87
SC	2.39	1.71	0.09	138	18	0.18	0.09	0.93	2.21
SC	1.93	2.18	0.03	144	12	0.01	0.01	0.99	1.91
SC	1.07	2.49	0.01	150	6	-0.14	-0.26	0.80	1.20
SC	0.63	2.86	0.00	153	3	-0.06	-0.18	0.86	0.69
SC	0.23	2.53	0.01	155	1	0.05	0.38	0.70	0.19
VA	-7.23	-3.50	0.00	120	36	-8.36	-4.19	0.00	1.12
VA	-1.61	-0.74	0.46	132	24	-5.76	-3.88	0.00	4.16
VA	-1.26	-0.81	0.42	138	18	-4.79	-3.39	0.00	3.53
VA	-0.63	-0.59	0.56	144	12	-3.03	-2.58	0.01	2.40
VA	-0.32	-0.63	0.53	150	6	-2.30	-2.01	0.05	1.98
VA	-0.29	-0.88	0.38	153	3	-1.41	-1.96	0.05	1.12
VA	-0.04	-0.30	0.77	155	1	-0.31	-1.15	0.25	0.27

Table 23: Regressions of Future Returns on Past 5-Year α^1 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 CAPM alphas for accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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. T-S is the total sample mean γ_1s less the survivor sample. Horizon is in months.

$$r_{pt} = \alpha^1_{pt} + \beta_{p,t} r_{mt} + e_{pt}$$

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^1_{pt} + u_{p(t,t+\tau)}$$

CAPM TOTAL						Survivors			
	Mean γ_1	t	prob>|t|	obs	Horizon	Mean γ_1	T	prob>|t|	T-S
EG	4.14	0.76	0.45	120	36	1.15	0.16	0.87	2.99
EG	1.02	0.26	0.80	132	24	-6.41	-1.36	0.18	7.43
EG	1.23	0.36	0.72	138	18	-5.19	-1.35	0.18	6.42
EG	1.24	0.51	0.61	144	12	-3.58	-1.43	0.16	4.82
EG	0.00	0.00	1.00	150	6	-2.13	-1.93	0.06	2.13
EG	0.02	0.03	0.98	153	3	-0.90	-1.43	0.16	0.92
EG	0.05	0.21	0.83	155	1	-0.15	-0.50	0.62	0.21
MO	4.31	1.48	0.14	120	36	1.77	0.43	0.66	2.53
MO	3.49	1.62	0.11	132	24	2.32	0.87	0.39	1.16
MO	3.07	1.83	0.07	138	18	2.46	0.96	0.34	0.61
MO	2.31	1.90	0.06	144	12	1.86	1.11	0.27	0.45
MO	0.62	1.00	0.32	150	6	0.99	1.15	0.25	-0.37
MO	0.17	0.55	0.58	153	3	0.42	0.92	0.36	-0.25
MO	0.04	0.36	0.72	155	1	0.12	0.76	0.45	-0.08
SC	1.51	0.28	0.78	120	36	-12.31	-1.69	0.09	13.82
SC	3.81	1.05	0.29	132	24	-3.97	-0.76	0.45	7.78
SC	2.38	0.82	0.41	138	18	-2.54	-0.68	0.50	4.92
SC	1.93	1.16	0.25	144	12	-0.79	-0.45	0.65	2.72
SC	1.24	1.62	0.11	150	6	-0.61	-0.86	0.39	1.85
SC	0.89	2.36	0.02	153	3	-0.04	-0.09	0.93	0.93
SC	0.36	2.48	0.01	155	1	0.06	0.37	0.71	0.29
VA	-29.41	-3.51	0.00	120	36	-8.69	-1.94	0.06	-20.72
VA	-20.92	-3.83	0.00	132	24	-3.92	-0.59	0.56	-17.00
VA	-14.73	-3.62	0.00	138	18	-2.88	-0.52	0.61	-11.85
VA	-4.62	-2.89	0.00	150	6	0.10	0.04	0.97	-4.72
VA	-2.45	-3.00	0.00	153	3	-0.40	-0.37	0.71	-2.05
VA	-0.86	-2.81	0.01	155	1	-0.10	-0.28	0.78	-0.76

Table 24: Regressions of Future Returns on Past 3-Year α^0 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 CAPM alphas for accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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. T-S is the total sample mean γ_1s less the survivor sample. Horizon is in months.

$$\alpha^0_{pt} = R_{pt} - R_{mt}$$

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha^0_{pt} + u_{p(t,t+\tau)}$$

	TOTAL					Survivors			
	Mean g1	t	prob>|t|	obs	horizon	Mean g1	t	prob>|t|	T-S
EG	-0.07	-0.88	0.38	120	36	-0.26	-1.84	0.07	0.18
EG	-0.03	-0.49	0.63	132	24	-0.17	-1.60	0.11	0.14
EG	-0.02	-0.29	0.77	138	18	-0.14	-1.58	0.12	0.12
EG	0.00	0.10	0.92	144	12	-0.10	-1.64	0.10	0.11
EG	0.00	-0.17	0.87	150	6	-0.05	-1.74	0.08	0.04
EG	0.00	0.00	1.00	153	3	-0.02	-1.49	0.14	0.02
EG	0.00	0.05	0.96	155	1	0.00	-0.89	0.37	0.00
MO	0.05	0.93	0.35	120	36	-0.01	-0.06	0.95	0.05
MO	0.02	0.46	0.65	132	24	0.01	0.11	0.91	0.01
MO	-0.01	-0.16	0.88	138	18	-0.01	-0.29	0.77	0.01
MO	-0.01	-0.63	0.53	144	12	-0.02	-0.73	0.46	0.01
MO	-0.01	-1.09	0.28	150	6	-0.02	-1.05	0.29	0.00
MO	-0.01	-1.24	0.22	153	3	-0.01	-1.40	0.16	0.00
MO	0.00	-0.98	0.33	155	1	0.00	-1.29	0.20	0.00
SC	0.16	1.82	0.07	120	36	0.04	0.30	0.77	0.11
SC	0.09	1.58	0.12	132	24	0.06	0.68	0.50	0.03
SC	0.05	1.21	0.23	138	18	0.05	0.85	0.40	0.00
SC	0.04	1.85	0.07	144	12	0.04	1.65	0.10	0.00
SC	0.02	1.92	0.06	150	6	0.02	1.42	0.16	0.00
SC	0.01	1.74	0.08	153	3	0.01	1.37	0.17	0.00
SC	0.00	1.66	0.10	155	1	0.00	1.33	0.19	0.00
VA	-0.39	-4.65	0.00	120	36	-0.21	-3.21	0.00	-0.18
VA	-0.24	-4.19	0.00	132	24	-0.21	-2.30	0.02	-0.03
VA	-0.17	-4.13	0.00	138	18	-0.16	-2.14	0.03	-0.01
VA	-0.09	-3.02	0.00	144	12	-0.10	-1.77	0.08	0.01
VA	-0.03	-1.63	0.10	150	6	-0.04	-1.19	0.23	0.00
VA	-0.02	-1.59	0.11	153	3	-0.03	-1.64	0.10	0.01
VA	-0.01	-1.44	0.15	155	1	-0.01	-1.82	0.07	0.01

