

The Efficacy of Active and Passive Investment Strategies in the Institutional and Mutual Fund Spheres

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Abstract

We provide an empirical examination of the efficacy of active and passive investment strategies in the institutional and mutual fund spheres. The domestic equity mutual (i.e., retail) fund market is found to be in Grossman and Stiglitz (1980) style informational equilibrium. Controlling for asset-pricing anomalies, benchmark inefficiencies, model misspecification, and the effects of uniformed liquidity-motivated trade, the mean active participant earns pre-fee risk-adjusted excess returns; post-fees, returns are commensurate with that of the market proxy. In the institutional (i.e., pension) fund universe, participants exhibit abnormal selectivity abilities on both a pre- and post-fees basis. These estimates of abnormal performance confound conventional interpretations of the efficient markets paradigm. Motivated by the search for an explanation as to generic comparative advantages manifest amongst active portfolio managers, we conjecture that the sophistication of heterogeneous investor clienteles exerts a deterministic influence on the abnormal performance realised by active participants.

JEL Classification: G11; G12; G14; G23

Key words: Active; Passive; Mutual funds; Pension funds; Market timing; Security selection; Individuals; Institutions

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This paper presents an empirical exposition of the relative investment ability of active and passive participants. Investment ability is assessed through the prism of the semi-strong form of the martingale hypothesis. We adopt a rational expectations equilibrium informational view of securities markets and assume that competitive equilibrium is consistent with capital market efficiency in the presence of costly arbitrage (see Grossman (1976), Grossman and Stiglitz (1980) and Grossman (1995)). Two questions are posed: (a) can ‘active’ participants, from both the institutional and mutual fund spheres, effectively exploit security price inefficiencies and/or forecast future market risk premia; and, (b) do ‘passive’ investment strategies offer superior risk-adjusted performance? Of course, this analysis has non-trivial implications for the rational, risk-averse individual and institutional agents’ optimal consumption-allocation strategy.¹

Our task is complicated by the joint-hypothesis problem of testing for market efficiency conditional on the imposed equilibrium model of returns. Therefore, when assessing the selectivity and market-timing abilities of active participants we apply seven ‘unconditional’ and ‘conditional’ measures of performance (see Jensen (1968) and Ferson and Schadt (1996) respectively). Specifically, we employ an unconditional zero-one market model, an unconditional and conditional one-factor model, an unconditional four-factor model, and unconditional and conditional one and multi-factor variants of the Treynor and Mazuy (1966) market-timing models. The use of the conditional methods is especially important considering that Jensen’s unconditional formulation encounters complications when the mean, volatility and higher moments of the market return experience predictable variation – viz., when the investment opportunity set is time-varying.

This study makes a number of important contributions to the theoretical and empirical literature. First, the institutional and mutual (i.e., retail) fund databases employed consist of all non-surviving and surviving active and passive domestic equity products extant during the period January 1st 1988 to December 31st 1998. To our knowledge, this is one of the most complete and bias-free set of managed fund data yet compiled. Moreover, it is believed to be the closest existing approximation to an institutional and/or mutual fund population.

Second, the extant literature pertaining to investment performance largely focuses on vehicles which service ‘individual’ investors, particularly those with interests in US equities. However, ² (e.g., commercial banks, pensions plans, and insurance companies) have come to dominate capital markets and it is natural that interest should shift towards investigating their performance. In Australia, in excess of 50% of the adult population now have either a direct or indirect exposure to the equities market. However, the institutional investor predominates, controlling 77% of all Australian equities. Similarly, in the US institutional ownership has proliferated and become an increasingly dominant feature of financial markets. In 1955, US institutions held 23% of all equities; this, however, paled in comparison to the significantly greater 77% individual ownership share (see Lakonishok, Shleifer and Vishny (1992)). By 1996 the landscape had changed – institutions now owned 53% of all US equities with

the individual share declining to 47%. Global institutional fund assets are 1.5 times greater than those invested in mutual funds. Coggin, Fabozzi and Rahmann (1993) report a 3:1 ratio in the proportion of US pension fund equity investment relative to mutual fund equity investment. The differential in the number of managers in each universe is also large. In the US, the total number of institutional funds exceeds the total number of mutual funds by a ratio of approximately 10:1.

Thus, the recent proliferation of institutional activity warrants - indeed demands - a detailed exploration of the institutional investor's decision-making processes. Yet despite the overwhelming number of studies pertaining to performance in the mutual fund sphere, the (apparent) absence of publicly available information regarding US pension fund portfolios has resulted in a dearth of evidence that evaluates the selectivity and timing abilities of active institutional participants. This is particularly anomalous in view of the relative importance of institutional funds vis-à-vis mutual funds in terms of their market share³ and moreover, the institutional universe's quite disparate incentive structures, investor clientele, and return generating process.⁴

Accordingly, we present the first simultaneous estimation of the conditional and unconditional 'selectivity' and 'market-timing'⁵ abilities of active participants residing in both the institutional and mutual fund spheres. The benefits of such analysis are obvious. Survival, selection and assessment biases afflict virtually all the classic studies of performance (for example, see Treynor (1965), Sharpe (1966), Jensen (1968), Henriksson (1984), Ippolito (1989), Coggin et al. (1993), Ferson and Schadt (1996), and Christopherson, Ferson and Glassman (1998)). There is also a manifest dependency on commercially disseminated data-sets which in no way accord with the idealised 'random draw'. In contrast, our evidence does not suffer from survivorship induced sample truncation.

Third, the extant literature provides no clear insights as to the expected influence of conditional methods on estimates of abnormal performance. For instance, Ferson and Schadt (1996) find that conditional alphas tend to be larger than their unconditional counterparts. Yet this suggests a perverse result: fund managers appear to reduce (increase) their systematic risk exposures when publicly available information implies high (low) expected market returns. Ferson and Warther (1996) attribute such behaviour to a positive correlation between expected market returns and the flow of new money into funds through time, combined with a negative relation between net capital-flows and fund betas. Simply, large flow-shocks induce a departure from the target efficient portfolio and compel participants to engage in material amounts of 'uninformed liquidity-motivated trading' (see Edelen (1999)). We seek to resolve the uncertainty by proposing that the influence of investor flows on abnormal performance is a function of the magnitude of the shock. Where conditional benchmarks control for the relation between aggregate fund flows and time-varying expected returns, conditional estimates of abnormal performance in the institutional universe should exceed those produced under the auspices of traditional unconditional methods. It is conceivable that the converse is true in the mutual fund universe.

Fourth, the existing evidence fails to provide a detailed exegesis of the returns delivered by passive participants; rather, their presence has been implicitly proxied by the market portfolio. Hence, most prior studies predicate inferences upon a tenuous equilibration of the returns realised by index funds and those associated with that of the market. However, there are reasons to expect a divergence between the two. Specifically, where the performance of index funds materially departs from that anticipated in an idealised (frictionless) world, i.e., where index funds fail to perfectly replicate the target index, and incur tracking error, prior analyses are flawed. This is particularly problematic when a market is deemed to be in Grossman and Stiglitz style informational equilibrium since one cannot define the ‘optimal’ consumption-allocation strategy. That is, in competitive equilibrium, rational, risk-averse individual and institutional agents will have no preference with respect to active or passive participants. Our study is not afflicted by such difficulties. Rather, we evaluate the efficacy of both active and passive investment strategies and thus provide the first complete explication of the investment alternatives offered to the individual and institutional investor clientele.

I. Capital Market Detail

This paper begins with a brief statistical overview of the Australian capital market. Such, of course, is relevant to an evaluation of the external validity of our analysis.

A. The Australian Equities Market

The Australian equities market is one of the most liquid, transparent and competitive exchanges in the world. In the year to 31st December 1998, the value of trading rose by 11.8% to a record \$256 billion. An unprecedented 6.7 million transactions took place and domestic market capitalisation rose by 18.1% to a new high of \$536.2 billion. Indeed, Frino and McCorry (1995) conclude in a comparative analysis of the New York Stock Exchange (NYSE) and the Australian Stock Exchange (ASX) that the latter provides lower execution costs after controlling for stock price, trading activity and price volatility. The higher execution costs on the NYSE are a pervasive phenomenon occurring on average across all securities. Further, Aitken and Frino (1996) consider the execution costs associated with institutional trades on the ASX and compare their results with US findings. They find that the costs of conducting large transactions in the Australian equities market are small, and no greater than 0.30% of the value of a round trip transaction.

Importantly, this market was selected because it facilitates a number of novel experimental opportunities. First, while US mutual fund data were accessible, we could not be certain that they were entirely free of all survival and selection related biases. Second, there is scant publicly available

information about US pension fund portfolios and that which is disseminated is more often than not afflicted by non-trivial survival and/or selection biases which prevent robust empirical inferences (see Lakonishok et al. (1992), Coggin et al. (1993), and Christopherson et al. (1998)). On the other hand, the Australian equities market provides a unique, bias-free forum with which to assess the efficacy of active and passive investment strategies in the two quite different fund universes.

B. The Asset Management Industry

The expansion of the Australian asset management industry parallels the US experience. The value of the Australian sourced managed fund industry's total assets under management was \$526.9 billion at December 1998, 321% higher than the \$164 billion under management in 1990. In 1998, the overall market grew by 13.9%, with the institutional investment market growing by 18.3% (\$326 billion in assets under management) relative to the mutual fund market's growth of 7.5% (\$201 billion in assets under management). The size of the domestic asset management industry also compares favourably with other developed Asia-Pacific nations. For example, total funds under management in Singapore and Hong Kong are less than one-quarter and one-third of the size of the Australian market respectively.⁶

C. The Pension Fund Market

Australia constitutes the seventh largest pension fund market in the world. The institutional (viz., pension) fund industry has grown principally because the government instituted a compulsory national defined contribution retirement savings scheme with its Superannuation Guarantee legislation of 1 July 1992. The result was an increase in superannuation coverage from 72% in 1991 to 90% in 1994 and a five-fold increase in assets under institutional funds management. The legislation mandates minimum employer contributions into qualified industry or corporate superannuation funds (i.e., pension plans), reaching 9% of employee salaries by 2002.⁷ Meanwhile, mandated employee contributions and government co-contributions have also been introduced. Combined, these schemes will lead to a target contribution rate of 15% of total pay by 2002.

Thus, Australia has embraced pension fund capitalism with great enthusiasm. Assets in pension funds now comfortably exceed the money in bank deposits. The growth of the recently introduced compulsory superannuation system persists, with employers injecting 7% of earnings for much of the workforce, while contributions continue at almost \$40 billion per annum. These elements of the Superannuation Guarantee legislation are expected to underpin significant retirement savings flows into the equities market well into the 21st century.

II. The Data

In both the institutional and retail fund spheres, we collect data from six asset consultancies: Assirt, InTech, the Frank Russell Company, Morningstar, Rainmaker Information, and William M Mercer. In addition, quantitative and qualitative data were obtained from ABN AMRO, Intersec Research, John A. Nolan and Associates, Macquarie Investment Management, and Salomon Smith Barney.

A. *The Retail Fund Database*

Our retail fund database consists of monthly data on non-surviving and surviving open-end active and passive Australian domestic equity products extant during the period January 1st 1988 to December 31st 1998, inclusive. We identify 198 unique mutual funds offering their services over the period of interest, 83 of which ceased to exist. The data on each fund includes information on their ‘asset-class’ (category) and investment ‘style’ (subcategory), investment objective and strategy, unit pricing, income return, and capital gains distributions. To our knowledge, this is one of the most complete set of retail (viz., mutual) fund data ever compiled. More precisely, we believe that this provides the closest approximation of a mutual fund ‘population’ thus far, with the database historically containing 100% of total industry assets.⁸

With respect to informational intermediaries, the domestic mutual fund market is concentrated and two asset consultancies predominate: Assirt and Morningstar. We obtain data from both. While the Morningstar database is commercially solicited, Assirt’s is not. However, the Morningstar database with which we were furnished materially differs from its commercial counterpart. Specifically, Morningstar tailored the universe such that it includes all equity mutual funds that ceased to exist over the sample period. The Assirt database similarly consists of all surviving and non-surviving products extant during the period. Significantly, both firms purport to hold the ‘population’ of active and passive equity funds. In view of this, our data-set is considered to be survivor bias free.

The Assirt data are especially unique. First, as noted above, they are not publicly available. Furthermore, Assirt generously provided unfettered access to their otherwise exclusive holdings. Indeed, significant resources were expended in constructing the database specifically for our purposes. Their data are more comprehensive relative to the Morningstar universe insofar as they contain a slightly larger pool of participants.⁹

Each fund’s raw performance is reported on a monthly basis and estimated net of expenses (albeit, gross of front-end load charges and exit fees), while inclusive of capital appreciation, income and capital gains distributions. The unadjusted return series are as complete as can be practically obtained. The data on each fund ends only when they cease to exist, through either natural attrition, merger or take-over. In all cases, the consultancies estimate the performance of a product through to the month of termination. For

funds being wound up, returns past the termination date are not considered. In this event, the portfolio manager's investment objectives will significantly differ from those of continuing funds.¹⁰

Importantly, we impose no minimum asset size requirement. This is in contrast to much of the prior literature. The tendency to use such criteria is curious, considering the strong correlation between the incidence of attrition and fund size (see Joye, da Silva Rosa, Jarnecic and Walter (2000b)).¹¹ A minimum four-quarter price history is the only explicit inclusion criteria imposed. Relative to the three-year thresholds that proliferate in contemporary evidence, this particular horizon serves to mitigate look-ahead biases and minimise the impact of a possible relation between fund age and mortality rates.

In addition to the performance-related information, Assirt and Morningstar furnished us with an exceptionally rich set of cross-sectional and time-series net asset value (NAV) data, reported monthly. In Section V we derive various estimates of net capital-flow from this data, the frequency of which is superior to that employed in the recent literature (see, for example, Sirri and Tufano (1998) and Del Grucio and Tkac (1999)).

In contrast to previous studies, we placed no restrictions on the investment objectives of the funds included in the database.¹² All active domestic equity vehicles, be they diversified or specialist (i.e., value, growth, small 'cap' or large 'cap') were included in the analysis. However, all non-equity, international equity, or multiple asset-class products were excluded. Evaluating the performance of funds that invest outside the domestic equity opportunity-set can be exceptionally problematic, particularly where the need arises for a diverse set of multiple asset-class benchmarks. Hence, the exclusive use of equity funds justifies our reliance on equity indices with dividend reinvestment. Intriguingly, our inquiries also revealed that while the consultancies' universes were formally restricted to domestic equity funds, five vehicles held portfolio exposures to international equities. Given the aforementioned evaluative difficulties, these products were excluded from the analysis.

Reported style categories and asset allocations are difficult to verify. That is, they are normally self-defined, subjective and open to the possibility of 'gaming'. To circumvent these complications we performed our own cursory style analysis. Each fund's raw return time-series was regressed upon the market, small 'cap', large 'cap', value, and growth indices such that it was possible to discern ex post style exposures and risk-return profiles. Coupled with the fund's stated objectives, this process permitted a more accurate classification of the universe of products, essential to subsequent analysis.

In closing this description, it is pertinent to note that Australian regulatory bodies do not impose mandatory disclosure requirements on institutional or retail asset managers with respect to the management expense ratios (MERs) charged to their respective clienteles. Accordingly, such information is very difficult to acquire. Fortunately, however, both Assirt and Morningstar have assembled MERs from their universe of mutual funds. Morningstar collect their expense ratios on an annual basis, in cross-section and through time. The Assirt sample is less complete with fewer aggregate observations, albeit that the

frequency of their MERs is somewhat finer, i.e., they are reported on a monthly and/or quarterly basis. In short, despite the absence of explicit reporting requirements we were able to overcome idiosyncratic deficiencies and pool the two samples. The final sample constitutes what is considered to be one of the most comprehensive domestic equity expense ratio databases.

B. The Institutional (Pension) Fund Database

Our institutional fund database consists of all non-surviving and surviving active and passive domestic equity products extant during the period January 1st 1988 to December 31st 1998, inclusive. We identify 123 unique institutional domestic equity funds. Of these, 19 funds failed to survive at some point over the survey period. Certainly, this is the most complete and bias-free set of institutional fund data ever compiled. Moreover, it is considered to be the closest extant approximation of an institutional fund population. Indeed, total assets exceed published estimates.¹³

We thus obtain the first survivorship-bias free sample of institutional investment vehicles (viz., pension funds).¹⁴ All prior studies (Lakonishok et al. (1992), Coggin et al. (1993), Christopherson et al. (1998) and Blake, Lehmann and Timmerman (1999)) have been restricted to examining surviving funds only.¹⁵ Indeed, absent Joye et al. (2000b), there exists no evidence on the influence of managerial attrition on estimates of abnormal performance and persistence in the institutional sphere.