APPENDIX B: SCHMOOZING AND SURVIVORSHIP BIAS IN RELATION TO PERSISTENCE

We present an extension to Brown et al's (1992) model of survivorship bias on measures of persistence. Our extension is to add a non-performance-related variable to the survivorship criteria. The original model and our extension are presented below.

Brown et al in their appendix present the following model, in which an account survives if the sum of its two-period performance is positive. While Brown et al do not specify the measure of return, it may be useful to think of the return measures for funds x and y as measures of excess return, α, from either our four factor conditional model or a Jensen's α. The survival criteria for two accounts, x and y, and is summarized by c.

Where

$$c=\{x_1 + x_2 > 0, y_1 + y_2 > 0\}.$$

It is assumed that performance is independent and identically distributed across accounts, therefore,

$$P[x_2 > y_2 | x_1 > y_1] = P[x_2 > y_2] = 1/2$$

persistence in the model is defined to exist if the probability of fund x outperforming fund y in both periods is greater than one half. There is an impact on persistence of sample selection based on survivorship. The probability of fund x outperforming fund y in both periods given that they both survive is

$$P[x_2 > y_2 \mid x_1 > y_1, c].$$

From Bayes' Theorem

$$P[x_2 > y_2 \mid x_1 > y_1, c] = P[x_2 > y_2, x_1 > y_1, c] / P[x_1 > y_1, c]$$

And again by Bayes' Theorem,

$$P[x_1 > y_1, c] = P[x_1 > y_1 \mid c]P[c]$$

From independence, it follows that

$$P[x_1 > y_1 \mid c] = 1/2$$

If the distributions are symmetric about the origin then

$$P[c] = 1/4$$

and

$$P[x_1 > y_1, c] = (1/2)(1/4) = 1/8$$

Brown et al then show that

$$P[x_2 > y_2, x_1 > y_1, c] = P[x_2 > y_2, x_1 > y_1, x_2 + x_1 > 0, y_2 + y_1 > 0]$$

Since survival of x is implied by the other three conditions,

$$= P[x_2 > y_2, x_1 > y_1, x_2 + x_1 > 0, y_2 + y_1 > 0]$$

$$= \int_{-\infty}^{\infty}\int_{y_1}^{\infty} dF\left\{\int_{-y_1}^{\infty}\int_{y_2}^{\infty} dF dF_{y_2}\right\} dF_{y_1} = \int_{-\infty}^{\infty}(1 - F(y_1))\left\{\int_{-y_1}^{\infty}(1 - F(y_2))dF_{y_2}\right\} dF_{y_1}$$

$$= \int_{-\infty}^{\infty}(1 - F(y_1))\left\{\int_{-y_1}^{\infty}(1 - F(y_2))dF_{y_2}\right\} dF_{y_1} \text{ (by symmetry)}$$

$$= \int_{-\infty}^{\infty}(1 - F(y_1))\left[F(y_2) - \frac{1}{2}(F^2(y_2))\Big|_{-y_1}^{\infty}\right] dF_{y_1} = \frac{1}{2}\int_{-\infty}^{\infty}(1 - F(y_1))(1 - F(-y_1))^2 dF_{y_1}$$

$$= \frac{1}{2}\int_{-\infty}^{\infty}(1 - F(y_1))(F^2(y_1))dF_{y_1} \text{ (by symmetry)}$$

$$= \frac{1}{2}\left(\frac{1}{3}F^3(y_1) - \frac{1}{4}F^4(y_1)\Big|_{-\infty}^{\infty}\right)$$

$$= \frac{1}{2}\left(\frac{1}{3} - \frac{1}{4}\right) = \frac{1}{24}$$

and

$$P[x2 > y2 \mid x1 > y1, c] = \frac{1/24}{1/8} = \frac{1}{3}.$$

The impact from survivorship is therefore to decrease the evidence of persistence, since the probability of *x* outperforming *y* in both periods is less than one half.

We expand the Brown et al's two-period model by adding a constant, *k*, to the survival criteria, *c*. The new survival criterion is *c, where**

$$c^{*}=\{x_1 + x_2 + k > 0, y_1 + y_2 + k > 0\}.$$

The constant, k, represents a level of non-performance related benefit provided by investment managers to pension plans. Lakonishok et al. (1992) have named such non-performance ability as "schmoozing."[9] Our task then becomes to see whether

$$P[x_2 > y_2 \mid x_1 > y_1, c^*] = P[x_2 > y_2,\ x_1 > y_1, c^*] / P[x_1 > y_1 \mid c^*] P[c^*]$$

is less than, equal to, or greater than one-third. If the probability is greater than one-third, then the schmoozing factor weakens the Brown et al result of survivorship dampening evidence of persistence. Indeed, their one-third means reversals, not persistence.

From the Brown et al. assumptions of i.i.d., we know

$$P[x_1 > y_1 \mid c^*] = 1/2$$

The problem to solve becomes

$$P[x_2 > y_2 \mid x_1 > y_1, c^*] = P[x_2 > y_2,\ x_1 > y_1, c^*] / (0.5 P[c^*])$$

We move on to solving the denominator, $P[c^*]$:

---

[9] *"Money managers who can provide a good story about their strategy have a comparative advantage. In fact, the product sold by the professional money managers is not just good performance but schmoozing, frequent discussion of investment strategies, and other forms of hand holding."*, page 375, Lakonishok et al (1992)

$P(c^*) = P(x_1 + x_2 + k > 0)P(y_1 + y_2 + k > 0)$

Since x and y are i.i.d., we look at one half of the equation.

$$P(x_1 + x_2 + k > 0) = \int_{-\infty}^{\infty} \int_{-x_2-k}^{\infty} dF_{x_1} dF_{x_2} = \int_{-\infty}^{\infty} \left[F_{x_1} \Big|_{-x_2-k}^{\infty} \right] dF_{x_2}$$

$$= \int_{-\infty}^{\infty} [1 - F(-x_2 - k)] dF_{x_2}$$

As in Brown et al, by symmetry about the origin,

$$= \int_{-\infty}^{\infty} [1 - (1 - F(x_2 + k)] dF_{x_2}$$

$$= \int_{-\infty}^{\infty} [F(x_2 + k)] dF_{x_2}$$

$$P(c^*) = \left\{ \left[\int_{-\infty}^{\infty} [F(x_2 + k)] dF_{x_2} \right] \right\}^2 = \{E[F(x + k)]\}^2$$

Next, we solve for the numerator, $P[x_2 > y_2, x_1 > y_1, c^*]$.

$$= \int_{-\infty}^{\infty} \int_{y_1}^{\infty} dF \left\{ \int_{-y_1-k}^{\infty} \int_{y_2}^{\infty} dF dF_{y_2} \right\} dF_{y_1} = \int_{-\infty}^{\infty} (1 - F(y_1)) \left\{ \int_{-y_1-k}^{\infty} (1 - F(y_2)) dF_{y_2} \right\} dF_{y_1}$$

$$= \int_{-\infty}^{\infty} (1 - F(y_1)) \left\{ \int_{-y_1-k}^{\infty} (1 - F(y_2)) dF_{y_2} \right\} dF_{y_1}$$

$$= \int_{-\infty}^{\infty} (1 - F(y_1)) \left[F(y_2) - \frac{1}{2} (F^2(y_2)) \Big|_{-y_1-k}^{\infty} \right] dF_{y_1}$$

$$= \frac{1}{2} \int_{-\infty}^{\infty} (1 - F(y_1))(1 - F(-y_1 - k))^2 dF_{y_1}$$

$$= \frac{1}{2} \int_{-\infty}^{\infty} (1 - F(y_1))(F^2(y_1 + k)) dF_{y_1} \text{ (by symmetry)}$$

$$= \frac{1}{2} \int_{-\infty}^{\infty} (1 - F(y_1))(F^2(y_1 + k)) dF_{y_1} = \frac{1}{2} E[(1 - F(y_1))(F^2(y_1 + k))]$$

We now add back the denominator.

$$=\frac{\left\{\int_{-\infty}^{\infty}\left\{0.5F^2(x+k)-0.5F(x)F^2(x+k)\right\}dF_x\right\}}{0.5\left\{\left[\int_{-\infty}^{\infty}[F(x+k)]dF_x\right]\right\}^2}=\frac{\left\{\int_{-\infty}^{\infty}\left\{F^2(x+k)-F(x)F^2(x+k)\right\}dF_x\right\}}{\left\{\left[\int_{-\infty}^{\infty}[F(x+k)]dF_x\right]\right\}^2}$$

If $k=0$, then $\frac{\left\{\int_{-\infty}^{\infty}\left\{F^2(x)-F^3(x)\right\}dF_x\right\}}{\left\{\left[\int_{-\infty}^{\infty}[F(x)]dF_x\right]\right\}^2}=\frac{\left\{\left\{\left[\frac{1}{3}F^3(x)-\frac{1}{4}F^4(x)\right]_{-\infty}^{\infty}\right\}\right\}}{\left\{\frac{1}{2}F^2(x)\Big|_{-\infty}^{\infty}\right\}^2}$

$$=\frac{\left[\frac{1}{3}-\frac{1}{4}\right]}{\left\{\frac{1}{2}\right\}^2}=\frac{\left[\frac{4}{12}-\frac{3}{12}\right]}{\left\{\frac{1}{2}\right\}^2}=\frac{\left[\frac{1}{12}\right]}{\left[\frac{1}{4}\right]}=\frac{1}{3}<\frac{1}{2}$$

So, if $k=0$, we get the Brown et al. result that two-period survivorship increases the probability of performance reversals between accounts since the probability of persistence is less than half. The impact of two-period survival model on evidence of persistence is to decrease the probability of persistence.

As stated earlier, the impact of schmoozing and survivorship on evidence of persistence comes down to whether the following expression is greater than, less than or equal to one-third.

$$\frac{\left\{\int_{-\infty}^{\infty}\left\{F^2(x+k)-F(x)F^2(x+k)\right\}dF_x\right\}}{\left\{\left[\int_{-\infty}^{\infty}[F(x+k)]dF_x\right]\right\}^2}.$$

We can rewrite this in terms of expectations and substituting $w=F(x+k)$ and $y=F(x)$.

$$
\begin{aligned}
&= \frac{E\left[F^2(x+k)(1-F(x))\right]}{\left(E[F(x+k)]\right)^2} \\
&= \frac{E\left[w^2(1-y)\right]}{\left(E[w]\right)^2} \\
&= \frac{E\left[w^2\right]-E\left[w^2 y\right]}{\left(E[w]\right)^2} = \frac{\operatorname{var}(w)+E[w]^2-\operatorname{cov}\left(w^2,y\right)-E\left[w^2\right]E[y]}{\left(E[w]\right)^2} \\
&= \frac{\operatorname{var}(w)-\operatorname{cov}\left(w^2,y\right)-E\left[w^2\right]\frac{1}{2}}{\left(E[w]\right)^2}+1 \\
&= \frac{\operatorname{var}(w)-\operatorname{cov}\left(w^2,y\right)-\frac{1}{2}\left(\operatorname{var}(w)+E[w]^2\right)}{\left(E[w]\right)^2}+1 \\
&= \frac{\frac{1}{2}\operatorname{var}(w)-\operatorname{cov}\left(w^2,y\right)}{\left(E[w]\right)^2}+\frac{1}{2} = \frac{\operatorname{var}(w)-2\operatorname{cov}\left(w^2,y\right)}{2\left(E[w]\right)^2}+\frac{1}{2}
\end{aligned}
$$

We know that when $k=0$, we have the Brown et al result of one-third. When k goes to infinity the cumulative distribution function, $F(x+k)$ goes to one, and the variances and covariances go to zero. The result is that there is no survivorship bias on persistence as the probability of x outperforming y in both periods goes to one-half.