The data are sourced from five of the largest asset consultancies operating in the domestic pension fund market: InTech, the Frank Russell Company, Morningstar, Rainmaker Information and William M. Mercer. These five sources yield information on 396 funds (including duplications) or approximately 1,769 manager years. The use of all independent portfolios offered by each fund complex ensures that our analysis is not afflicted by selection biases implicit when one chooses a ‘representative’ fund (see, for instance, Christopherson et al. (1998)). This also helps to reduce the possibility of managers ‘cherry-picking’ by substituting a better performing return series in favour of an existing portfolio.

We analyse gross (i.e., pre fees, income and capital gains tax) returns because, unlike the retail fund industry, fees vary considerably according to the particular client (see Section V, part A).¹⁶ However, to allow for generic comparisons with the mutual fund sphere, we also adjust institutional performance to a post-fee approximate. The net asset values of each individual product are reported monthly. Consequently, we also employ a rich sample of time-series institutional flow data. Previously, only annual measures of net capital-flow have been used.

The institutional data are subjected to a number of integrity tests. First, where two funds were apparently alike, we regressed the contemporaneous performance and NAV time-series value upon one another to verify that they were exact. Having identified what we thought were unique products, each individual fund complex (approximately 60) was subsequently contacted to determine whether the

estimates were indeed correct. To be confident that the size of the institutional fund population had not been overestimated, we regressed the raw return time-series upon the market, small 'cap', large 'cap', value, and growth indices such that it was possible to precisely discern each product's particular ex post style exposure and risk-return profile.¹⁷ To mitigate any remaining equivocality we compared each fund's unconditional one and four-factor alpha, associated standard error, and the length of the performance time-series. Insofar as there have been no prior attempts to quantify the total number of individual products and fund complexes operating in the domestic equity institutional fund sphere, this work constitutes an important precursor to our research.

Finally, despite the absence of mandatory MER reporting requirements, we were also able to obtain a complete (cross-sectional and time-series) domestic equity institutional expense ratio database. Specifically, the data were pooled from the InTech, Morningstar and William M Mercers's samples.

C. Benchmarks and Public-information Variables

A number of indices were obtained for use as equity benchmarks in the various performance-evaluation models. We also acquired three macroeconomic predictor variables to be used as lagged predetermined public-information proxies in conditional variants of the Capital Asset-Pricing Model (CAPM) and Treynor and Mazuy's (1966) market-timing model. These data were sourced as follows.

- (i) The ASX provided data on the All Ordinaries Accumulation Index, the ASX 100 Leaders Accumulation Index, and the ASX Small Ordinaries Accumulation Index.
- (ii) The Frank Russell Company provided complete historical records of the ASX/Russell All Growth Index, the ASX/Russell Growth 100 Index, the ASX/Russell Small Growth Index, ASX/Russell All Value Index, the ASX/Russell Value 100 Index, and the ASX/Russell Small Value Index. The SBC Composite Bond Index was sourced from ABN AMRO.
- (iii) The vector of lagged public-information proxies are those which prior literature has revealed as having explanatory power with respect to time-series variation in expected returns. Specifically, the variables are (i) the 30-day Treasury bill yield, (ii) the dividend yield on the All Ordinaries Accumulation Index, and (iii) the term structure or treasury yield spread, which reflects the relationship between the interest rate and the term to maturity for securities of similar risk (i.e., long-term bonds less short-term bonds). The 30-day Treasury bill yield was sourced from Reserve Bank of Australia's Bulletin Electronic Database. The ASX provided the dividend yield on the All Ordinaries Accumulation Index, which was also cross-referenced against the dividend yield

obtained from the Reserve Bank of Australia's Bulletin Electronic Database. The treasury yield spread is simply the constant-maturity 10-year Treasury bond yield less the 3-month Treasury bill yield, the latter of which was collected from the Reserve Bank of Australia's Bulletin Electronic Database. All these variables have featured prominently in the predictability literature and hence it is reasonable to presume that agents are aware of their explanatory power.

III. Experimental Design

This paper focuses on the relative investment ability of the vehicles that service the institutional and individual investor clienteles, i.e., active institutional and mutual fund participants. We evaluate 'investment ability' through the prism of the efficient markets concept. Two questions are addressed: (a) can 'active' investors, from both the institutional and mutual fund spheres, effectively exploit security price inefficiencies and/or forecast future market risk premia? And, (b) do 'passive' investment strategies offer superior risk-adjusted performance? Academic research has yet to resolve this debate despite its implications for the capital-allocation strategies of individual and institutional investors. The ambiguity manifest is of particular concern when one considers the economic role of markets: perturbing an agent's ability to make utility-maximising consumption-allocation decisions ultimately inhibits the flow of capital to its most efficient and productive use.

Our task is complicated by the joint-hypothesis problem of testing market efficiency conditional on the imposed equilibrium model of returns. Therefore, when assessing the selectivity and market-timing abilities of active participants, over the 11 year sample period, 1988 to 1998, we apply several unconditional and conditional measures of performance,¹⁸ specifically:

- (i) excess returns relative to the market proxy;
- (ii) risk-adjusted excess returns from the 'unconditional' CAPM;
- (iii) risk-adjusted excess returns from the 'conditional' CAPM;
- (iv) risk-adjusted excess returns from an unconditional 'multi-beta attribution' model;
- (v) Treynor and Mazuy's (1966) 'unconditional' quadratic CAPM;
- (vi) Treynor and Mazuy's (1966) 'conditional' quadratic CAPM; and
- (vii) a 'multi-factor' variant of Treynor and Mazuy's (1966) unconditional quadratic CAPM.

A. *The Unconditional CAPM*

The classic approach to evaluating performance, developed by Jensen (1968), is based on an ex post variant of the Sharpe (1964) and Litner (1965) model of equilibrium expected returns. Under Jensen's 'unconditional' one-factor formulation, the market line represents the returns delivered by a naïve

investment strategy. Given time-invariant alphas and betas, the following time-series regression provides an estimate of the selectivity abilities of active participants,

$$r_{pt} - r_{ft} = a_p + b_p(r_{mt} - r_{ft}) + e_{pt}, \quad (1)$$

where $r_{pt} - r_{ft}$ is the manager's return in excess of the risk-free rate (proxied by the 30-day treasury bill yield); $r_{mt} - r_{ft}$ is the excess return of the 'market portfolio' (proxied by the All Ordinaries Accumulation Index); a_p is an 'unconditional' estimate of the manager's actual, per-period, risk-adjusted excess or abnormal return which is equal to zero under the null; b_p is the sensitivity of the fund's excess return to the return realised by the mean-variance efficient market portfolio in excess of the risk-free rate; and e_p is a stochastic disturbance term, with mean of zero.

Significantly, the unconditional CAPM assumes that a portfolio manager's (systematic) risk levels remain stationary through time. Hence, Jensen's formulation encounters complications when the mean, volatility and higher moments of the market return experience predictable variation – viz., when the investment opportunity set is time-varying. The unconditional alphas and betas become biased estimates of their unconditional means, assuming that the covariance between the fund's beta and the conditional benchmark return is non-zero.¹⁹

B. *The Conditional One-factor CAPM*

Deficiencies associated with the CAPM have prompted Ferson and Harvey (1999) to proclaim that the asset-pricing literature is in a 'state of turmoil'. Moreover, recent theoretical and empirical evidence suggests that 'conditional' variants of simple asset-pricing models may have higher explanatory power with respect to the cross-sectional distribution of returns (see Chan and Chen (1988), Cochrane (1992), and Jagannathan and Wang (1996); and for rejections of the CAPM for conditional returns see, Ferson, Kandel and Stambaugh (1987), Bollerslev, Engle and Wooldridge (1988), and Harvey (1989)).

Bansai and Harvey (1996), Chen and Knez (1996), Ferson and Schadt (1996) and Dahlquist and Soderlind (1999) advocate, in various forms, the use of *conditional performance-evaluation*. Particularly, Ferson and Schadt (1996) assert that traditional, unconditional models can ascribe abnormal performance to an investment strategy based only on public information. Traditional interpretations cannot, therefore, accord with notions of an efficient market in the semi-strong form sense. However, incorporating macroeconomic variables into the performance-evaluation model ensures that prices 'fully reflect' all readily available, public information, and thus precludes one from spuriously attributing abnormal performance to active investment strategies premised upon such.

Thus, adjusting the unconditional one-factor model by multiplying the market return with $b_p(Z_{t-1})$ results in its conditional one-factor analogue,²⁰

$$r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft}, z_{t-1}) + e_{pt}, \quad (2)$$

where the variable, z_{t-1} , constitutes a public-information proxy available at t-1 for predicting future market risk premia. The vector, $(r_{mt} - r_{ft}, z_{t-1})$, prevents public-information based trading strategies from being ascribed with superior selectivity or timing ability. Differences between the unconditional and conditional alphas are a function of the average value of the interaction term d_{2p} , which reflects the sensitivity of conditional betas to the lagged economy wide predictor variables. Our particular interpretation of the conditional one-factor model is estimated as follows,

$$r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft}, TB_{t-1}) + d_{3p}(r_{mt} - r_{ft}, DY_{t-1}) + d_{4p}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}, \quad (3)$$

where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute the lagged vector of public-information proxies available at t-1 for predicting future market risk premia, viz., TB_{t-1} , is the 30-day treasury bill yield (see Breen, Glosten and Jagannathan (1989) and Ferson (1989)); DY_{t-1} , is the dividend yield on the All Ordinaries Accumulation Index (see Fama and French (1988)); TS_{t-1} , is the term structure or treasury yield spread (see Fama and French (1989)) which reflects the relationship between the interest rate and the term to maturity for securities of similar risk (i.e., long-term bonds less short-term bonds), and where the other terms are as previously defined.

C. The Unconditional Four-factor Model

Elton, Gruber, Das and Hlavka²¹ (1993) demonstrate that even in the absence of superior managerial ability, the inclusion of non-S&P500 assets in managed fund portfolios, say small stocks, may result in non-zero alphas (see Ippolito (1989)). The magnitude of this influence is a direct function of the fraction of non-S&P assets held. In their three-factor model, Elton, Gruber, Das and Hlavka introduced two new (size and bond) indices that captured the relevant (style) characteristics of fund performance. Subsequently, Elton, Gruber, and Blake (1996a) advocate the use of a fourth factor to account for value and growth biases. This is particularly pertinent given the high explanatory power of the book-to-market ratio with respect to the cross-sectional distribution of returns (see Chan, Hamao and Lakonishok (1991) and Fama and French (1993, 1994)).²² The four-factor model's ability to control for the differing investment styles of active participants suggests that employing multi-index constructs facilitates more accurate performance-evaluation (see also Elton, Gruber and Blake (1997)).²³

Accordingly, we apply a multi-beta attribution model similar to that used by Elton, Gruber and Blake (1996a) and Gruber (1996). In order to ameliorate potential multicollinearity, we do not orthogonalise the additional indices with the market proxy. Rather, the control indices are interpreted as zero-investment portfolios and we take differential returns; i.e., size exposures are captured through the differential return from large and small ‘cap’ portfolios, and the style proxy is estimated as the differential return from the growth and value indices.²⁴ Thus our estimate of abnormal performance, the unconditional four-factor alpha, derives from the intercept in the following time-series regression,²⁵

$$r_{pt} - r_{ft} = a_p + b_p(r_{mt} - r_{ft}) + b_{lsp}(r_{lt} - r_{st}) + b_{vgp}(r_{vt} - r_{gt}) + b_{dp}(r_{dt} - r_{ft}) + e_{pt}, \quad (4)$$

where $r_{lt} - r_{st}$ is the differential return between a large ‘cap’ portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small ‘cap’ portfolio (proxied by the ASX Small Ordinaries Accumulation Index); $r_{vt} - r_{gt}$ is the differential return between the growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index); $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index), and where other terms are as previously defined.

D. Treynor and Mazuy’s (1966) Unconditional Quadratic CAPM

It is important to differentiate between the ‘macro’ and ‘micro’ forecasting abilities of active participants. Macro-forecasting (market-timing) refers to the allocation of capital amongst broad classes of investments, often restricted to equities and short-term government debt. The successful market timer increases the portfolio weight on equities prior to a general rise in the market index and consequently the portfolio beta and the slope of the characteristic line are functionally related to the market’s risk premium. Conversely, micro-forecasting (stock selection) refers to the buying and selling of individual assets in an attempt to exploit security price inefficiencies, given a model of expected returns such as in Sharpe (1964).

Market-timing strategies impose a significant limitation on traditional estimates of abnormal performance. A manager who systematically varies a fund’s beta in response to private information signals may, under the time-invariant assumptions of the CAPM, be erroneously interpreted as having exercised selectivity strategies. The most widely applied performance-evaluation model, Jensen’s (1968) empirical analogue of the CAPM, assumes that portfolio risk remains stationary through time and thus ignores the possibility of market-timing strategies. Accordingly, if a fund manager engages in market-timing activity such will induce a downward (upward) bias into conventional estimates of abnormal performance (systematic risk).^{26 27}

We apply Treynor and Mazuy’s²⁸ (1966) classic unconditional model of market-timing, expressed here in quadratic form,²⁹

$$r_{p,t} - r_{ft} = a_p + d_{1p}(r_{m,t} - r_{ft}) + d_{2p}(r_{m,t} - r_{ft})^2 + e_{p,t}, \quad (5)$$

where the coefficient, d_{2p} , measures a portfolio manager's market-timing ability. Intuitively, the market-timing coefficient, d_{2p} , is positive (negative) in situations where the manager increases (decreases) the portfolio's beta prior to signals suggestive of favourable (unfavourable) future equity market conditions. Thus the manager's portfolio weights are a non-linear function of the expected market return. The null hypothesis of no abnormal market-timing ability implies that d_{2p} will be zero.

E. Treynor and Mazuy's (1966) Conditional Quadratic CAPM

Ferson and Schadt (1996) modify Treynor and Mazuy's (1966) unconditional quadratic CAPM to account for time-variation in risks and expected returns. They assume that, under the auspices of Admati, Bhattacharya, Ross and Pfleiderer's (1986) two-asset model, a manager observes the public-information vector, $(z_{t-1}, r_{m,t} + h)$, at time t-1 and allocates capital between a risky and riskless asset. Thus, the fund's beta reflects the portfolio's weight on the market proxy and is a linear function of z_{t-1} and the future market return plus noise, $(z_{t-1}, r_{m,t} + h)$. Substituting in this linear function, the conditional Treynor and Mazuy model may be estimated as follows,

$$r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft}, z_{t-1}) + d_{3p}(r_{mt} - r_{ft})^2 + e_{pt}, \quad (6)$$

where $d_{2p}(r_{mt} - r_{ft}, z_{t-1})$ controls for that proportion of return attributable to public information. Our particular variant is described here as,

$$r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft}, TB_{t-1}) + d_{3p}(r_{mt} - r_{ft}, DY_{t-1}) + d_{4p}(r_{mt} - r_{ft}, TS_{t-1}) + d_{5p}(r_{mt} - r_{ft})^2 + e_{pt}, \quad (7)$$

where the coefficients d_{2p} , d_{3p} , and d_{4p} capture the correlation between the fund beta and the future market risk premia attributable to the lagged predictor variables; the coefficient d_{5p} captures the sensitivity of the fund's beta to the private information signal, and where all other terms are as previously defined. Thus, according to this interpretation, managers who systematically employ public-information to time the market will not be attributed with abnormal macro-forecasting performance.

F. Multi-Factor Variants of Treynor and Mazuy's (1966) Unconditional Market-timing Model

Finally, to control for the differing investment styles employed by portfolio managers we also formulate a multi-factor variant of Treynor and Mazuy's (1966) unconditional market-timing model. Specifically,

$$r_{pt} - r_{ft} = a_p + b_p(r_{mt} - r_{ft}) + b_{lsp}(r_{lt} - r_{st}) + b_{vgp}(r_{vt} - r_{gt}) + b_{dp}(r_{dt} - r_{ft}) + d_p(r_{mt} - r_{ft})^2 + e_{pt}, \quad (8)$$

where the coefficient, d_p , measures the participant's market-timing ability, and all other variables are as previously defined.

IV. Conjectures

Our rich comparative data-set accommodates a number of *a priori* conjectures with respect to cross-sectional differences in the selectivity and timing parameter estimates.

First, the use of data free of all survival and selection biases, and overtly, the analysis of two distinct 'populations', should furnish new insights into the risk-return dynamics that characterise the institutional and mutual fund spheres. Relative to that presented in the past, this unique inquiry may result in materially different estimates of the security selectivity and market-timing abilities of each agent-type.