An Example of Standard Normal Distribution with Schmoozing

If we make a further assumption that x and y are standard normal variables (we have already assumed i.i.d and symmetric about the origin), we can plot the above function by drawing randomly from a standard normal distribution to estimate the expectations with a variety of k's. For ten thousand random draws from a standard normal distribution, our resulting graph confirms that the function is greater than one-third (see Figure 8) and less than or equal to one-half. Schmoozing, however, is never large enough to completely overcome the effect of survivorship on persistence. The probability of persistence given survivorship and schmoozing is always less than or equal to 0.5. As k goes to infinity, the selection bias created by survivorship disappears.

AN EXAMPLE OF UNIFORM DISTRIBUTION WITH SCHMOOZING

A uniform distribution example shows that the probability is greater than a third and less than a half with k over the relevant range from zero to one, so that schmoozing decreases reversals (increases persistence). Assume x and y are two account returns that are i.i.d., uniformly distributed between −0.5 and 0.5. The probability of persistence in the uniform distribution example becomes

$$\frac{E\left[F(x+k)^2(1-F(x))\right]}{\left(E[F(x+k)]\right)^2}, \text{ where}$$

$$F(x+k)=\int_{-0.5}^{x+k} dt = t\Big|_{-0.5}^{x+k} = x+k+0.5 \quad \text{and}$$

$$E[F(x+k)]=\int_{-0.5}^{0.5-k} x+k+0.5dx+\int_{0.5-k}^{0.5}\int_{-0.5}^{0.5} dtdx$$

$$=\frac{x^2}{2}+xk+0.5x\Big|_{-0.5}^{0.5-k}+\int_{0.5-k}^{0.5} 1dx$$

$$=\frac{(0.5-k)^2}{2}+(0.5-k)k+0.5(0.5-k)-\frac{(0.5)^2}{2}+(0.5)k+0.5(0.5)+x\Big|_{0.5-k}^{0.5}$$

$$=0.5-0.5k^2+k$$

The numerator is

$$P[x_2 > y_2, x_1 > y_1, y_1 + y_2 + k > 0]$$

$$= \int_{-0.5}^{0.5-k}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-y_1-k}^{0.5}\int_{y_2}^{0.5} dF_{x_2}dF_{y_2}\right\}dF_{y_1} + \int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-0.5}^{0.5}\int_{y_2}^{0.5} dF_{x_2}dF_{y_2}\right\}dF_{y_1}$$

We split the problem in half, solving the first half,

$$\int_{-0.5}^{0.5-k}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-y_1-k}^{0.5}\left(x_2\Big|_{y_2}^{0.5}\right)dF_{y_2}\right\}dF_{y_1} = \int_{-0.5}^{0.5-k}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-y_1-k}^{0.5}(0.5 - y_2)dF_{y_2}\right\}dF_{y_1}$$

$$= \int_{-0.5}^{0.5-k}\int_{y_1}^{0.5} dF_{x_1}\left\{\left(0.5y_2 - 0.5y_2^2\right)\Big|_{-y_1-k}^{0.5}\right\}dF_{y_1}$$

$$= \int_{-0.5}^{0.5-k}\int_{y_1}^{0.5} dF_{x_1}\left\{0.125 + 0.5y_1 + 0.5k + 0.5y_1^2 + y_1k + 0.5k^2\right\}dF_{y_1}$$

$$= \int_{-0.5}^{0.5-k}(0.5 - y_1)\left\{0.125 + 0.5y_1 + 0.5k + 0.5y_1^2 + y_1k + 0.5k^2\right\}dF_{y_1}$$

$$= \int_{-0.5}^{0.5-k}\left\{0.0625 + 0.125y_1 + 0.25k - 0.25y_1^2 + 0.25k^2 - 0.5y_1^3 - y_1^2k - 0.5y_1k^2\right\}dF_{y_1}$$

$$= y_1\left(\frac{1}{16} + \frac{k}{4} + \frac{k^2}{4}\right) + y_1^2\left(\frac{1}{16} - \frac{k^2}{4}\right) + y_1^3\left(-\frac{1}{12} - \frac{k}{3}\right) - \frac{1}{8}y_1^4\Bigg|_{-0.5}^{0.5-k}$$

$$= \frac{1}{24} + \frac{k}{6} - \frac{k^3}{6} - \frac{k^4}{24}$$

Having solved the first half, we now solve the second half of the problem,

$$\int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-0.5}^{0.5}\int_{y_2}^{0.5} dF_{x_2}dF_{y_2}\right\}dF_{y_1} = \int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\left\{\int_{-0.5}^{0.5}(0.5-y_2)dF_{y_2}\right\}dF_{y_1}$$

$$= \int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\left\{0.5y_2 - 0.5y_2^2\Big|_{-0.5}^{0.5}\right\}dF_{y_1} = \int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\{0.25-0.125+0.25+0.125\}dF_{y_1}$$

$$= \int_{0.5-k}^{0.5}\int_{y_1}^{0.5} dF_{x_1}\{(0.5)\}dF_{y_1} = 0.5\int_{0.5-k}^{0.5}(0.5-y_1)dF_{y_1} = 0.25y_1 - 0.25y_1^2\Big|_{0.5-k}^{0.5}$$

$$= \frac{k^2}{4}$$

We combine the three pieces together and our solution is

$$P[x_2 > y_2 \mid x_1 > y_1, c^*] = \frac{\frac{1}{24} + \frac{1}{6}k + \frac{k^2}{4} - \frac{1}{6}k^3 - \frac{1}{24}k^4}{\frac{1}{2}\left(\frac{1}{2} + k - \frac{1}{2}k^2\right)^2}$$

If we graph the result (see Figure 10) in the appropriate range for k, $0 < k < 1$. We see that the result is everywhere greater than 1/3 and less than 1/2—the Brown et al non-schmoozing result. Schmoozing decreases the probability of reversals between accounts x and y compared to the two-stage survival model derived by Brown et al (1992). As in the normal distribution case, k is never large enough to overcome the reversals due to the survivorship bias.