A secondary proposition concerns differentials in the underlying assets held by mutual and institutional funds. An investigation into the cross-sectional characteristics of the two investor types is particularly intriguing insofar as it constitutes a microeconomic study of the firm and sheds light on microstructural frictions that influence portfolio-choice behaviour. Institutional participants are often well-diversified investment vehicles, limiting themselves to the larger, less volatile and more liquid securities. Loads of idiosyncratic risk are less likely and systematic risk levels regularly converge toward unity. Indeed, the substantial size of institutional portfolios, and thus the market impact costs they incur, preclude investments in thinly traded, non-market proxy assets (see Chan and Lakonishok (1993), Keim and Madhavan (1997) and Berkowitz, Logue, Noser and Eugene (1988)). Consequently, in the institutional universe, one and multi-factor formulations should not provide significantly different estimates of abnormal performance.

In contrast, it is probable that 'boutique-style' mutual fund managers hold a greater proportion of stocks not included in the market proxy. The less diversified nature of their activities (i.e., an aversion to stocks with low idiosyncratic volatility) results in higher residual risk levels and prompts departures from the efficient frontier. This conjecture is consistent with Falkenstein's (1996) finding that mutual funds demonstrate a nonlinear preference toward stocks with high volatility. Insofar as multi-factor formulations control for asset-pricing anomalies and differing investment styles, such models should have superior predictive abilities with respect to the time-series distribution of mutual fund returns.

Third, we also anticipate significant differences in the direction of estimates deriving from the conditional and unconditional constructs. The extant literature provides no clear insights as to the expected influence of conditional methods on estimates of abnormal performance. For instance, Ferson and Schadt (1996) find that conditional alphas tend to be larger than their unconditional counterparts. Yet this implies a perverse result: fund managers appear to reduce (increase) their systematic risk exposures when publicly available information implies high (low) expected market returns. Ferson and Warther (1996) attribute such behaviour to a positive correlation between expected market returns and the flow of new money into funds through time, combined with a negative relation between net capital-flows and fund betas. Simply, large flow-shocks induce a departure from the target efficient portfolio and compel participants to engage in material amounts of uninformed liquidity-motivated trading (see also Edelen (1999)). We resolve this uncertainty by proposing that the influence of investor flows on abnormal performance is a function of the magnitude of the shock. For instance, capital-flows should have a relatively greater impact on the investment activities of institutional fund participants. Whereas net flows into institutional funds average approximately \$6 million per month, the mean monthly flow into mutual funds is just \$300,000 (see Tables I and V). Importantly, this may induce an inverse relation between systematic risk levels and future market risk premia. Where conditional benchmarks control for the relation between aggregate fund flows and time-varying expected returns, conditional estimates of abnormal performance in the institutional universe will exceed those produced under the auspices of traditional unconditional methods. The converse should be true in the mutual fund universe.

Finally, we expect differences in the cross-sectional variation of ex post performance. From an institutional fund's perspective, genuine ex ante ability which results in superior ex post performance may increase assets under management and thus the management fee received. However, the incentive to take non-trivial risks may not be strong. Large ex post returns deriving from superior selectivity ability may also greatly elevate the probability of 'relative' underperformance (see Blake et al. (1999)). And the loss of a 'mandate' - an investment management contract - is likely to be an order of magnitude greater than the increase in the management fee. Where institutional funds are assessed on relative performance, there exists an implicit incentive to minimise tracking error (i.e., diversifiable risk). That is, attempts will be made to avoid significant departures from static benchmarks. This behaviour is reinforced by the presence of myriad asset consulting firms³⁰ and the relative sophistication³¹ of the institutional clientele. Yet no such incentive exists in the mutual fund sphere. Rather, managers appear to be rewarded for raw outperformance and loads of idiosyncratic risk (see Joye, da Silva Rosa, Jarnecic and Walter (2000c)). The absence of asset consultancy's enforcing sophisticated performance-evaluation, and the relative naïvete of individual investors, predisposes mutual funds to pursuing high variance selectivity strategies. In view of this, we anticipate far greater dispersion in the cross-sectional estimates of abnormal performance in the mutual fund market.

V. Empirical Analysis

The empirical analysis is dissected into a number of parts. First, in Section A we discuss summary (non-parametric) statistics pertaining to both the institutional and mutual fund populations. Subsequently, in Section B we provide estimates of abnormal institutional and mutual fund selectivity ability. Section C examines the impact of investor flows on managerial performance and the effects of adjusting benchmarks to control for liquidity-motivated trading. In Section D, we consider the macro-forecasting abilities of institutional and mutual fund participants. Section E investigates a possible nexus between investor sophistication and managerial performance. Finally, in Section F we explore the efficacy of passive investment strategies.

A. Comparative Summary Statistics

Table I depicts unadjusted time-series summary statistics averaged across both the active institutional and mutual fund populations, through the 1988-1998 sample period. It is apparent that there are significant disparities in the cost structures and return generating processes that characterise each sphere.

Whereas individuals are levied with a mean management expense ratio of 212 basis points over the period, institutions pay just 84 basis points.³² These differences derive from the costs inherent in servicing each clientele. The magnitude of institutional investments (mean annual flow of \$60 million) present opportunities to exploit economies of scale particularly where there exists an inverse relation between operating expenses and assets under management. On the other hand, catering to relatively small individual investors (mean flow of \$3.26 million per annum) is a high cost exercise often requiring sophisticated distributional networks.³³

It is worthwhile noting that there are a number of trade-offs associated with the incidence of investor flow and the size of investment vehicles. For instance, we shall see later that capital-flows can exert a significant influence on the abnormal performance of active participants. Further, while fund size affords scale opportunities and might account for, at least in part, the disparate pricing structures, it comes at a cost. The sheer magnitude of institutional assets under management (mean fund size of \$492 million) vis-à-vis their retail counterparts (mean fund size of \$116 million) invariably impedes selectivity activities; transaction costs will rise and the investment opportunity set may decline.

The population rates of attrition cast a revealing light on the idiosyncratic return generating processes. Over the period surveyed, 42% of the mutual funds ceased to exist, through either merger, takeover, or natural attrition. In contrast, only 16% of the institutional population failed to survive. This dissimilitude, doubtless correlated with the contemporaneous volatility estimates, poses a number of interesting questions. What caused the striking differential in the relative rates of attrition? Moreover, does

the extant survivorship-related literature, restricted as it is to evaluating the performance of mutual funds, hold any relevance with respect to the risk-return profiles of institutional funds? Our estimates of attrition should not be considered extraordinary. Indeed, they are very similar to those found in the one US mutual fund sample that can be confidently considered bias free (see Carhart (1995)).³⁴ However, at this juncture the reader is referred to Joye et al. (2000b) for a more detailed analysis of the effects of conditioning on survival in each universe.

The actual performance characteristics also intimate toward some interesting return dynamics.³⁵ Relative to the market proxy, the mean active institutional fund participant delivered 1.67% per annum in post-fee outperformance. Conversely, the average mutual fund underperformed by 2.5% per annum, post-fees. While not explicitly reported, tracking error estimates also corroborate our conjectures regarding the cross-sectional dispersion of returns relative to static benchmarks,³⁶ with the standard deviation of institutional excess returns significantly less than that attributed to mutual funds.³⁷ These raw performance estimates are remarkably similar to those evidenced in US samples. Both Malkiel (1995) and Gruber (1996) find that the mean mutual fund underperforms the S&P500 by around 1.83% and 1.94% per annum respectively.³⁸ The scant literature pertaining to the performance of US institutional funds also appears to suggest that they too exhibit abnormal selectivity and/or timing abilities (see, for example, Coggin et al. (1993) and Christopherson et al. (1998)), albeit that a multiplicity of attrition and selection related biases call this analysis into question.

Yet the crude nature of these summary statistics precludes us from making robust inferences, and thus our puzzle with respect to the ‘semi-strong form’ of the martingale hypothesis remains unperturbed.

[Please insert Table I about here]

B. Estimates of Abnormal Selectivity Ability

Tables II and III present mean time-series selectivity estimates averaged across the mutual and institutional fund populations, during the period January 1st 1988 to December 31st 1998. We employ three performance-evaluation techniques: the unconditional one-factor CAPM, the conditional CAPM, and an unconditional four-factor attribution model.

B.1 Mutual Funds

Table II depicts the results of our selectivity analysis in the mutual fund sphere. Irrespective of the performance-evaluation technique employed, the population of active equity mutual funds underperform the market proxy, post-fees. This result is robust to all known survival, selection and methodological related biases. The mean unconditional one-factor risk-adjusted excess return³⁹ is -2.4% per annum, post-

fees, and statistically significant at the 1% level. Pre-fees, mutual funds still underperform by 40 basis points. Approximately, 14 (nine) of the alpha point estimates are negative (positive) and statistically significant at the 1% level, while 59% of all alpha coefficients are negative. By chance alone one would expect only two to three statistically significant alphas. Interestingly, the low predictive capacity of the one-factor model is congruent with the notion that mutual funds are not fully diversified investment vehicles. Observe that the mean market beta is just 0.70. This, coupled with the poor explanatory power of the single-index construct,⁴⁰ indicates that mutual funds adopt significant levels of non-systematic risk, captured by the residual term in (i), which propagates material departures from the characteristic line. Such loadings of idiosyncratic risk might also account for the differentials noted above in the standard deviation of institutional and mutual fund excess returns. In contrast to the pension fund universe, there seems to be no overwhelming incentive for mutual funds to optimise tracking error relative to the market proxy. That is, where individual investors do not punish deviations from the market line mutual fund managers will be predisposed to pursuing high variance selectivity strategies.

The relatively weak predictive capacities of the asset-pricing techniques might also be partly attributed to the survivorship-free nature of our sample. In particular, loads of non-systematic risk adopted by ‘non-surviving’ funds and the low diversification levels that characterise their portfolios tend to attenuate the explanatory power of these tests (see Joye et al. (2000b)). For example, if we restrict our examination to the surviving sample of mutual funds, adjusted r-square increases, in relative terms, by 20%.

When migrating to the conditional one-factor model, risk-adjusted performance deteriorates to a statistically significant -2.8% per annum, post-fees. The distribution of alphas shifts leftward and an additional four of the conditional one-factor alpha point estimates are now significantly negative at the 1% level. Indeed, 61% of all conditional alphas are negative. The inclusion of the additional public-information proxies marginally elevates the explanatory power of the model, with the adjusted R-square increasing slightly. Note also in Table II that in the mutual fund market, 72% (60%) of the statistically significant coefficients on the lagged 30 day Treasury Bill yield (dividend yield) interaction variable are negative (positive). Similarly, 75% of the significant coefficients relating to the shape of the term structure are negative. Since high dividend yields, low short-term interest rates and a negatively sloped term structure predict high stock returns, mutual fund betas tend to be *positively* correlated with expected market risk premia.

The direction of the conditional and unconditional parameter estimates is entirely consistent with that previously articulated. Evidently, flow-shocks do not coerce mutual fund managers into engaging in material volumes of uninformed liquidity-motivated trading. More precisely, the incidence of new capital-flows does not force a departure from the target efficient portfolio, and an inverse relation between systematic risk and expected market returns is not manifest. This particularly interesting result substantiates

the conjectures of Edelen (1999)⁴¹ and sheds light on the evidence provided by Cai, Chan and Yamada (1997). The indirect cost of liquidity in performance-evaluation studies, i.e., the inverse relation between a fund's market beta and net capital-flows, is a function of the magnitude of the flow-shock. In the *absence* of such, the costs of the liquidity service that fund managers provide is not a concern and one does not anticipate an increase in the estimated conditional alpha coefficients. Rather, conditional models simply serve to accommodate time-varying expectations. Accordingly, they preclude ascribing abnormal selectivity abilities to public-information based trading strategies and elevate the accuracy of performance-evaluation studies. The deterioration in mutual fund performance evidenced under the conditional one-factor model is logically consistent with a market characterised by continuous, incremental capital-flows which *fail* to perturb the trading activities of management.⁴²

The evidence presented thus far might lead us to conclude, in a manner similar to Jensen (1968), that security prices behave according to the strong form of the martingale hypothesis. Figure 1 clearly conveys this story; the inability of active mutual fund participants to effectively exploit price inefficiencies is particularly manifest in the disproportionately large left tail of the population frequency distribution (i.e., below and to the right of the market line).⁴³ Across both the conditional and unconditional one-factor models we can confidently reject the null hypothesis of a mean alpha which is indistinguishable from zero. Such accords with conventional notions of an informationally efficient market in which active managers do not consistently deliver pre- or post-fee risk-adjusted excess returns.

However, in this sphere a completely different perspective is cast by the unconditional four-factor model. On a post-fees basis, the mean alpha is statistically indistinguishable from zero; pre-fees, mutual funds outperform by 1.86% per annum. Twenty six of the four-factor alpha point estimates are now positive (relative to 16 one-factor estimates) and statistically significant at the 5% level, and only 44% of all alpha coefficients are negative. The model's relative explanatory power also increases by a further 8%. Figure 1 depicts the rightward shift in the distribution of risk-adjusted excess returns. The left tail of the population is considerably smaller and alphas now appear to scatter randomly about the market line. Thus, a simple adjustment to mitigate the inefficiency of the single-index portfolio has removed the inference that the mean alpha is significantly negative. Pre-fees, active participants have successfully employed selectivity strategies; post-fees, they yield individual investors with returns which approximate an ex post efficient market portfolio (viz., one which accounts for the transaction costs incurred by passive participants; see Section F).

This ordering of results is entirely congruous with that previously proposed. An examination of the parameter estimates in Table II reveals a size bias in the investment style of mutual funds over the sample period. Our mimicking size factor measures the differential in the returns to large and small 'cap' portfolios. A positive (negative) coefficient on the size index indicates that the fund's underlying assets are tilted toward large (small) 'cap' securities relative to the market proxy. The coefficient on the size proxy is

statistically significant at the 1% level, and 88 (44%) of the point estimates are significantly negative at a 95% confidence interval. Patently, stocks held by these funds are smaller than those included in the market portfolio. Thus, single-index benchmarks, insofar as they fail to capture the multifarious investment styles that characterise the mutual fund sphere, provide spurious estimates of abnormal performance. Specifically, in the absence of ex post managerial ability, the propensity to acquire non-market proxy assets will result in non-zero one-factor alphas (see Ippolito (1989) and Elton et al.'s (1993) subsequent critique). The magnitude of the bias induced into the measure of performance is a direct function of the fund's exposure to assets excluded from the market portfolio. The cross-sectional dispersion in betas and the significant differences in the (time-invariant and time-varying) one and multi-factor risk-adjustment mechanisms also suggests that in the mutual fund universe, the use of 'relative' performance-evaluation methods, with an implicit beta of one, might obscure non-trivial cross-sectional variation in risk-adjusted returns.

Our analysis of the mutual fund market approximates much of the US evidence presented by Grinblatt and Titman (1989a, 1993), Ippolito (1989), Lee and Rahmann (1990), Malkiel (1995) and Edelen (1999).⁴⁴ Indeed, Grinblatt and Titman's (1989a) research illustrates the similarities between the two equity markets. Their estimate of (annualised) abnormal performance in the US mutual fund universe differs to ours by merely 0.10% per annum.

B.2 Institutional Funds

Table III depicts the mean time-series selectivity estimates averaged across the institutional fund population. The results present a striking contrast. Over the sample period, active institutional participants exhibited abnormal selectivity abilities on both a pre- and post-fees basis. All measures of performance yield positive and statistically significant alpha estimates at the 1% level. Employing Jensen's unconditional CAPM, the mean active institutional fund delivers 2.24% per annum in pre-fee risk-adjusted excess returns. Post-fees, the mean fund outperforms by 1.4% per annum. Some 83% of the unconditional one-factor alphas are positive and 36% (44) are significantly positive at the 5% level. Certainly, there are more positive alphas than one would attribute to chance; under the null we would anticipate just three positive and three negative intercepts. Further, the one-factor model has exceptional explanatory power with respect to the time-series variation in institutional fund returns, with an adjusted R-square of 0.86.