SIZE OF SCHMOOZING

We can estimate a boundary for the size of k from the probability of survival, $P(x_1 + x_2 + k > 0)$. We know from our data that each year since 1987 about 4-15% of the accounts do not survive within each style group. The death rate is calculated as the number of terminated accounts during a year divided by the number of accounts at the beginning of the year. Since some of the accounts will be too young to be up for the survival criteria if the length of the two periods is greater than one year, the actual rate of termination for accounts must be higher. We graph the probability of survival as a function of k (see Figure 9). Given our death rate, the most k could be would be approximately two (or two standard deviations given that we have assumed a standard normal probability distribution). A schmoozing factor of two gives a 91.5% survival rate. A fund survives if the two-period performance is greater than minus two standard deviations from the mean.

CONCLUSIONS ABOUT SCHMOOZING

Given our results in the main body of the paper with reversals from survivorship bias, we believe that the schmoozing level is small compared to the reversals induced by the two-stage survivor model in the overall sample. If Lakonishok et al (1992) are correct and there is schmoozing in the pension account industry, the impact of schmoozing given is not large enough to offset the dampening effect on persistence from survivorship.

If schmoozing were defined simply as a non-performance related criterion, then a dynamic population would have the same impact on the survivorship bias on persistence as schmoozing. Assume a population of accounts is growing—as small cap, growth and value were in the early part of our sample. Accounts may survive with poor relative performance for an investment management firm because there are not enough good competitors to absorb both new accounts and account-switching among existing managers. That is there may be, in effect, a positive k for dynamic populations in the early growth phase. The positive k could come from the diversification benefits to different style investing. Given our results on survivorship, it would appear that even with a dynamic population the level of schmoozing is not large enough to offset the survivorship bias that caused significant reversals for small cap and value accounts. As the population moved from dynamic to static, the reversals should increase. This ignores the effect due to actual persistence by the funds. We can only observe the combination of actual persistence or ability and reversals from survivorship.

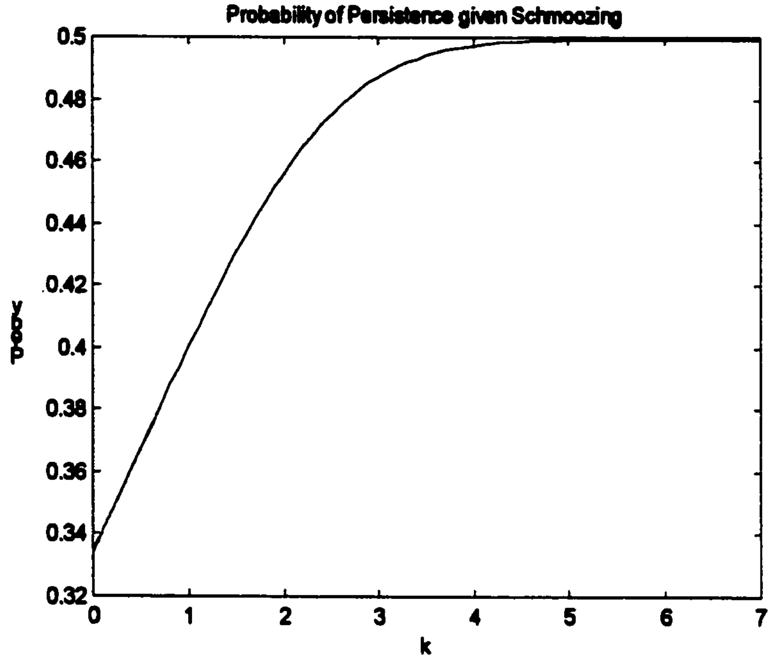


Figure 8: Probability of Persistence given Schmoozing, k, and Normal Distribution

The figure represents plotting the probability of persistence given a two-period survival criteria and a level of schmoozing, k. We drew from a standard normal distribution ten thousand times to estimate the standard normal distribution.

$$P(x_2 > y_2 \mid x_1 > y_1, c^*)$$
$$x, y \sim N(0,1)$$
$$k \geq 0$$

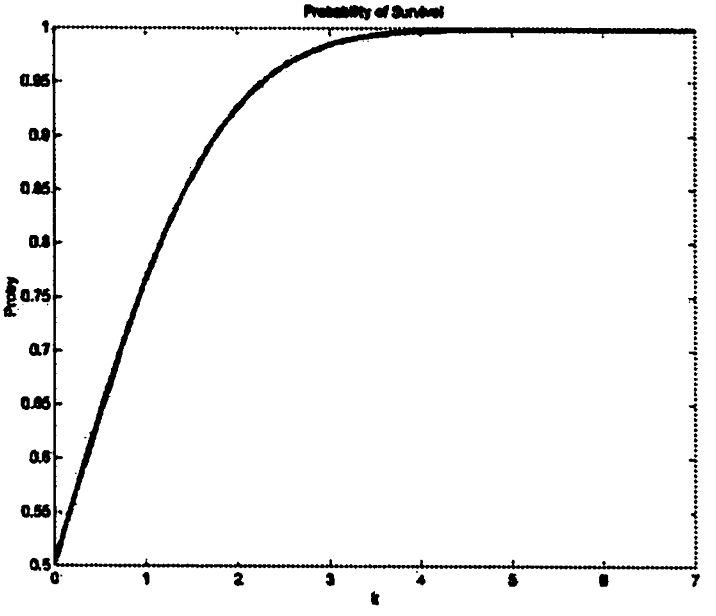


Figure 9: Probability of Survival given Schmoozing, *k*, and Normal Distribution for α

The figure represents plotting the probability of survival given a two-period survival criteria and a level of schmoozing, *k*. We drew from a standard normal distribution one thousand times to estimate the standard normal distribution.

$$P(x_1 + x_2 + k > 0)$$
$$x \sim N(0,1)$$
$$k \geq 0$$

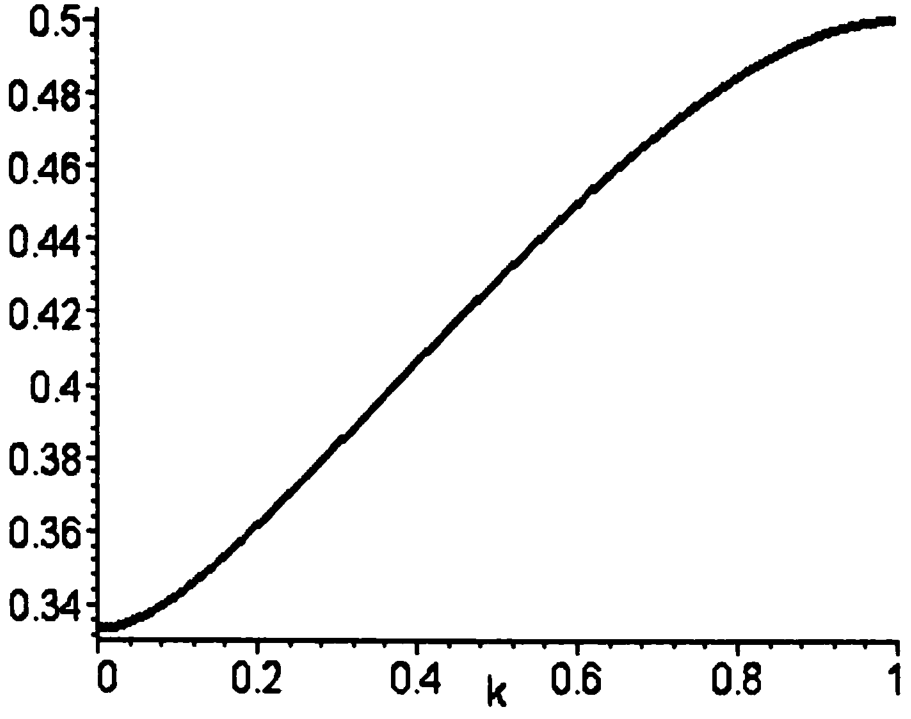


Figure 10: Probability of Persistence given Schmoozing, *k*, and Uniform Distribution

The figure represents plotting the probability of persistence given a two-period survival criteria and a level of schmoozing, *k*. The uniform distribution is bounded by -0.5 and 0.5 and *k* ranges from 0 to 1.

$$P(x_2 > y_2 \mid x_1 > y_1, c^*)$$
$$x, y \sim U(-0.5, -0.5)$$
$$1 \geq k \geq 0$$

APPENDIX C: LAGGED OWN RETURN AS A CONDITIONAL VARIABLE

Within the literature for incentives for investment managers, there is a branch that examines the tournament or competitive nature of the industry. Two of the more recent articles in this area are Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997). Both papers study the behavior of mutual funds. Most of the research that has been done on incentives for investment managers has employed mutual fund data. The persistence and asset flow work in our paper has relevance to this literature. Asset flow and persistence are part of the incentive relationships investment managers have with pension plans. If pension plans follow performance with their assets as we have found, then there is an implicit incentive to perform well and perform relatively well to competitors.

We present in this appendix an extension of our conditional asset-pricing model that relates to the work on incentives and risk taking behavior. We add lagged own return for each account as a conditional variable to our model for calculating the dynamic alpha. In the mutual fund literature, managers change their behavior (risk-taking) based on past relative performance in the tournament framework. For our tests, we include lagged returns of one and two years. We do not believe the pension market is set to annual tournaments, but that longer horizon performance is more important for pension plans. This is consistent with our findings of asset outflows being correlated with two and three year performance.

PERFORMANCE MEASURES

As earlier, the measure of return we employ for past returns is the dynamic alpha from a conditional four-factor model. The main difference between the model present here and the one employed earlier is in the conditional or informational variables (see equation 12).

We have added lagged own return for either one or two years to the Z vector of information variables.

$$
\begin{aligned}
& r_{pt+1} = a_{0p} + A'_p z_t + b_{0pb} r_{bt+1} + B'_{pb} z_t r_{bt+1} + u_{pt+1} \\
& \beta_{pb}(Z_t) = b_{0pb} + B'_{pb} z_t \\
& z_t = Z_t - E(Z) \\
& \alpha^{4DL} = a_{0p} + A'_p z_t
\end{aligned}
\tag{12}
$$

Where

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

z = a vector of the five demeaned lagged information variables—market dividend yield, detrended bill rate (subtracting the 12 month moving average), January dummy, term spread, and lagged own return of either one or two years.

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 Russell 1000™ for four factor model

R_f = return of US Treasury bills

u_t = is the error term and is assumed to be distributed *(0, σ_p^2)* for each portfolio or account, *p*.

We measure the significance of predictability by measuring the significance of γ_1, which is the regression coefficient on our new measure of dynamic alpha, α^{4DL} (see equation 13). Consistent with our earlier work, we employ a weighted least squares approach using the appraisal ratio and employ Newey-West lag weights for the overlapping data to adjust the standard errors in the Fama-MacBeth t-statistics.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4DL} + u_{p(t,t+\tau)} \tag{13}$$

RESULTS

The introduction of the lagged return as a conditioning variable lowers the number of significant coefficients and as the horizon of lagged return is lengthened the significance continues to decrease (see Table 25 in comparison to Tables 3 and 11). Lagged own returns as an informational variable lower the level of predictability of the dynamic alpha.

Since the use of lagged returns induces an extra look-ahead bias, we also review our results of requiring eight years of data versus five plus years of data (Table 11 versus Table 3). The drop off in the number of significant horizons due to the addition of lagged own returns is greater than the drop off due to the extra 3-year look-ahead bias that is evident when we restricted accounts to have at least eight years of data. We do not recommend the addition of lagged own returns when employing dynamic alphas to predict future returns.