The unconditional four-factor model appears to have marginally superior predictive capacities, accounting for 89% of time-series variation in fund returns. Indeed, 41 (34%) of the four-factor point estimates are positive and statistically significant, while two are significantly negative. Importantly, 19% (32%) of the coefficients on the size factor are significantly negative (positive) with the mean coefficient significantly negative at the 1% level. Thus, the underlying assets held by institutional funds are not significantly different from those of the market proxy. Interestingly, the time-weighted alphas are

consistently lower than the equally weighted average alphas. This suggests, contrary to the evidence in the mutual fund universe, that the younger institutional funds outperform their longer established counterparts. Alternatively, the difference may reflect relatively inferior performance in the latter part of the sample.⁴⁵

Our estimates of abnormal institutional fund performance cannot be attributed to any known attrition or methodological induced biases. Moreover, they confound conventional interpretations of the efficient markets paradigm. Our findings also lend credence to the selectivity estimates of Coggin et al. (1993) and Christopherson et al. (1998). Whilst not explicitly articulated upon, Christopherson et al. find that US equity pension fund managers historically deliver substantial risk-adjusted excess returns, irrespective of the benchmark employed. Their reluctance to provide any explication most probably derives from the non-trivial survival and selection related biases to which their sample is subject and/or the controversy such would cause in light of the extant literature.⁴⁶ Notwithstanding the above, the similarities between our analyses are striking. Christopherson et al.'s results suggest that the mean US institutional product outperformed by 2.4% per annum relative to an unconditional four-factor style index benchmark. Aside from contradicting most evidence pertaining to the efficacy of active investment strategies, their findings also appear to be consistent with the presence of 'informed' participants in the Grossman and Stiglitz (1980) sense. Interestingly, the consistency across the two sets of results begs the question as to what impact attrition related biases have had on the extant pension fund literature (see Joye et al. (2000b)). Note also that the high correlation between raw institutional returns and the estimates of selectivity ability deriving from the diverse set of performance-evaluation techniques is explained by the tendency of fund betas to cluster in a tight band around unity. This latter point also indicates that the practice of employing 'relative' measures of abnormal performance in the institutional universe should not camouflage significant cross-sectional variation in risk-adjusted excess returns.

The conditional one-factor results similarly substantiate our prior expectations with respect to the direction of estimates deriving from the conditional and unconditional constructs. In contrast to that found in the mutual fund sphere, the conditional alphas provide the most *favourable* interpretation of the selectivity abilities of active participants. The mean conditional alpha is 2.63% and statistically significant at the 1% level. And 47 (39%) of the conditional point estimates are significantly positive at the 5% level. This finding accords with the proposition that the incidence of capital-flows has a relatively greater impact on the investment activities of pension fund participants. It appears that large, discrete flow-shocks propagate significant fluctuations in the cash positions of institutional funds and cause deviations from the target efficient portfolio. In turn, investors are compelled to engage in material amounts of uninformed liquidity-motivated trading, the latter of which induces an inverse relation between systematic risk levels and future market risk premia.⁴⁷ Put simply, flow affects the fund's beta at the wrong time. Where conditional benchmarks control for the relation between aggregate fund flows and time varying expected returns, conditional alphas exceed their unconditional counterparts.⁴⁸ And if institutional flows have a

material impact on participant performance, conditional estimations (insofar as they account for a fund's flow-induced trading activity) will yield superior inferences with respect to the efficacy of active investment strategies. Our evidence pertaining to the negative relation between net capital-flows and fund betas provides further empirical support for Edelen's (1999) empirical and theoretical claims, and when combined with those from the mutual fund sphere, reconcile the ambiguity manifest in the extant literature with respect to the anticipated influence of conditional methods on estimates of abnormal performance.⁴⁹ However, a more rigorous parametric analysis of the relation between investor flow and managerial performance is required to confirm this explanation.⁵⁰

The results also confirm our conjectures regarding the composition of institutional and mutual fund portfolios. Institutional participants seem to limit themselves to the larger, more liquid securities included in the market proxy, with both the one and four-factor mean unconditional systematic risk levels tending towards unity; viz., 0.95.⁵¹ Figure 2 illustrates the comparatively well-diversified nature of the institutional portfolios and their apparent aversion to loadings of residual risk. Consequently, there are not great disparities between the one and four-factor estimations of abnormal performance (see Figure 2). In the mutual fund sphere, however, there are frequent departures from the efficient frontier and thus the attributive abilities of the four-factor model provide more accurate estimations of the efficacy of active investment strategies.

In order to verify the robustness of our conjectures we conduct additional analyses of each universe's portfolio holdings. Specifically, we run two separate regressions. In the first, we regress the institutional and mutual fund unadjusted return series on the value and growth portfolio proxies. In the second, we use the large and small 'cap' indices as separate explanatory variables. Table IV illustrates the results. Consistent with previous findings, it is evident in Table IV that institutional fund participants have significant exposures to large 'cap' stocks. The coefficient on the large 'cap' (small 'cap') portfolio is 0.840 (0.139) and statistically significant at the 1% level. Conversely, mutual funds have comparatively greater exposures to (non-market proxy) small 'cap' securities and, as previously suspected, a disproportionate appetite for loadings of non-systematic risk. Clearly, there are striking disparities in the mean institutional and mutual fund manager's portfolio preferences.

We also verify the expected differences in the cross-sectional variation of ex post performance. While in the pension fund universe there is a remarkably narrow 25% range in the distribution of unconditional four-factor alphas, the mutual fund sphere is characterised by extreme variability in the cross-sectional distribution of risk-adjusted returns (see Figure 1).⁵² The dispersion of mutual fund returns is exacerbated by the exceptionally poor performance of non-surviving funds. In particular, four funds underperformed on an annualised risk-adjusted basis by -33%, -25%, -22%, and -17.4% respectively for the short period in which they were alive (their average age was just 27 months). This contributes to the significant variance in cross-sectional (realised) performance. Specifically, there is a 52% distributional

range in the unconditional four-factor alpha. Excluding these products reduces dispersion to a somewhat more comparable 38% range. Significantly, this finding casts into stark relief the cost associated with imposing stringent time-series thresholds. Had we adopted the methodology of, say, Elton, Gruber and Blake (1996a), and imposed a minimum 36 month price history, 36% of the non-surviving sample of funds would have been excluded.⁵³ Thus the tendency to use excessively restrictive time-series thresholds⁵⁴ promotes spurious inferences with respect to extrapolating the abnormal performance of a sample of funds to that of the population. This may be especially manifest where there is a strong correlation between the rate of attrition and fund age. Our evidence is, therefore, consistent with the emphasis placed by Carhart (1995) on the importance of choosing data sets and methodologies free of both selection and survival biases.

Complications associated with the extant literature aside, the narrow cross-sectional distribution of institutional alphas remains a striking empirical regularity. Evidently, there exist incentives for institutional participants to optimise their asset allocations - and by construction, tracking error (i.e., diversifiable risk) - relative to their peer group and/or a static benchmark such as the market proxy.⁵⁵ Frequent evaluations by asset consultancies, the sophistication of the institutional clientele, and the prevailing fee structures⁵⁶ create disincentives to pursuing idiosyncratic risks, particularly relative to their peer group. Indeed, irrespective of performance, managers are often dismissed for deviating from their investment guidelines. For example, in the 1997 Nelson/Wilshire Survey on Plan Sponsor Attitudes, 73.1% and 52% of respondents respectively placed 'consistent application of the investment process' and 'adherence to stated guidelines' among the three most important factors determining manager retention. Further, a Greenwich Associates survey found that in 1994, 26% of all institutional managers terminated by sponsors had violated a specific investment restriction.

Our analysis pertaining to the cross-sectional variation in ex post performance and portfolio composition is consistent with that first documented by Falkenstein (1996). Employing two-years worth of data, Falkenstein finds that both volatility and idiosyncratic volatility have significant explanatory power with respect to aggregate mutual fund holdings of individual securities. In part, he attributes the mutual fund manager's aversion to low variance stocks to the strategies espoused by Lynch (1992). We advocate the alternative explanation that it is specific 'investor characteristics', peculiar to the sphere under study, which have a deterministic influence on cross-sectional disparities in the equity holdings of institutional and mutual fund participants and, by implication, their return generating process.

For instance, the absence of asset consultancy's enforcing sophisticated performance-evaluation, and the relative naïvete of individual investors may predispose mutual funds to pursuing high variance selectivity strategies. More precisely, the inelastic demand of consumers with respect to poor performance, and the individual investor's propensity to 'ride losers' (viz., the 'disposition effect'; see Shefrin and Statman (1985)) results in a phenomenon whereby extended periods of sub-optimal performance go

relatively unpunished (see Sirri and Tufano (1998) and Joye et al. (2000c)).⁵⁷ Such ‘asymmetric’ performance-flow relations create incentive structures which have call option-like payoffs. In turn, this non-linear pay-off function engenders ‘risk-shifting’ behaviour amongst poorly performing mutual funds; that is, loads of idiosyncratic risk may be taken on in expectation of maximising future payoffs (see Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), Busse (1998) and Koski and Pontiff (1999)).

This propensity of mutual fund managers to manipulate portfolio risk, as a function of the (non-linear) economic incentives they face, has significant consequences for our analysis of portfolio composition. Specifically, active mutual fund participants will adopt significantly higher levels of non-systematic risk and materially depart from the characteristic line. Relative to that documented in the institutional sphere, this behaviour is manifest in: (i) a decline in portfolio diversification (systematic risk) and a preference for non-market proxy assets with high idiosyncratic volatility; (ii) the reduced explanatory power of the performance-evaluation techniques; and (iii) cross-sectional disparities in the one and multi-factor point estimates. On the other hand, the size and sophistication⁵⁸ of institutional capital-flows presents an implicit contract that greatly diminishes the incentive for active participants to take non-trivial risks.⁵⁹ While superior selectivity ability may result in significant ex post performance, it also elevates the probability of ‘relative’ underperformance. And the loss of an institutional ‘mandate’, resulting from material increases in tracking error (viz., diversifiable risk), is likely to be an order of magnitude greater than the increase in a performance-related management fee. Hence, in contrast to the mutual fund sphere, institutional investment vehicles seem to have strong incentives to reduce idiosyncratic risk and thus increase diversification.

[Please insert Tables I to IV and Figures 1 and 2 about here]

C. The Flow-Performance (Performance-Flow) Relation

Given our prior explication of the disparities in the selectivity estimates deriving from the conditional and unconditional constructs it is pertinent to digress and parametrically examine the flow-performance (performance-flow) relation. In part C.1, we consider the contrasting magnitude of the individual and institutional investor’s consumption-allocation decisions. Part C.2 quantifies the impact of investor flow on managerial performance and presents a simple statistical test to discern differences in each agent-type’s elasticity of demand with respect to past alpha. Finally, in part C.3 we investigate the effect of incorporating a lagged net capital-flow variable into the asset-pricing technique.

Undeniably, individual and institutional investors exhibit a strong predilection to chasing past fund performance. For example, the salience of a ‘track record’ has been empirically substantiated by Gruber (1996), Goetzmann and Peles (1997), Sirri and Tufano (1998) and Joye et al. (2000c) in their analyses of

the ‘performance-flow’ relation. Recently however, it has been conjectured, yet not empirically tested, that ‘dual causality’ might propagate managerial mean reversion. Such ‘flow-induced mean reversion’ could arise for several reasons. First, in prior analysis we confirm the existence of a ‘size effect’ wherein many ‘star managers’ have small portfolios with respect to assets under management; that is, there exists an inverse relation between abnormal performance and net asset values.⁶⁰ Yet this outstanding performance invariably attracts significant capital inflows, and over time, the smaller participants who populate the right tail of an alpha distribution often become quasi ‘market’ (or index) funds. Importantly, these large capital-flows create multifarious complications for investment management (i.e., diseconomies of scale). For instance, the universe of available stocks tends to decline and transaction costs often increase. Legal and practical constraints on equity ownership and the burden associated with liquidity requirements may also result in a reduced investment opportunity set. Further, much touted market impact costs, associated with trade in illiquid assets, impede the participant’s ability to effectively exploit security price inefficiencies (see Berkowitz et al. (1988), Keim and Madhavan (1991) and Chan and Lakonishok (1993)). Accordingly, in subsequent periods these products tend to deliver performance which is inferior to that realised in the past.⁶¹

Of course, flow-induced managerial mean reversion is closely related to Edelen’s (1999) ‘flow-shock effect’ and thus has non-trivial implications for our ‘conditional’ estimates of abnormal performance. Recall that a fund’s abnormal performance may be dissected into two components: positive alpha attributable to discretionary (i.e., information motivated) trade and a negative component associated with liquidity-motivated (i.e., exogenous supply-noise) trade. Edelen finds that inferences with respect to the efficacy of active investment strategies change dramatically once we account for the latter.⁶² It is important, therefore, that one attempts to extricate the contaminating influence of investor flows from the performance-evaluation technique and appropriately appraise a manager’s signal-processing skill. Given sufficient magnitude, a ‘flow-shock effect’ should manifest itself in the form of an inverse relation between investor flow and the future risk-adjusted performance realised by active participants. This is likely to be apparent more so in the institutional sphere, considering the size and elasticity of the institutional investor’s capital-allocation strategies. On the other hand, the small, incremental and indiscriminate nature of the individual agent’s capital-flows may not induce significant departures from the target efficient portfolio.

C.1. Univariate Analysis of the Performance-Flow Relation

Table V displays summary cash-flow⁶³ statistics deriving from both the institutional and mutual fund populations. Unmistakably, there are considerably larger pools of capital in the institutional universe. For example, where the mean institutional (mutual) fund size was \$272 million (\$48 million) during the sample period, average assets at December 1998 were estimated to be \$492 million (\$116 million)

respectively. These figures compare well with those evidenced in the US and UK capital markets.⁶⁴ Table V also conveys the contrasting magnitude of individual and institutional capital-flows. The mean absolute flow into the average active institutional product was \$59.39 million per annum. Conversely, the mean annual absolute flow into the average mutual fund was just \$3.64 million.

[Please insert Table V and Figures 3 to 4 about here]

To further examine the size of this disparity we allocate institutional and mutual funds into six equally-weighted portfolios (hexiles) on the basis of their past [-36,0] month unconditional one-factor alpha and measure capital-flows to each hexile over an immediately subsequent period of [0,+6], [0,+12], [0,+18], and [0,+24] months.⁶⁵ The hexiles are in ascending order of performance, i.e., the funds allocated to the first hexile are the poorest performers while the sixth hexile comprises the best performing funds.

Figures 3 and 4 depict the results. In the mutual fund universe, the sixth fractile of funds receives \$18.52 million (31.76%) in net absolute (normalised) capital-flows in the [0,+18] months subsequent to ranking on past [-36,0] month one-factor alpha. In contrast, the contemporaneous absolute (normalised) flow in the institutional sphere is \$197.82 million (77.95%). If we extend the evaluation period by another [0,+6] months, the net absolute (normalised) flows to the top hexile of funds are \$21.57 million (29.53%) and \$275.66 million (105.52%) respectively. While this enormous disparity in the elasticity of the individual and institutional investor's response to past performance appears to corroborate our conjectures regarding the influence of 'flow-shocks' on the trading activity of active institutional and mutual fund participants, we must defer definitive inferences to more robust parametric analyses.

C.2 Parametric Analysis of the Flow-Performance Relation

A generic description of our simple parametric method is provided as follows. Throughout the sample period the unconditional four-factor alpha is cross-sectionally regressed on absolute capital-flows lagged [-6,0], [-12,0], and [-18,0] months and, given some persistence in performance (see Joye et al. (2000c)), a contemporaneously lagged four-factor alpha.⁶⁶ This analysis is performed independently in both the institutional and mutual fund spheres, and conducted using different lag structures to capture possible delayed responses in the relationships between investor flows and fund returns. Whilst we estimate many different variants on the theme, the standard specification is,

$$a_{t+i}^4 = g_0 + \sum g_i CF_{t-i}^a + g_2 a_{t-i}^4 + n_t \quad (9)$$

where a_{t+i}^4 is the unconditional four-factor alpha estimated over the period t+i; ΣCF_{t-i}^a is the lagged absolute flow computed in period t-i; and a_{t-i}^4 is the contemporaneously lagged unconditional four-factor alpha estimated in period t-i. To mitigate potential cross-sectional correlation amongst alphas and investor flows we employ White's (1980) heteroskedasticity-consistent variances and standard errors. Since, for reasons previously articulated, the impact of a given level capital-flows on future fund performance is likely to be inversely related to fund size, we allocate funds into hexiles on the premise of net asset values.

Tables VI to VII depict our findings. In the first column, Div 1 (Div 6) illustrates specifications estimated on the smallest (largest) hexile of funds. The results are striking. Irrefutably, institutional investor capital-flows considerably influence the risk-adjusted returns of small active participants. The coefficients on the lagged [-6,0], [-12,0], and [-18,0] month institutional flow in the first (i.e., smallest) hexile of funds are statistically significant and negative at the 5% level, with t-ratios equal to -1.73, -4.13 and -2.82 respectively. Indeed, lagged [-6,0] month institutional capital-flows impact upon the performance of the first two hexiles of funds, sorted by net asset value. This flow-shock effect is most evident when we regress the future [0,+12] month four-factor alpha on the lagged [-12,0] month capital-flow.

Our evidence substantiates, therefore, the proposition that the incidence of large institutional investor flows adversely affect managerial behaviour. Where 'star managers' hold small portfolios with respect to assets under management, significant capital inflows impede the participant's ability to identify and exploit mis-priced securities. Specifically, the sudden growth in assets propagates non-trivial amounts of uninformed liquidity-motivated trading and/or market impact costs that materially detract from future fund performance.

Not surprisingly, institutional capital-flows have little effect on the future risk-adjusted performance of large investment vehicles. In fact, the lagged [-18,0] month flow has significantly *positive* explanatory power with respect to the future [0,+12] month four-factor alpha realised by funds residing in hexiles three, four and six. That is, an increase in institutional allocations engenders increases in future fund performance. Intuitively, this is quite plausible in the presence of persistence (see Joye et al. (2000c)). Where institutional investors are predisposed to pursuing persistence-based capital-allocation strategies, an increase in flow and thus fund size will by necessity be correlated with a temporal increase in the future risk-adjusted returns delivered by active participants, assuming that performance does persist.⁶⁷ This is similar to the 'smart-money effect' first identified by Gruber (1996).

Consistent with *a priori* conjectures, flow-induced managerial mean reversion is not a pervasive phenomenon in the mutual fund universe. There is some evidence of a flow-shock effect, with the lagged [-6,0] and [-12,0] month capital-flow coefficients in the second hexile of funds statistically significant and positive at the 1% and 10% level respectively. In all estimations however, the trading activities of the first hexile of mutual funds remains unperturbed by the individual investor's capital-allocation decisions. Again, the proliferation of persistence-based consumption-allocation strategies most probably accounts for the

significantly positive lagged 18 month flow coefficient in the sixth hexile of products. To ensure that our findings are robust, we estimate the aforesaid regressions on the entire population of institutional and mutual funds. The results, available from the authors upon request, confirm that this is a small fund phenomenon, with all coefficients statistically indistinguishable from zero.

To identify statistical differentials in the nature of individual and institutional flows we also interact a mutual fund dummy variable, DMF_t , with the various performance metrics, $(DMF_t, \sum_{k=1}^k d_{t-i}^k)$, taking the value of one for funds that reside in the mutual fund sphere and zero otherwise. Hence, we *jointly* estimate the following generic cross-sectional regression on both the institutional and mutual fund populations,⁶⁸

$$CF_t^{n/a} = b_0 + \sum_{k=1}^k b_{kt} d_{t-i}^k + b_2 DMF_t + b_3 (DMF_t, \sum_{k=1}^k d_{t-i}^k) + e_t, \quad (10)$$

where CF_t^a denotes the absolute net flow in period t, assumed to occur in the middle of the month; d_{t-i}^k is the performance proxy k, estimated over the monthly period t-i, and b_{kt} is the dependent variable's sensitivity to performance proxy k.⁶⁹

The results, reported in Appendix I, suggest that there exist considerable disparities in the individual and institutional agent's elasticity of demand with respect to past performance. Observe in column three that all interaction variables are negative and statistically significant at the 1% level. The coefficients yield insights into a significant difference in each clientele's response to the residual returns delivered by active participants.

[Please insert Table VI about here]

For example, institutional portfolio managers who realise a 1% monthly increase in past [-36,0] month four- (one-) factor monthly alpha receive an *additional* \$28.21 million (\$26.72 million) in net monthly capital-flows relative to their active mutual fund counterparts. Annually, this constitutes a \$338.5 million (\$320.6 million) differential in the individual and institutional investor's response to past one-factor (four-factor) performance.

[Please Insert Table VII about here]

Patently, the evidence substantiates the conjectures of Section IV with regard to cross-sectional disparities in the conditional and unconditional estimates of abnormal performance. Whereas the size and lumpy (i.e., discrete) nature of institutional mandates invariably induces significant amounts of uninformed

liquidity-motivated trading, the individual investor's capital-allocation strategies appear to be comparatively innocuous. That is, flow-shocks do not force mutual fund managers to depart from the target efficient portfolio and thus an inverse relation between systematic risk and expected market returns is not manifest. These findings serve, therefore, to reconcile the contrasting 'conditional' interpretations of abnormal performance manifest in the selectivity analysis and in prior literature. The influence of investor flows on abnormal performance is a function of the magnitude of the shock. Simply, the *deterioration* in mutual fund performance evidenced under the conditional model is consistent with a market characterised by incremental capital-flows that *fail* to affect the trading activities of management.

C.3 Introducing Flow into the Performance-evaluation Technique

In light of the above exposition, it is instructive to estimate the participant's informational-assimilation ability while attempting to control for the contaminating influence of each clientele's capital-allocation decisions. This allows us to more rigorously assess the efficacy of a manager's selectivity strategies, absent liquidity demands, and hence the degree to which participants are actually informed in the Grossman and Stiglitz (1980) sense. We make a simple adjustment to our unconditional performance-evaluation techniques,⁷⁰ with the addition of a lagged absolute net cash-flow regressor, CF_{t-i}^a , to control for future-period liquidity-motivated trading.⁷¹ This method is intuitively appealing insofar as current-period cash-flows adversely affect future and not contemporaneous period returns.⁷²

While space constraints prevent us from explicitly reporting the results, it is clear that once we calibrate our unconditional benchmarks to reflect the costs of providing liquidity, inferences with respect to institutional performance alter. First, the lagged [-3,0] month net capital-flow variable is statistically significant and negative at the 5% level. Adopting this particular lag structure elevates the mean institutional four-factor alpha by approximately 15 basis points per annum. However, a simple t-test to discern differences between the unadjusted and flow-adjusted alpha distributions yields an insignificant t-ratio of -1.456.

Our estimations reveal that it is past [-6,0] month institutional capital-flows which have the greatest explanatory power with respect to time-series variation in future-period returns. When we employ the one and four-factor flow-adjusted techniques, the t-ratio on the lagged six-month cash-flow variable is significantly negative at the 5% level, while the mean institutional alpha increases by 25 basis points per annum relative to the base specification. Further, the unadjusted and flow-adjusted alpha point estimates are now statistically distinct at the 5% level. Inspection of the lagged cash-flow coefficients illustrates that a monthly \$10 million increase in net institutional allocations induces an annual 1.69% decrease in excess return.⁷³ Hence, in accordance with previous experiments, our flow-adjusted asset-pricing techniques

demonstrate that, in aggregate, the consumption-allocation strategies of institutional investors adversely impact upon the selectivity abilities of active participants.

Yet consistent with prior analysis, this effect is not manifest in the mutual fund universe. Rather, irrespective of the specification adopted, the individual agent's investment capital exerts little influence on managerial behaviour.

D. Estimates of Abnormal Market-timing Abilities

Tables VIII and IX respectively display annualised time-series parameter estimates averaged across the mutual and institutional fund populations, throughout the 1988-1998 sample period. These derive from conditional and unconditional, one and multi-factor variants of Treynor and Mazuy's (1966) quadratic CAPM.

Applying a data-set free of all known survival and selection biases we find little evidence of the oft touted 'perverse' market-timing ability; i.e., where, given an assumed reaction function, agents reduce (increase) their portfolio's exposure to equities prior to an expectation of increased (reduced) stock market returns (see Jagannathan and Korajczyk (1986)). Indeed, when adopting a somewhat more sophisticated interpretation of managerial behaviour it appears that active institutional and mutual fund participants have been able to successfully forecast future market risk premia, albeit not in a statistically robust fashion. These findings distinctly contrast much of the extant literature. Our empirical results also confirm the prior explication of the selectivity abilities of the two fund-types, and thus the implications of this analysis for the efficient markets paradigm.⁷⁴ The dissimilarities between the results reported here and prior evidence are attributed to survival, selection and model misspecification related biases (see Joye et al. 2000b)).

D.1. Mutual Funds

The mean conditional one-factor mutual fund market-timing coefficient (i.e., the coefficient on the squared excess market return) is positive and statistically significant at the 10% level. The point estimate from the multi-factor market-timing model is also positive, although we cannot on average reject the null (where $d_{2p} = 0$), given a t-ratio of 0.098. And while the more primitive unconditional single-factor timing value is slightly negative, it is statistically indistinguishable from zero.⁷⁵

The direction of the parameter estimates, across both the conditional and unconditional models, is consistent with that documented in the selectivity analysis. Indeed, the generic conclusions remain the same; when applying single factor formulations, the mean active mutual fund manager fails to deliver pre- or post-fee risk-adjusted excess returns. The mean one-factor unconditional (conditional) alpha point estimate is -2.392% (-3.371%) and statistically significant at the 1% level. Thus, subsequent to the

introduction of the lagged macroeconomic predictor variables, performance deteriorates by approximately 40 basis points.

Controlling for style biases, size exposures, asset-pricing anomalies and non-market proxy assets materially increases estimates of abnormal performance. In contrast to the dour perspectives of the single-index models, the mean multi-factor alpha is, post-fees, indistinguishable from zero. Pre-fees, mutual funds successfully employ security selectivity strategies, extracting rents from passive participants. Post-fees, they yield risk-adjusted returns commensurate with that of an ex post market portfolio. The magnitude of the alpha coefficients relative to those estimated in Section V, part A.1 indicates that the market-timing activities of mutual funds have detracted only slightly from total risk-adjusted performance.

D.2. Institutional Funds

Employing the more advanced performance-evaluation techniques, we also fail to find evidence of perverse market-timing in the active institutional fund sphere. This result contradicts the scarce extant (unconditional one-factor) evidence pertaining to the efficacy of institutional macro-forecasting strategies (see Coggin et al. (1993)). The mean conditional and multi-factor timing values are positive, albeit statistically indistinguishable from zero. Hence it would seem that institutional agents are able to effectively anticipate future market movements. That is, they will decrease (increase) the portfolio's exposure to the riskless asset prior to an expected increase (decrease) in equity market returns. The dissenting and significantly negative unconditional one-factor market-timing point estimate is attributed to biases induced by model misspecification. Specifically, Treynor and Mazuy's unconditional one-factor formulation does not control for the relation between aggregate flows and time varying expected returns. Edelen (1999) demonstrates that where this is true, flow-shocks of sufficient magnitude will propagate a proliferation of negative timing values. Accordingly, it would seem that this evidence is simply a manifestation of an institutional universe characterised by large and discrete capital-flows. An alternative explanation may lie in the portfolio composition of institutional funds, which tend to be heavily biased toward large 'cap' securities (see Section V, part A.2). An examination of the skewness of the large 'cap' proxy relative to that of the market reveals that the former has call-option-like characteristics vis-à-vis the latter. This may have resulted in the artificial proliferation of negative institutional timing coefficients.⁷⁶

The alpha estimates also substantiate our prior explication of institutional selectivity strategies. Irrespective of the method of assessment, active institutional participants realise statistically significant pre- and post-fee risk-adjusted excess returns. The mean unconditional one- (four-) factor alpha is 3.08% (2.817%) per annum and statistically significant at the 1% level.⁷⁷ This aptitude for exploiting price inefficiencies cannot be reconciled with conventional interpretations of informationally efficient markets.

D.3 Extrapolation

These findings contradict the extensive empirical literature which supports the notion that active mutual fund managers have exceptionally poor, viz., perverse, market-timing abilities.⁷⁸ Our results also differ to the one existing paper that evaluates the macro-forecasting abilities of institutional participants (see Coggin et al. (1993)). They do, however, lend credence to the recent theoretical and empirical claims of Ferson and Schadt (1996) and Edelen (1999).⁷⁹ This is significant because (i) prior ‘conditional’ market-timing evidence has been subjected to attrition induced biases and (ii) the extant literature pertaining to conditional methods has been restricted to the mutual fund universe. That is, it is not clear as to whether the results of Becker, Ferson, Myers and Schill (1999) are applicable to institutional investment vehicles.

Whilst doubtlessly controversial, the statistical insignificance of macro-forecasting strategies employed in the institutional and mutual fund spheres should not be interpreted as anomalous; popular wisdom perceives market-timing to be a treacherous activity fraught with many difficulties. Moreover, it is quite possible that the literature to date has placed too much emphasis on such pursuits.⁸⁰ Consider for instance, the diminutive magnitude of the timing values. The influence of timing on the portfolio return is assessed by multiplying the tiny decimal fraction, d_{2p} , with the squared decimal fraction $(R_m)^2$. Hence, our evidence indicates that market-timing strategies have at best only a marginal impact on total portfolio performance.⁸¹

[Please insert Table VIII and Table IX about here]

In contrast to Cai, Chan and Yamada (1997) and Bollen and Busse (1999) we are able to confirm Ferson and Schadt’s (1996) finding that modifying the Treynor and Mazuy (1966) approach to condition on public-information mitigates what little perceived ‘perverse’ macro-forecasting ability exists. This result, robust to an examination of two different investor populations, is important considering the recent ambiguity with respect to the influence of conditional methods. In both spheres, where the mean unconditional one-factor market-timing coefficient is negative, its conditional counterpart is positive. Thus, incorporating the lagged public-information proxies materially shifts the distribution of statistically significant coefficients to the right. In the mutual fund universe, where ten (15) of the unconditional one-factor point estimates are significantly positive (negative), 19 conditional coefficients are significantly positive and 13 significantly negative.⁸² The ability of conditional models to ameliorate the perverse market-timing phenomena is also manifest in the institutional universe. While 11 (14) of the statistically significant conditional market-timing coefficients are positive (negative), excluding the lagged macroeconomic variables results in 17 negative and seven positive point estimates. And finally, in both spheres we verify the statistical independence of the conditional and unconditional timing and security selectivity estimates through the non-parametric Wilcoxon Matched Pairs test and the Student’s t-test. All

coefficients are statistically distinguishable at the 5% level. Such evidence serves to motivate the future application of ‘conditional’ performance-evaluation, and casts some doubt on the recent literature suggesting otherwise.⁸³

E. Investor Sophistication – An Independent Variable?

In closing our analysis, it is worth noting that an appreciation for the sophistication of ‘heterogeneous investor clienteles’ sharpens insights with respect to the marked contrariety in the selectivity abilities of active institutional and mutual fund participants. To date, finance theory has ignored the disparities in the institutional and mutual fund industries, and no attempt has been made to present a thesis that unifies the behavioural differentials patently evident. Academics provide little explanation for the multifarious structures, incentives and return generating processes that proliferate in the two markets. An analysis of the interaction between the naïve and non-performance discriminating individual agent,⁸⁴ the informationally efficient institutional agent, and the vehicles which service their investment needs casts a revealing light on the diversity manifest. That is, heterogeneity in the sophistication of each investor clientele motivates rich insights with respect to cross-sectional disparities in the information sets of ‘informed’ agents.

Our theory is motivated by the search for an explanation as to the generic comparative advantages manifest amongst active portfolio managers; that is, what accounts for systematic disparities in institutional and mutual fund performance? We propose that heterogeneous investor clienteles exert a deterministic influence on the abnormal performance realised by active participants. And *ex ante* differentials in institutional and mutual fund risk-return dynamics arise endogenously as a function of the sophistication of the contemporaneous investor clientele; viz., investor sophistication acts as the ‘discount rate’ of performance.

For example, the magnitude and discontinuous nature of pension fund flows may be such that they enable a sophisticated institutional clientele to exercise influence over the trajectory of future fund performance. This complex performance-flow relation would appear to present an implicit contract that *precludes* persistently poor performance (see, for instance, Joye et al. (2000c)). On the other hand, the incremental and continuous nature of mutual fund flows, the absence of asset consultancy’s enforcing sophisticated performance-evaluation, and the relative naïvete of individual agents ensure that the costs implicit in sub-optimal mutual fund performance are of second order.

The disparity in investor sophistication might therefore propagate a disparity in the information sets associated with active participants. If this were true, and investor sophistication did mandate a minimum required rate of return, one would anticipate differentials in the abnormal performance of institutional and mutual fund products. Indeed, our evidence confirms such suggesting that the post-fee risk-adjusted excess returns realised by the former dominate that of the latter. The striking contrast in the efficacy of

institutional and mutual fund selectivity strategies might thus be in part attributable to (or perhaps, functionally dependent upon) the heterogeneous information sets of their contemporaneous clientele. These issues should prove to be a fertile ground for future theoretical research.