Table 25: Regressions of Future Returns on Past 5-Year α^{4DL}

The table shows average γ_1 from a regression of future returns over τ periods (1-36 months) over past 60 month dynamic alphas with lagged own return as a conditioning variable (1 or 2 two years) for accounts existing for at least 5 years. There are 522 (295 survivors) accounts 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 τ-1 Newey-West lags. Annualized Mean γ_1 is calculated by divided the mean γ_1 by the length in years of the horizon. Horizon is in months.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt}^{4DL} + u_{p(t,t+\tau)}$$

One-year lagged return

TOTAL					SURVIVORS			
Mean γ_1	t	prob>|t|	months	horizon	Mean γ_1	t	prob>|t|	Tot-Sur
2.04	2.16	0.03	108	36	0.45	0.47	0.64	1.59
1.96	2.22	0.03	120	24	1.06	1.42	0.16	0.90
1.69	2.00	0.05	126	18	0.89	1.26	0.21	0.80
1.16	2.36	0.02	132	12	0.76	1.70	0.09	0.40
0.34	1.36	0.18	138	6	0.28	1.56	0.12	0.06
0.10	0.71	0.48	141	3	0.06	0.45	0.65	0.05
0.07	1.20	0.23	144	1	0.05	0.95	0.35	0.01

Two-year lagged return

TOTAL					SURVIVORS			
Mean γ_1	t	prob>|t|	months	horizon	Mean γ_1	t	prob>|t|	Tot-Sur
1.62	1.38	0.17	108	36	1.07	1.11	0.27	0.55
1.21	1.43	0.16	120	24	1.41	1.53	0.13	-0.21
1.27	1.46	0.15	126	18	1.34	1.90	0.06	-0.07
0.79	1.51	0.13	132	12	0.86	2.10	0.04	-0.06
0.38	1.79	0.08	138	6	0.23	1.40	0.16	0.15
0.12	0.84	0.40	141	3	0.05	0.49	0.63	0.06
0.03	0.59	0.55	144	1	-0.04	-0.82	0.42	0.07

APPENDIX D: STATISTICAL ISSUES

In the methodology adopted for our study, there are two related statistical issues we address here. The main issue of bias in our predictive regression is an errors-in-variables problem. The predictive regression (equation 2) is a cross-sectional regression of future returns on past dynamic alphas. The dynamic alphas are estimated from a regression of the conditional model (equation 1). Since the dynamic alphas are estimated, they are measured with error. Thus, the errors-in-variables problem arises. The other related problem is the bias induced by regressing on lagged variables that are highly autocorrelated over time, in the construction of the dynamic alphas. This finite sample problem is studied by Stambaugh (1999) and Torous and Yan (1999), among others. In Stambaugh (1999) a bias occurs in the regression if changes in the lagged variables are correlated with the regression errors.

Stambaugh (1999) and Torous and Yan (1999) show that a bias is produced in time-series regressions employing lagged variables whose innovations are correlated with the dependent variable. Stambaugh demonstrates the bias produced by using lagged dividend yield in a predictive regression. Lagged dividend yield is one of our conditioning variables. It is also one of the variables used in most other conditional pricing models—Christopherson, Ferson, and Glassman (1998), Zheng (1999), and Becker et al (1999). Torous and Yan discuss dividend yield, book-to-market ratio, and default spread as possible sources of bias in predictive regressions. Torous and Yan suggest confidence bounds for testing the significance of the predictive regression.

In the conditional asset-pricing model we employ, there are high autocorrelations in the information variables—term spread of 0.85, dividend yield of 0.98, and Treasury bills of 0.95 (see table 12)—over the entire period of 1979 to 1996. The correlations among these three information variables are negative.

While both Stambaugh and Torous and Yan raise the issue with respect to predictive regressions, similar to our first stage regressions, these two issues of errors-in-variables and predictive regressions are not independent in our two-stage regressions. If there is a bias due to the use of lagged variables in the time-series model, then the bias may be carried through to the second regression as an errors-in-variables problem.

Cochrane (2001) outlines the Fama and Macbeth (1973) methodology to address the errors-in-variable problem in asset pricing tests. We follow the methodology by first estimating the alphas through rolling sixty month time series regressions. The second step is to estimate the gammas through monthly cross-sectional regressions. The third step is to calculate the Fama and Macbeth t-statistic for the gammas based on the mean of monthly coefficients and the standard errors from the testing period. The standard errors are corrected for cross-sectional correlation.

Shanken (1992) introduces a further refinement for correcting for the errors-in-variables problem. Shanken finds Fama and Macbeth procedure underestimates the standard errors of the mean cross sectional regression coefficient. Shanken shows his correction using maximum likelihood is asymptotically equivalent to a Generalized Least Squares (GLS) estimate of the cross sectional regression standard error, and this is the technique that we follow. We actually employ a weighted least squares (WLS) approach to estimating the gammas in our second stage cross-sectional regression, since full covariance matrix GLS is not feasible. Further support for this method is found in Kandel and Stambaugh (1995) and Roll and Ross (1994). The added benefit of the WLS approach, as mentioned in Christopherson et al (1998), is that the weights are equivalent to using an appraisal ratio which Brown et al. (1992) suggest as an adjustment for survivorship bias when dead accounts and survivors have differing variances. The WLS approach handles both the potential for problems with heteroscedasticity and survivorship bias due to heteroscedasticity. Heteroscedasticity may arise either between our total and survivor sample or among the equity style groupings.

First, we run a regression at each time period for each account for the past 60 months for the dynamic alpha coefficient estimates. The dynamic alphas are calculated using the coefficient estimates and the contemporaneous information variables (see equation 14). As estimates, the dynamic alphas are measured with error, e_{pt}. If these errors are independent of the actual future returns and of the "true" alphas, they produce an attenuation bias in the second stage, cross-sectional regressions. This means that the estimates of γ_1 are closer to zero than the true values of γ_1, and we are likely to understate the amount of persistence as a result. Also, the errors in the estimated alphas are most likely cross-sectionally correlated. We therefore test the significance of the slope coefficient on the dynamic alpha using the Fama and Macbeth t-statistic, which accounts for cross-sectional correlation. There may also be serial correlation in the measurement errors of our alphas. Christopherson et al (1998) point out that by using excess returns regressed cross-sectionally on dynamic alphas, instead of alphas on alphas, we avoid spurious persistence due to autocorrelation in the errors of the dynamic alphas. In summary, our procedure is as follows. The time-series regression is:

$$\begin{aligned}
r_{pt+1} &= a_{0p} + A_p' z_t + b_{0pb} r_{bt+1} + B_{pb}' z_t r_{bt+1} + u_{pt+1} \\
\hat{\alpha}_{pt}{}^{4CD} &= \hat{a}_{0p} + \hat{A}_p' z_t \qquad\qquad (14) \\
\hat{\alpha}_{pt}{}^{4CD} &= \alpha_{pt}{}^{4CD} + e_{pt}
\end{aligned}$$