F. The Efficacy of Passive Investment Strategies

The pre-eminence of the efficient markets paradigm has prompted the proliferation of passive management. In 1998, US index funds claimed one fifth (\$US42.1 billion) of all new flows into the mutual fund market, a 27% increase relative to 1997 levels. And during the first quarter of 1999, passive vehicles were allocated another \$US21.4 billion, with the sector's total assets rising to \$US270.2 billion. In Australia, the indexed investment market grew by \$14 billion in the 12 months to December 1998 (from \$27.1 billion in 1997 to \$41.3 billion in December 1998, with 21 managers offering indexed portfolios). Indexing now represents 13.3% of the overall Australian sourced investment market. These trends reflect an annualised growth rate of 40%, twice the rate of growth in the institutional market and three times the rate of growth of the overall investment management market during the same period.

Our motives for examining the performance of passive participants are described as follows. First, in the analysis presented above, we found that a mutual fund market in Grossman and Stiglitz style equilibrium prevented us from defining the 'optimal' consumption-allocation strategy. Where ex post returns were commensurate with that of the market proxy rational, risk-averse individual agents had no preference with respect to active or passive participants. Yet it would be premature to assume that investors can necessarily access the returns delivered by the market portfolio. Indeed, any examination of the efficacy of active investment strategies is implicitly predicated upon a tenuous equilibration of the returns realised by index funds and those associated with that of the market. However, there is strong support for a disparity between the two. Whilst passive investment strategies are easy enough to employ in an idealised (i.e., frictionless) world, in reality they encounter myriad difficulties when attempting to replicate the market proxy. These complexities arise as a function of index compositional changes, corporate activity, cash-flows, illiquidity, market volatility, the reinvestment of dividends, and transactions costs (see Chiang (1998)). Such difficulties induce 'tracking error' and heterogeneity amongst the funds themselves. In particular, passive managers encounter an inverse relation between tracking error and transactions costs: higher (lower) tracking error, as a consequence of less (more) frequent trading when mimicking the benchmark, reduces (increases) transactions costs. Given these differences in trading environments, it is paramount that we evaluate the efficacy of passive investment strategies.

We assess the performance of the passive fund population over the entire sample period, applying six of the evaluation techniques described earlier; viz., the unconditional (conditional) one-factor model, the unconditional four-factor model, and Treynor and Mazuy's (1966) unconditional (conditional) one and

multi-factor market-timing models. Only ‘market-linked’ index funds are included in the sample. These products attempt to perfectly replicate the risk-return profile of the market portfolio and thus constitute the purest form of passive management.⁸⁵ Funds engaging in ‘enhanced’ equities strategies are excluded. Such vehicles cannot be considered a perfect ex post substitute for the market proxy as they subscribe to both active and passive investment philosophies.⁸⁶ Ex ante, one expects passive participants to exhibit, in the presence of an efficient market proxy, systematic risk levels nigh on unity, and to obtain risk-adjusted performance that is indistinguishable from zero. If naïve strategies yield abnormal performance, our benchmarks are inefficient. Thus, this analysis also serves to illustrate that the selectivity and timing estimates derive purely from the portfolio management abilities of active participants.^{87 88}

F.1 Empirical Analysis

Table X depicts the annualised time-series statistics averaged across the population of passive funds. It is evident that passive participants have exceptional replication abilities, delivering investors both the risks and returns of the market portfolio. This is despite the costs they incur when mimicking the compositional changes of a target index oblivious to the constraints they face.

Consistent with prior expectations, all intercepts are statistically indistinguishable from zero. Relative to the unconditional (conditional) one-factor model, there is an annual pre-fee 11 (five) basis point differential between the risk-adjusted excess returns realised by the population of passive funds and that of the market proxy. On a time-weighted basis, the mean pre-fee differential is just seven and 0.02 basis points per annum respectively. Applying the four-factor model, the average annual alpha is 0.015% per annum. These results also hold for the selectivity estimates of the conditional and unconditional, one and multi-factor, Treynor and Mazuy market-timing models. Diversification levels are almost perfectly aligned with that of the market with the systematic risk estimates from the unconditional one and multi-factor factor selectivity and timing models statistically indistinguishable from one (that is, 0.999, 0.998, 1.000, and 0.998 respectively). The explanatory power of each model is also striking, with a minimum adjusted R-square of 99.8%.

Pre-fees, passive funds offer individual and institutional investors access to the risk-return profile of the market portfolio. There are though disparities in the cost structures associated with servicing each investor clientele. As at September 1999, the mean passive institutional fund MER was just 0.10% per annum. Thus ex post, investments in index funds still provide institutional agents with risk-adjusted performance commensurate with that of the market proxy. Individual investors are less fortunate. Our data suggests that the mean passive mutual fund MER is approximately 0.75% per annum. Index funds do not therefore furnish individuals with market-like post-fee performance. Specifically, the costs associated with servicing individuals result in a risk-adjusted performance shortfall of approximately 70 basis points per annum.

[Please insert Table X about here]

Accordingly, this concurrent examination of the active and passive populations affords a number of significant insights. First, it is erroneous to assume that individual investors can necessarily access the returns delivered by the market portfolio. And where the post-fee performance of passive participants does depart materially from that of the target index, prior analyses of the efficacy of active (mutual fund) investment strategies may be somewhat dubious. For instance, Malkiel's (1995) conclusion that active management generally fails to provide excess returns and 'that the advantage of passive management

⁸⁹ Rather, definitive inferences require a robust and simultaneous examination of the returns delivered by passive participants. However, the converse is true for analyses of institutional funds. It would seem that, given the insignificant expense ratios and exceptional replication abilities of passive funds, one may subsume the latter with the presence of the market proxy.⁹⁰

VI. Summary and Conclusion

Our concurrent estimation of the unconditional and conditional selectivity and market-timing abilities of the population of participants in both the institutional and mutual fund spheres, insulated from survival, selection and methodological induced biases, has furnished a number of innovations.

First, it is evident that isolated examinations of the mutual fund market do not facilitate robust inferences with respect to the semi-strong form of the martingale hypothesis. Indeed, our simultaneous analysis of both spheres serves to demonstrate that equity markets may not be efficient in the sense that was once presumed. Significantly, we identify material disparities in pricing structures and underlying risk-return dynamics characteristic of the institutional and mutual fund spheres. *Ipsa facto*, an efficient mutual fund market need not imply an informationally efficient equity market in aggregate.

It is also apparent that the mutual fund market is in Grossman and Stiglitz (1980) style informational equilibrium. Controlling for asset-pricing anomalies, benchmark inefficiencies and model misspecification, the mean active participant earns *pre-fee* risk-adjusted excess returns. Thus, in the mutual fund sphere, the arbitrage function is incomplete, and informed traders extract rents from passive participants which are sufficient to compensate them for their costly information gathering activities. This is entirely congruous with a rational expectations equilibrium informational view of securities markets. That is, the allocational role of markets ensures that noise will be induced into the signal extraction process, creating incentives for agents to conduct their costly information search. Accordingly, in competitive equilibrium, ex post returns are less than or equal to that of the market proxy. This evidence is also consistent with capital market efficiency in the presence of *costly arbitrage*. It is however inconsistent with

an equilibrium defined by ‘full-information’ prices and the elimination of all arbitrage profits (see Fama (1970)).

Further, the nature of competitive equilibrium in the Grossman and Stiglitz sense is such that it prevents us from defining, *ex ante*, the ‘optimal’ consumption-allocation strategy that maximises the utility of rational, risk-averse individual agents. That is, where *ex post* returns are commensurate with that of the market proxy individual investors should have no preference (in equilibrium) with respect to active or passive participants.

Second, in the institutional fund market, active participants exhibit abnormal selectivity abilities on both a pre- and post-fees basis. These estimates of abnormal performance cannot be attributed to any known attrition or methodological induced biases. Moreover, they confound conventional interpretations of the efficient markets paradigm. That is, such constitutes a significant capital market anomaly. This is especially important considering the dearth of empirical evidence pertaining to the seemingly more important investment activities of institutional investment vehicles.

We present two possible explanations for this phenomenon. First, conventional risk-adjustment techniques may not control for the risks implicit in the costly information gathering activities of informed participants. If costly search is associated with an uncertain stream of future payoffs, investors will demand higher rates of return. Accordingly, while the institutional fund market may be in informational equilibrium, deficiencies inherent in conventional risk-adjustment techniques prevent a precise estimation of selectivity ability. Alternatively, where the informativeness of the price system depends endogenously upon the number of individuals who are informed, equity markets may yet to have obtained their equilibrium degree of disequilibrium - *viz.*, where arbitrageurs make an equiproportionate (private) return from their (privately) costly activity.

We conjecture that the abnormal performance realised by institutional fund managers is a globally pervasive phenomenon.⁹¹ Certainly, this cannot be attributed to idiosyncratic market characteristics. Our analysis also lends credence to the results of Christopherson et al. (1998). This bears particular significance insofar as it illustrates the transferability of the findings to US markets. The anomalous performance of institutional participants also confirms the proposition that there are diminishing returns to isolated examinations of the mutual fund market. Moreover, it is *not* possible from the confines of any particular sphere to make inferences with respect to the informational efficiency of the equity market in aggregate. This calls into question the many published studies which have declared that the semi-strong form of the martingale hypothesis holds in lieu of the systematic inability of mutual fund managers to effectively exploit security price inefficiencies (see, for instance, Jensen, (1968) and Malkiel (1995) among others).

In the institutional sphere, a final consequence of our analysis concerns the ability to define the ‘optimal’ consumption-allocation decision of the rational, risk-averse institutional agent. We propose that institutional investors, when faced with a choice under conditions of uncertainty, maximise their utility by

selecting a combination of active investment strategies. In this market, we conclude in a vein not dissimilar to Grossman (1995), that the suboptimality of passive investment strategies holds, *a fortiori*.

What explains such generic comparative advantages amongst active portfolio managers? More specifically, what motivates the disparities in institutional and mutual fund performance? Our central conjecture is that ‘heterogeneous investor clienteles’ exert a deterministic influence on the abnormal performance realised by active participants. Thus, *ex ante* differentials in institutional and mutual fund risk-return dynamics arise endogenously as a function of the sophistication of the contemporaneous investor clientele; viz., investor sophistication acts as the ‘discount rate’ of performance. The magnitude and discrete nature of pension fund flows may be such that they enable a sophisticated institutional clientele to exercise influence over the trajectory of future fund performance. This complex performance-flow relation would appear to present an implicit contract that *precludes* persistently poor performance. On the other hand, the small and stable nature of mutual fund flows, the absence of asset consultancy’s enforcing sophisticated performance-evaluation, and the relative naivete of individual agents ensure that the costs implicit in sub-optimal performance are of second order. And thus the striking contrast in the efficacy of institutional and mutual fund selectivity strategies is in part attributable to (or perhaps, functionally dependent upon) the heterogeneous information sets of their contemporaneous clienteles.⁹²

Our analysis of the efficacy of active investment strategies in both the institutional and mutual fund spheres also delivered other findings of note. These are described as follows.

- (i) Institutional capital-flows exert a considerable influence on the risk-adjusted returns of small active participants. This ‘flow-shock effect’ is most evident when we regress the future [0,+12] month four-factor alpha on the lagged [-12,0] month capital-flow. The evidence substantiates, therefore, the proposition that the incidence of large investor flows adversely impact upon managerial behaviour. Where ‘star managers’ hold small portfolios with respect to assets under management, significant capital inflows impede their ability to effectively exploit price inefficiencies. Specifically, the sudden growth in assets propagates non-trivial amounts of uninformed liquidity-motivated trading and/or market impact costs that materially detract from future fund performance.
- (ii) Yet flow-induced managerial mean reversion is *not* a pervasive phenomenon in the mutual fund universe. In all estimations, the trading activities of the first hexile of mutual funds remains unperturbed by the individual investor’s capital-allocation decisions.
- (iii) Calibrating unconditional asset-pricing techniques to reflect the costs of providing liquidity alters inferences with respect to the institutional participant’s informational-assimilation ability.

However, consistent with prior analysis, flow-induced liquidity-motivated trade is not manifest in the mutual fund universe.

- (iv) Hence, the indirect cost of liquidity in performance-evaluation studies, i.e., the inverse relation between a fund's market beta and net capital-flows, is a function of the magnitude of the flow-shock. In the *absence* of such, one does not anticipate an increase in estimated conditional alpha coefficients. Rather, conditional models simply serve to accommodate time-varying expectations. Accordingly, they preclude ascribing abnormal investment ability to public-information based trading strategies and elevate the accuracy of performance-evaluation studies. The deterioration in mutual fund performance evidenced under the conditional one-factor model is logically consistent with a market characterised by continuous, incremental capital-flows that fail to perturb the trading activities of management. That is, the incidence of new capital-flows does not force a departure from the target efficient portfolio and an inverse relation between systematic risk and expected market returns is not manifest.
- (v) In contrast, conditional alphas provide the most optimistic interpretation of the selectivity abilities of active institutional participants. This finding accords with the proposition that the incidence of capital-flows has a relatively greater impact on the investment activities of institutional participants. Large, discrete flow-shocks propagate significant fluctuations in the cash positions of institutional funds and cause deviations from the target efficient portfolio. In turn, investors are compelled to engage in material amounts of uninformed liquidity-motivated trading, which induces an inverse relation between systematic risk levels and future market risk premia. Where conditional benchmarks control for the relation between aggregate fund flows and time varying expected returns (i.e., where they account for a fund's flow-induced tracking trading activity) they yield superior inferences with respect to the efficacy of active investment strategies. These results resolve the ambiguity manifest with respect to the anticipated influence of conditional methods on estimates of abnormal performance.
- (vi) In an analysis of the portfolio holdings of each universe, we find that institutional participants limit themselves to the larger and more liquid securities included in the market proxy. Consequently, there are not great disparities between the one and four-factor estimations of abnormal performance. On the other hand, mutual funds have significantly greater exposures to volatile non-market proxy small 'cap' securities and an appetite for loadings of non-systematic risk. Hence, single-index benchmarks (insofar as they fail to capture the multifarious investment styles that characterise the mutual fund sphere) provide spurious estimates of abnormal performance.

- (vii) We verify the concentrated nature of returns realised by institutional participants. While in the pension fund universe there is a remarkably narrow 25% range in the distribution of unconditional four-factor alphas, the mutual fund sphere is characterised by extreme variability in the cross-sectional distribution of returns. Evidently, there exist incentives for institutional participants to optimise their asset allocations - and by construction, tracking error (i.e., diversifiable risk) - relative to their peer group and/or a static benchmark. Conversely, mutual funds appear predisposed to taking non-trivial risks.
- (viii) We conjecture that specific ‘investor characteristics’, peculiar to the sphere under study, have a deterministic influence on cross-sectional disparities in the equity holdings of institutional and mutual fund participants and, by implication, their return generating process. For instance, the inelastic demand of consumers with respect to poor performance, and the individual investor’s propensity to ‘ride losers’ results in a phenomenon whereby extended periods of sub-optimal performance go relatively unpunished. Such ‘asymmetric’ performance-flow relations create incentive structures that have call option-like payoffs. In turn, this non-linear pay-off function engenders ‘risk-shifting’ behaviour amongst poorly performing mutual funds; that is, loads of idiosyncratic risk may be taken on in expectation of maximising future payoffs. The propensity of mutual fund managers to manipulate portfolio risk has significant consequences for analyses of portfolio composition. Specifically, active mutual fund participants may adopt considerably higher levels of non-systematic risk and materially depart from the characteristic line. Relative to that documented in the institutional sphere, this behaviour is manifest in: (i) a decline in portfolio diversification (systematic risk) and a preference for non-market proxy assets with high idiosyncratic volatility; (ii) the reduced explanatory power of the performance-evaluation techniques; and (iii) cross-sectional disparities in the one and multi-factor point estimates. On the other hand, the size and sophistication of institutional capital-flows presents an implicit contract that greatly diminishes the incentive for active participants to take non-trivial risks. While superior selectivity ability may result in significant ex post performance, it also elevates the probability of ‘relative’ underperformance. Hence, in contrast to the mutual fund sphere institutional investment vehicles seem to have ex post incentives to reduce idiosyncratic risk and thus increase diversification.
- (ix) We find little evidence of the oft touted ‘perverse’ market-timing ability. Indeed, active institutional and mutual fund participants have been able to successfully forecast future market risk premia, albeit not in a statistically robust fashion. These findings, robust to any known survival, selection or

methodological related biases, contradict the extensive empirical literature which supports the notion that active mutual fund managers have exceptionally poor, viz., perverse, market-timing abilities. Our results also differ to the one existing paper that evaluates the macro-forecasting abilities of institutional participants (Coggin et al. (1993)). This is significant because (i) prior ‘conditional’ market-timing evidence has been subjected to attrition induced biases and (ii) the extant literature pertaining to conditional methods has been restricted to the mutual fund universe.

- (x) Further, we argue that the literature to date has placed too much emphasis on macro-forecasting pursuits, with the evidence indicating that timing strategies have at best a marginal impact on total portfolio performance.
- (xi) In contrast to Cai, Chan and Yamada (1997) and Bollen and Busse (1999) we are able to confirm Ferson and Schadt’s (1996) finding that modifying the Treynor and Mazuy (1966) approach to condition on public-information mitigates what little perceived ‘perverse’ macro-forecasting ability exists. This result is important considering the recent ambiguity with respect to the influence of conditional methods.

Finally, in reflecting upon our analysis of the efficacy of passive investment strategies we close by stating three important points.

- (i) First, passive participants have exceptional replication abilities, delivering investors both the risks and returns of the market portfolio. This is despite the costs they incur when mimicking the compositional changes of a target index oblivious to the constraints they face.
- (ii) However, there are disparities in the cost structures associated with servicing each investor clientele. As at September 1999, the mean passive institutional fund MER was just 0.10% per annum. Thus ex post, investments in index funds still provide institutional agents with risk-adjusted performance commensurate with that of the market proxy. On the other hand, the mean passive mutual fund MER is 0.75% per annum. It is incorrect to assume therefore that individual investors can necessarily access the returns delivered by the market portfolio.
- (iii) And while institutional investors have a preference for active investment strategies, the individual agent’s steady-state preferences are indeterminate.

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Table I
Summary Statistics
Active Institutional and Mutual Fund Populations

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the active institutional and mutual fund populations, from January 1st 1988 to December 31st 1998. Excess returns are calculated relative to the market proxy, the All Ordinaries Accumulation Index. The time-weighted average return series assigns a weight to each fund's product based on the number of periods it was alive. The information ratio is defined as the excess return series divided by the tracking error. The information ratio is a measure of the manager's ability to convert risk into return. Thus, it is a measure of the efficiency of a manager. The skewness² statistic measures the symmetry of the distribution of excess returns. Positive skewness results if a distribution is skewed to the right, since average cubed discrepancies about the mean are positive. Skewness will be negative for distributions skewed to the left and close to zero for distributions, such as the normal, which are symmetric about their mean. Kurtosis is a measure of the weight in the tails of a probability density function. The higher the kurtosis, the more compact the distribution - or the more concentrated the excess returns are about the mean excess return. The institutional fund return series is reported pre-fees, whereas the mutual fund return series is reported post-fees. The average annualised (monthly) absolute capital-flow per fund, reported in \$m, is estimated according to: $CF_{it}^A = NAV_{it} - [NAV_{it-1} * (1 + r_{it})]$; where the absolute flow of fund i in month t, CF_{it}^A , is assumed to occur at the end the period. NAV_{it} denotes the net asset value of fund i in month t. CF_{it}^A is adjusted to remove the influence of fund i's investment returns, r_{it} , in month t.

Summary Statistics	Mutual Fund Population	Institutional Fund Population
Average Annualised Excess Return (% pa)	-2.487	2.511
Median Annualised Excess Return (% pa)	-2.057	1.967
Information Ratio (% pa)	-0.062	0.109
Time-Weighted Average Annualised Excess Return (% pa)	-1.846	1.869
Average Kurtosis (% pa)	2.157	3.174
Average Skewness (% pa)	-0.005	0.128
Average Fund Age (months)	74	75
Total Observations	14729	9555
Total No. Funds	198	121
Total No. Nonsurviving Funds	83	19
Attrition Rate (%)	42	16
Average Fund Size (\$m)	116	492
Average Annual Flow (\$m)	3.26	59.52
Mean MER (% pa)	2.12	0.84

²Henceforth, where:

$$Skewness = \frac{\sum_{i=1}^n (x_i - \bar{x})^3 / n}{s^3} \quad \text{and} \quad Kurtosis = \frac{\sum_{i=1}^n (x_i - \bar{x})^4 / n}{s^4}$$

Table II
Performance
Selectivity Estimates Applying the Unconditional CAPM, the Conditional CAPM, and the Unconditional Four-Factor Model
Active Mutual Fund Population

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of mutual funds, from January 1st 1988 to December 31st 1998. The coefficients α^{1uc} , α^{1c} , and α^{4uc} are, respectively, the unconditional one-factor alpha, conditional one-factor alpha, and the unconditional four-factor alpha intercepts deriving from the following time-series regressions:

$$\begin{aligned}
 \text{(i) Unconditional CAPM} & \quad r_{pt} - r_{ft} = \alpha_p^{1uc} + \beta_p(r_{mt} - r_{ft}) + e_{pt} \\
 \text{(ii) Conditional CAPM} & \quad r_{pt} - r_{ft} = \alpha_p^{1c} + \beta_p(r_{mt} - r_{ft}) + d_{pTB}(r_{mt} - r_{ft}, TB_{t-1}) + d_{pDY}(r_{mt} - r_{ft}, DY_{t-1}) + d_{pTS}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt} \\
 \text{(iii) Unconditional Four-Factor Attribution Model} & \quad r_{pt} - r_{ft} = \alpha_p^{4uc} + \beta_p(r_{mt} - r_{ft}) + \beta_{lsp}(r_{lt} - r_{st}) + \beta_{vgp}(r_{vt} - r_{gt}) + \beta_{dp}(r_{dt} - r_{ft}) + e_{pt}
 \end{aligned}$$

where $r_{pt} - r_{ft}$ is the excess return of a fund (relative to the 30-day treasury bill yield) and $r_{mt} - r_{ft}$ is the excess return on the All Ordinaries Accumulation Index; (ii) where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute lagged vectors of public-information proxies available at $t-1$ for predicting future market risk premia, viz., TB_{t-1} is the 30-day treasury bill yield; DY_{t-1} is the dividend yield on the All Ordinaries Accumulation Index, TS_{t-1} is the term structure (treasury yield spread) reflecting the relationship between the interest rate and the term to maturity for securities of similar risk (long-term less short-term bonds); and (iii) where $r_{lt} - r_{st}$ is the differential return between a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index), $r_{vt} - r_{gt}$ is the differential return between growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index), and $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index). The mutual fund return series is calculated on a post-fees basis. The time-weighted average α 's assign a weight to each product according to the number of periods for which it was alive. ARsq is the adjusted correlation coefficient. White's (1980) heteroskedastic consistent t-ratios are reported in parentheses. The number of positive (negative) and statistically significant (say) alphas, at the 5% level, are depicted as, Sig $\alpha > 0$ (Sig $\alpha < 0$). The non-parametric Wilcoxon Matched Pairs test (WMPT) and the standard Student's- t-test statistically distinguish between conditional and unconditional alphas. The null is that the population distribution of the paired differences is symmetric and hence the center of the distribution is zero.

Performance-evaluation Model	Time-Weighted α	Average α	β_p	δ_{TBp}	δ_{DYp}	δ_{TSp}	β_{lsp}	β_{vgp}	β_{dp}	ARSq	F-Value	Mean Age (months)	Monthly Obs	WMPT (t-test)
CAPM ^{UC}	-1.398	-2.392 (-4.379)	0.698 (-13.476)							0.514	92	74	14719	
CAPM ^C	-2.008	-2.786 (-4.417)	1.094 (0.242)	-0.703 (-0.809)	0.011 (0.222)	-0.068 (-3.206)				0.528	39	74	14719	(0.000)*
Attribution Model ^{4F UC}	-0.091	-0.252 (-0.457)	0.751 (-10.353)				-0.263 (-8.617)	-0.025 (-1.028)	2.055 (2.123)	0.553	43	74	14719	
Frequency Analysis of Parameter Estimates	Sig $\alpha > 0$ (Total $\alpha > 0$)	Sig $\alpha < 0$ (Total $\alpha < 0$)	Sig $\delta_{TBp} > 0$	Sig $\delta_{TBp} < 0$	Sig $\delta_{DYp} > 0$	Sig $\delta_{DYp} < 0$	Sig $\delta_{TSp} > 0$	Sig $\delta_{TSp} < 0$	Sig $\beta_{lsp} > 0$	Sig $\beta_{lsp} < 0$	Sig $\beta_{vgp} > 0$	Sig $\beta_{vgp} < 0$	Sig $\beta_{dp} > 0$	Sig $\beta_{dp} < 0$
CAPM ^{UC}	16 (82)	32 (116)												
CAPM ^C	19 (78)	32 (120)	16	42	26	18	15	46						
Attribution Model ^{4F UC}	26 (110)	20 (88)							10	88	10	20	7	77

where $H_0: \alpha = 0$, $H_1: \alpha > 0$, $H_0: \beta_p = 1$, $H_1: \beta_p < 1$, and $H_0: \beta_b d_i = 0$, $H_1: \beta_b d_i > 0$

* p-values are for a two-tailed test

Table III
Performance
Selectivity Estimates Applying the Unconditional CAPM, the Conditional CAPM, and the Unconditional Four-Factor Model
Active Institutional Fund Population

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of institutional funds, from January 1st 1988 to December 31st 1998. The coefficients α^{1uc} , α^{1c} , and α^{4uc} are, respectively, the unconditional one-factor alpha, conditional one-factor alpha, and the unconditional four-factor alpha intercepts deriving from the following time-series regressions:

(i) Unconditional CAPM $r_{pt} - r_{ft} = a_p^{1uc} + b_p(r_{mt} - r_{ft}) + e_{pt}$
(ii) Conditional CAPM $r_{pt} - r_{ft} = a_p^{1c} + b_p(r_{mt} - r_{ft}) + d_{pTB}(r_{mt} - r_{ft}, TB_{t-1}) + d_{pDY}(r_{mt} - r_{ft}, DY_{t-1}) + d_{pTS}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}$
(iii) Unconditional Four-Factor Attribution Model $r_{pt} - r_{ft} = a_p^{4uc} + b_p(r_{mt} - r_{ft}) + b_{lsp}(r_{lt} - r_{st}) + b_{vgp}(r_{vt} - r_{gt}) + b_{dip}(r_{dt} - r_{ft}) + e_{pt}$

where $r_{pt} - r_{ft}$ is the excess return of a fund (relative to the 30-day treasury bill yield) and $r_{mt} - r_{ft}$ is the excess return on the All Ordinaries Accumulation Index; (ii) where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute lagged vectors of public-information proxies available at $t-1$ for predicting future market risk premia, viz., TB_{t-1} is the 30-day treasury bill yield; DY_{t-1} is the dividend yield on the All Ordinaries Accumulation Index, TS_{t-1} is the term structure (treasury yield spread) reflecting the relationship between the interest rate and the term to maturity for securities of similar risk (long less short-term bonds); and (iii) where $r_{lt} - r_{st}$ is the differential return between a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index), $r_{vt} - r_{gt}$ is the differential return between growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index), and $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index). The institutional fund return series is calculated on a pre-fees basis. The time-weighted average α 's assign a weight to each product according to the number of periods for which it was alive. ARsq is the adjusted correlation coefficient. White's (1980) heteroskedastic consistent t-ratios are reported in parentheses. The number of positive (negative) and statistically significant (say) alphas, at the 5% level, are depicted as, Sig $\alpha > 0$ (Sig $\alpha < 0$). The non-parametric Wilcoxon Matched Pairs test (WMPT) and the standard Student's- t-test statistically distinguish between conditional and unconditional alphas. Under the null the population distribution of the paired differences is symmetric and the center of the distribution is zero.

Performance-evaluation Model	Time-Weighted α	Average α	β_p	δ_{TBp}	δ_{DYp}	δ_{TSp}	β_{lsp}	β_{vgp}	β_{dip}	ARsq	F-Value	Mean Age (months)	Monthly Obs	WMPT (t-test)
CAPM ^{UC}	2.101	2.244 (8.393)	0.948 (-6.125)							0.859	722	79	9539	0.045*
CAPM ^C	2.161	2.634 (8.075)	1.669 (3.777)	-0.125 (-0.392)	-0.165 (-4.455)	-0.041 (-3.898)				0.865	300	79	9539	(0.019)*
Attribution Model ^{4FUC}	2.220	2.370 (7.325)	0.964 (-5.174)				-0.125 (-4.681)	-0.013 (-1.187)	0.656 (1.281)	0.890	325	79	9539	
Frequency Analysis of Parameter Estimates	Sig $\alpha > 0$ (Total $\alpha > 0$)	Sig $\alpha < 0$ (Total $\alpha < 0$)	Sig $\delta_{TBp} > 0$	Sig $\delta_{TBp} < 0$	Sig $\delta_{DYp} > 0$	Sig $\delta_{DYp} < 0$	Sig $\delta_{TSp} > 0$	Sig $\delta_{TSp} < 0$	Sig $\beta_{lsp} > 0$	Sig $\beta_{lsp} < 0$	Sig $\beta_{vgp} > 0$	Sig $\beta_{vgp} < 0$	Sig $\beta_{dip} > 0$	Sig $\beta_{dip} < 0$
CAPM ^{UC}	44 (101)	0 (17)												
CAPM ^C	47 (106)	0 (15)	14	14	8	25	8	18						
Attribution Model ^{4FUC}	41 (95)	2 (25)							23	39	9	17	13	6

where $H_0: a = 0, H_1: a \neq 0, H_0: b_p = 1, H_1: b_p \neq 1$, and $H_0: b_b, d_i = 0, H_1: b_b, d_i \neq 0$

* p-values are for a two-tailed test

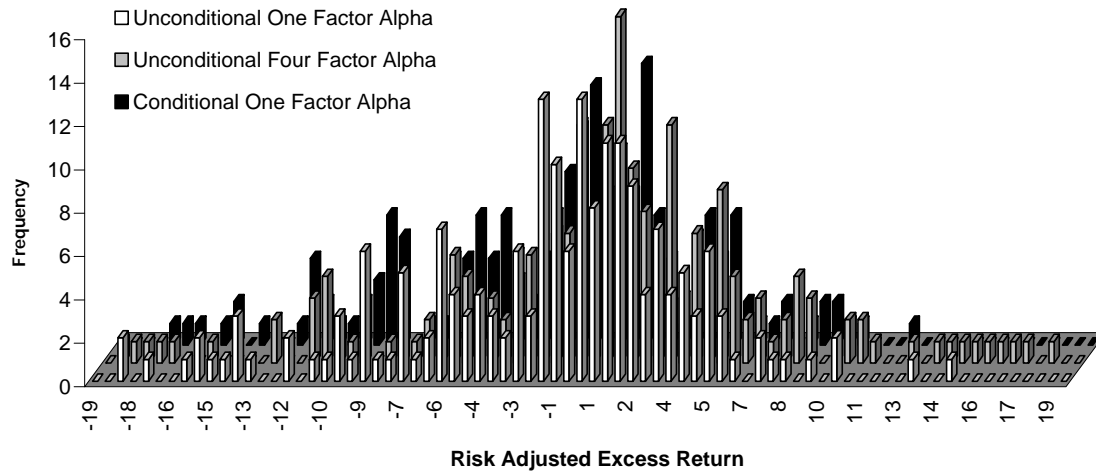


Figure 1. Frequency distribution of unconditional and conditional alphas. Mutual fund universe, 1988-98. Alpha estimates are net of fees. Beginning with the farthest distribution and progressing forward, alphas (i.e., the risk-adjusted excess returns) derive from the conditional one-factor, unconditional four-factor and unconditional one-factor performance-evaluation techniques. More precise descriptions are provided in the text.

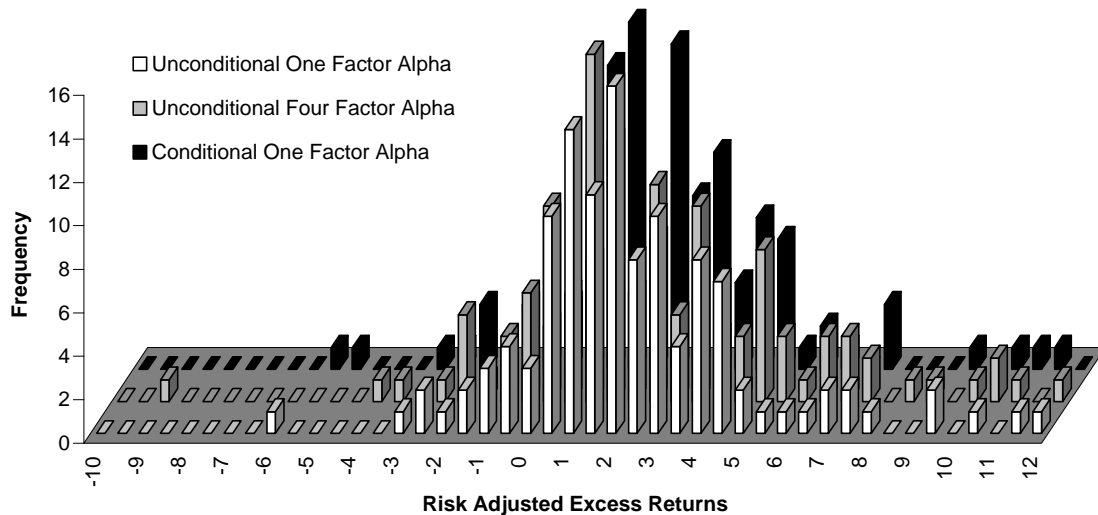


Figure 2. Frequency distribution of unconditional and conditional alphas. Institutional fund universe, 1988-98. Alpha estimates are gross of fees. Beginning with the farthest distribution and progressing forward, alphas (i.e., the risk-adjusted excess returns) derive from the conditional one-factor, unconditional four-factor and unconditional one-factor performance-evaluation techniques. More precise descriptions are provided in the text.