The dynamic alphas are employed in the second step cross-sectional regression of future returns on past dynamic alphas for each time period (see Equation 15 below), employing WLS with the weights being the inverse of the standard errors from the time-series regression. The t-statistic is calculated on the monthly averages of the cross-sectional regression coefficients with the standard errors adjusted using Newey-West weights for overlapping data when the horizon of the future return is greater than zero.

$$r_{p(t,t+\tau)} = \gamma_{0,t,\tau} + \gamma_{1,t,\tau} \hat{\alpha}_{pt}^{4CD} + u_{p(t,t+\tau)} \qquad (15)$$

VITA

David Hobson Myers

University of Washington

2001

I. Biographical Data

Place of Birth:	Portland, Oregon
Date of Birth:	18 January, 1960
Citizenship:	U.S.A.
Marital Status:	Married
Children:	One

II. Education

Undergraduate

1978-1983: Wesleyan University, Middletown, Connecticut, B.A. (Government)

Graduate

1985-1987: New York University, New York, New York, M.B.A. (Finance and International Business)

MBA Thesis

"Global Model for Relative Country Valuation", September 1987

1993-Present: University of Washington, Seattle, Washington (Ph.D. candidate-Finance)

Academic Awards

Beta Gamma Sigma, New York University

Recognition of Outstanding Teaching, University of Washington

III. Professional Employment Record

2000-Present Lecturer

	Lehigh University, Bethlehem, Pennsylvania
1993-1997:	Teaching and Research Assistant University of Washington, Seattle, Washington
1988-1993:	Senior Research Analyst and Assistant Vice President Frank Russell Company, Tacoma, Washington
1987-1988:	Chief Representative and Vice President InterSec Research Corp., Tokyo, Japan
1986-1987:	Vice President InterSec Research Corp., Stamford, Connecticut
1985-1986:	Research Analyst Daiwa International Capital Management, New York
1984:	Research Analyst Daiwa Securities Co., Ltd., Tokyo, Japan
1981 & 1983:	Legislative Assistant Oregon State Legislature, Salem, Oregon

IV. Research Activities

Conditional performance measurement:
Mutual funds and pension accounts
Portfolio strategies
Japan equity market
International investing
Stochastic programming applications to asset/liability management

V. Publication Record

Becker, Connie, Wayne Ferson, David Myers, and Michael Schill, "Conditional Market Timing with Benchmark Investors," *Journal of Financial Economics*, Vol. 52, No. 1, April 1999, pp. 119-148

Cariño, David, David Myers, and William Ziemba, "Concepts, Technical Issues, and Uses of the Russell-Yasuda Kasai Financial Planning Model," *Operations Research*, Vol. 46, No. 4 July-August 1998, pp. 450-462

Cariño, David, Terry Kent, David Myers, Celine Stacy, Mike Sylvanus, Andrew Turner, Kouji Watanabe, William Ziemba, "The Russell-Yasuda Kasai Model: An asset/liability model for a Japanese insurance company using multistage stochastic programming", *Interfaces*, January 1994. Article won second prize in the Franz Edelman Award for the Practice of Management Science, May, 1993.

Myers, David and Doug Stone, "Global Versus Regional Managers", *Russell Research Commentary*, February 1991

Myers, David and Craig Wainscott, "Strategic Asset Allocation: Japan and the US Investor", *Russell Research Commentary*, May 1990

Myers, David and Sachiko Ujiie, "Performance Measurement in Japan: The Coming of Age", *Benefits and Compensation International*, June 1988, pp. 26-32

VI. Conference Presentations

Myers, David, "Survivorship and Predictability in Pension Account Returns", European Financial Management Association, October 2000, Seattle, Washington

Myers, David, "Survivorship and Predictability in Pension Account Returns", Financial Management Association European Meetings Doctoral Seminar, May 2000, Edinburgh, Scotland

Myers, David, "Survivorship and Predictability in Pension Account Returns", European Financial Management Association Doctoral Seminar, June 2000, Athens, Greece

Cariño, David, Terry Kent, David Myers, Celine Stacy, Mike Sylvanus, Andrew Turner, Kouji Watanabe, and William Ziemba, "An Asset-Liability Model for a Japanese Insurance Company Using Multistage Stochastic Programming", Franz Edelman Award in Management Science Finalist Presentation at Spring 1993 TIMS/ORSA Meeting, Chicago, Illinois

Cariño, David, Terry Kent, David Myers, Celine Stacy, Mike Sylvanus, Andrew Turner, Kouji Watanabe, and William Ziemba, "An Asset-Liability Model for a Japanese Insurance Company Using Multistage Stochastic Programming", Third International AFIR Colloquium, Rome, Italy, March 1993

Myers, David, "Russell-Yasuda Model: The Business Environment and a Comparison with Mean-variance", Sixth International Conference on Stochastic Programming, Udine, Italy, September 1992

Myers, David, "Japanese Tokkin Managers versus ERISA Managers in Japan", Institute for Fiduciary Education, Tokyo, Japan, May 1988

VII. Teaching

Lehigh University

Investments and Portfolio Management, MBA
Autumn 2000 and Spring 2001
Investments, Undergraduate
Spring 2001

University of Washington

Teaching Effectiveness Seminar, Ph.D. students
Autumn 1995 and 1996
MBA Corporate Finance Teaching Assistant
Spring 1995
Corporate Finance, Undergraduate
Winter, Spring, and Autumn 1994
Winter 1995
Business Economics, Undergraduate
Spring 1996, Winter, and Spring 1997
Investments, Undergraduate
Summer 1997

Other Teaching Activities

Lead Teaching Assistant, Department of Finance and Business Economics
Spring 1994-Spring 1997
Lead Teaching Assistant, School of Business Administration
Summer 1995-Spring 1997
Recognition for Outstanding Teaching, 1995