Table IV
Portfolio Analysis
Active Institutional and Mutual Fund Populations

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of institutional and mutual funds, during the 1988-1998 period. The value, growth, small 'cap' and large 'cap' coefficients derive from the following time-series regressions:

(i) Style Analysis $r_{pt} = b + b_G(r_{Gt}) + b_V(r_{Vt}) + u_{it}$
(ii) Size Exposure $r_{pt} = b + b_L(r_{Lt}) + b_S(r_{St}) + u_{it}$

where r_{pt} is the return of a fund; r_{Gt} is the return delivered by a growth portfolio (proxied by the ASX Russell All Growth Index); r_{Vt} is the return delivered by a value portfolio (proxied ASX Russell All Value Index); r_{Lt} is the return from a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index); and r_{St} is the return from a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index). The institutional (mutual) fund return series is calculated on a pre- (post) fees basis. ARsq is the adjusted correlation coefficient. White's (1980) heteroskedastic consistent t-ratios are reported in parentheses. The number of positive (negative) and statistically significant coefficients are depicted as Sig $b_i > 0$ (Sig $b_i < 0$).

Portfolio Analysis	b_G	b_V	b_S	b_L	ARsq (Style)	ARsq (Size)
Mutual Style and Size Analysis	0.373 (9.820)	0.240 (13.300)	0.356 (11.686)	0.405 (14.929)	0.395	0.547
Institutional Style and Size Analysis	0.476 (24.638)	0.416 (27.977)	0.139 (9.184)	0.840 (26.586)	0.785	0.920
No. Significant Coefficients	Sig $b_G > 0$	Sig $b_G < 0$	Sig $b_V > 0$	Sig $b_V < 0$		
Mutual Funds	82	0	97	2		
Institutional Funds	98	0	97	0		
No. Significant Coefficients	Sig $b_L > 0$	Sig $b_L < 0$	Sig $b_S > 0$	Sig $b_S < 0$		
Mutual Funds	121	4	97	2		
Institutional Funds	104	0	70	1		

where $H_0: b_i = 0, H_1: b_i \neq 0$

Table V
Comparative Summary Statistics
Active Institutional and Mutual Fund Populations

This table depicts annualised time-series summary flow statistics averaged across the active institutional and mutual fund populations, during the period January 1st 1988 to December 31st 1998. Average Fund Size is reported in millions of dollars and equates to the mean value of net assets under management averaged both cross-sectionally and through time on a monthly basis. Average Fund Size (1988-1998) denotes the mean net asset value for the sample period January 1st 1988 to December 31st 1998. Average Fund Size (December, 1998) denotes mean net assets at December 31st 1998. The Average Annual Absolute CF^{E(M)} per fund, reported in millions of dollars, is estimated according to: $CF_{it}^a = NAV_{it} - (NAV_{it-1}(1+r_{it}))$ ($CF_{it}^a = \frac{NAV_{it} - (NAV_{it-1}(1+r_{it}))}{(1+r_{it})^2}$); where the absolute flow of fund i in month t, CF_{it}^a , given the superscript E(M), is assumed to occur at the end (middle) of the month. NAV_{it} denotes the net asset value of fund i in month t. CF_{it}^a is adjusted to remove the influence of fund i's investment returns, r_{it} , in month t. The Average Annual Normalised CF^{E(M)} per fund, divides the absolute monthly flow by the net asset value of the fund and measures new flow as a proportional growth rate. It is estimated according to $CF_{it}^n = CF_{it}^a / NAV_{it-1}$, where the incidence of CF_{it}^a is assumed to occur at the end (middle) of the month and all other variables are as previously defined.

Summary Statistics	Mutual Fund Population	Institutional Fund Population
Average Fund Size (1988-1998)	47.54	272.47
Average Fund Size (December, 1998)	115.87	492.08
Average Annual Absolute CF ^E (\$m)	3.26	59.52
Average Annual Absolute CF ^M (\$m)	3.64	59.39
Average Annual Normalised CF ^E (%)	72.90	145.82
Average Annual Normalised CF ^M (%)	73.96	144.91

Figure 3

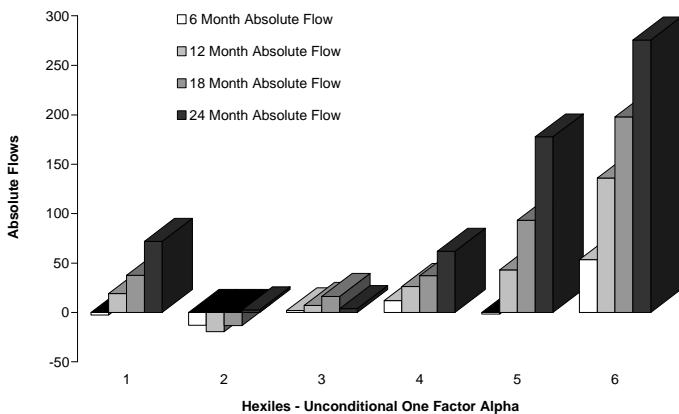
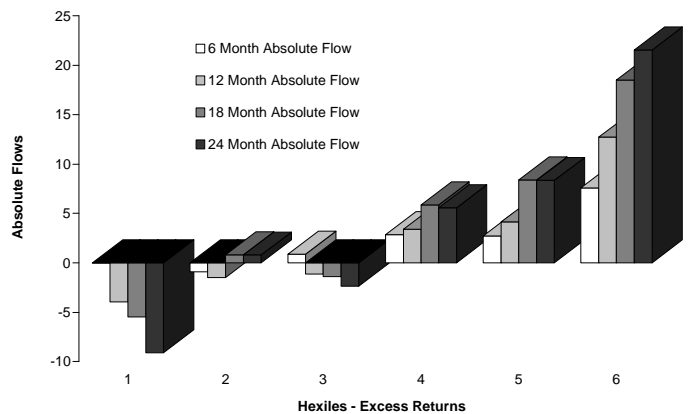


Figure 4



Figures 3 and 4. Absolute cash-flows occurring subsequent to forming hexiles based on the past 36 month unconditional one-factor alpha. Institutional (i.e., Figure 3) and mutual fund (i.e., Figure 4) universes respectively, 1990-1998. We allocate funds into six equally-weighted portfolios (hexiles) on the basis of their past 36 month unconditional one-factor alpha and measure absolute net capital-flows to each hexile over an immediately subsequent period of 6, 12, 18, and 24 months. The hexiles are in ascending order of performance.

Table VI
Flow-induced Managerial Mean Reversion
Active Institutional Fund Population

Throughout the sample period, 1988-1998, we estimate cross-sectional regressions of the unconditional four-factor alpha against absolute capital-flows lagged 6, 12, and 18 months and, given some persistence in performance, a contemporaneously lagged four-factor. We conjecture that significant capital inflows will have a greater impact on smaller funds. Thus, each year the institutional fund population is dissected into size-based hexiles. In the first column, Div 1 (Div 6) illustrates specifications estimated on the smallest (largest) hexile of funds. The generic estimation is specified as,

$$a_t^4 = g_0 + \sum g_i CF_{t-i}^a + g_2 a_{t-i}^4 + n_t ,$$

where a_t^4 is the unconditional four-factor alpha estimated over the period t; $\sum CF_{t-i}^a$ is the lagged absolute flow computed in period t-i; and where a_{t-i}^4 is the contemporaneous lagged unconditional four-factor alpha estimated in period t-i. The first column, ‘Specific Estimation’, depicts the particular model employed. t-ratios associated with the parameter estimates are depicted in columns two to four (reported in parentheses). Given the potential for cross-sectional correlation amongst alphas and flows we use White’s (1980) heteroskedasticity-consistent variances and standard errors.

Specific Estimation	$\sum CF_{t-i}^a$	a_t^4	g_0
<i>Div 1</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(-1.73)*	(0.74)	(1.59)
<i>Div 2</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(-1.70)*	(0.32)	(1.73)*
<i>Div 3</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.95)*	(-1.38)	(-0.21)
<i>Div 4</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.07)	(-0.27)	(0.45)
<i>Div 5</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(0.05)	(0.73)	(1.55)
<i>Div 6</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.17)	(0.83)	(1.58)
<i>Div 1</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(-4.13)^^	(0.78)	(1.56)
<i>Div 2</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(0.82)	(0.32)	(1.63)
<i>Div 3</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.51)	(-1.11)	(0.20)
<i>Div 4</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.37)	(-0.17)	(0.13)
<i>Div 5</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(-0.06)	(0.73)	(1.60)
<i>Div 6</i> $a_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 a_{12}^4$	(1.76)*	(0.70)	(1.41)
<i>Div 1</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(-2.82)^^	(0.78)	(1.51)
<i>Div 2</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(0.58)	(0.34)	(1.59)
<i>Div 3</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(1.66)*	(-1.17)	(0.09)
<i>Div 4</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(2.38)^^	(-0.32)	(-0.30)
<i>Div 5</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(-1.22)	(0.86)	(1.96)*
<i>Div 6</i> $a_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 a_{12}^4$	(2.25)*	(0.63)	(1.27)

*Statistically significant at the 5% level ^ Statistically significant at the 1% level

Table VII
Flow-induced Managerial Mean Reversion
Active Mutual Fund Population

Throughout the sample period, 1988-1998, we estimate cross-sectional regressions of the unconditional four-factor alpha against absolute capital-flows lagged 6, 12, and 18 months and, given some persistence in performance, a contemporaneously lagged four-factor. We conjecture that significant capital inflows will have a greater impact on smaller funds. Thus, each year the mutual fund population is dissected into size-based hexiles. In the first column, Div 1 (Div 6) illustrates specifications estimated on the smallest (largest) hexile of funds. The generic estimation is specified as,

$$\alpha_t^4 = g_0 + \sum g_i CF_{t-i}^a + g_2 \alpha_{t-i}^4 + n_t,$$

where α_t^4 is the unconditional four-factor alpha estimated over the period t; $\sum CF_{t-i}^a$ is the lagged absolute flow computed in period t-i; and where α_{t-i}^4 is the contemporaneous lagged unconditional four-factor alpha estimated in period t-i. The first column, 'Specific Estimation', depicts the particular model employed. t-ratios associated with the parameter estimates are depicted in columns two to four (reported in parentheses). Given the potential for cross-sectional correlation amongst alphas and flows we use White's (1980) heteroskedasticity-consistent variances and standard errors.

Specific Estimation	$\sum CF_{t-i}^a$	α_t^4	g_0
<i>Div 1</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-0.63)	(0.34)	(2.74) [^]
<i>Div 2</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-4.52) [^]	(1.35)	(3.13) [^]
<i>Div 3</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-0.58)	(-0.16)	(1.08)
<i>Div 4</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(1.58)	(1.51)	(1.47)
<i>Div 5</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(1.69)*	(2.38) [^]	(3.82) [^]
<i>Div 6</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(1.51)	(1.81)	(-0.48)
<i>Div 1</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-0.44)	(0.28)	(2.87) [^]
<i>Div 2</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-1.38)	(1.23)	(3.00) [^]
<i>Div 3</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(-0.53)	(-0.20)	(1.15)
<i>Div 4</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(0.79)	(1.62)	(1.21)
<i>Div 5</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(1.91)*	(2.49) [^]	(3.81) [^]
<i>Div 6</i> $\alpha_{12}^4 = b_0 + b_1 CF_{12}^a + b_2 \alpha_{12}^4$	(2.65) [^]	(1.83)*	(-0.75)
<i>Div 1</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(-0.13)	(0.29)	(2.89) [^]
<i>Div 2</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(-0.78)	(1.15)	(3.29) [^]
<i>Div 3</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(0.13)	(-0.23)	(1.17)
<i>Div 4</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(1.13)	(1.66)*	(1.23)
<i>Div 5</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(1.74)*	(2.42) [^]	(3.91) [^]
<i>Div 6</i> $\alpha_{12}^4 = b_0 + b_1 CF_{18}^a + b_2 \alpha_{12}^4$	(1.84)*	(1.85)*	(-0.65)

*Statistically significant at the 5% level ^ Statistically significant at the 1% level

Table VIII
Performance
Market-timing Estimates Applying Treynor and Mazuy's (1966) Unconditional Quadratic CAPM and Treynor and Mazuy's (1966) Conditional Quadratic CAPM
Active Mutual Fund Population

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of mutual, from January 1st 1988 to December 31st 1998. The unconditional (conditional) market-timing coefficient is the coefficient on the squared excess market return deriving from the following time-series regressions:

(i) Treynor and Mazuy's (1966) Unconditional Quadratic CAPM $r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + e_{pt}$
(ii) Multi-Factor Unconditional Quadratic CAPM $r_{pt} - r_{ft} = a_p^{4uc} + b_p(r_{mt} - r_{ft}) + b_{isp}(r_{it} - r_{st}) + b_{vsgp}(r_{vt} - r_{gt}) + b_{ap}(r_{dt} - r_{ft}) + d_p(r_{mt} - r_{ft})^2 + e_{pt}$
(iii) Treynor and Mazuy's (1966) Conditional Quadratic CAPM $r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + d_{3p}(r_{mt} - r_{ft}, TB_{t-1}) + d_{4p}(r_{mt} - r_{ft}, DY_{t-1}) + d_{5p}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}$

where $r_{pt} - r_{ft}$ is the excess return of a fund (relative to the 30-day treasury bill yield); $r_{mt} - r_{ft}$ is the excess return on the All Ordinaries Accumulation Index; and where the coefficient, d_{2p} , measures a portfolio manager's unconditional market-timing ability; (ii) where $r_{it} - r_{st}$ is the differential return between a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index), $r_{vt} - r_{gt}$ is the differential return between growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index), $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index); and where d_p , measures a portfolio manager's unconditional multi-factor market-timing ability; and (iii) where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute lagged vectors of public-information proxies available at $t-1$ for predicting future market risk premia, viz., TB_{t-1} is the 30-day treasury bill yield; DY_{t-1} is the dividend yield on the All Ordinaries Accumulation Index, TS_{t-1} is the term structure (treasury yield spread) reflecting the relationship between the interest rate and the term to maturity for securities of similar risk (long less short-term bonds); and where the coefficient, d'_{5p} , measures a portfolio manager's conditional market-timing ability. The mutual fund return series is calculated on a post-fees basis. The time-weighted average α 's assign a weight to each product according to the number of periods for which it was alive. ARsq is the adjusted correlation coefficient. White's (1980) heteroskedastic consistent t-ratios are reported in parentheses. The number of positive (negative) and statistically significant (at the 5% level) coefficients are depicted as Sig $d_{2p} > 0$ (Sig $d_{2p} < 0$). The non-parametric Wilcoxon Matched Pairs test (WMPT) and the standard Student's- t-test statistically distinguish between conditional and unconditional alphas and market-timing coefficients. The null suggests that the population distribution of the paired differences is symmetric and hence that the center of the distribution is zero.

Performance-evaluation Model	Time-Weighted α	Average α	d_{1p}	d_{2p}	d_{3p}	d_{4p}	d_{5p}	ARsq	F-Value	Mean Age (months)	Monthly Obs	d_{2p} WMPT (t-test)	α WMPT (t-test)
TM Quadratic CAPM ^{UC}	-0.931	-2.499 (-3.501)	0.694 (-13.248)	-0.00016 (-0.102)				0.515	62	74	14719	0.000 (0.019)	0.000 (0.000)
Multi-Factor Quadratic CAPM ^{UC}	0.231	-0.463 (-0.650)	0.747 (-10.235)	0.00016 (0.098)				0.555	38	74	14719		
TM Quadratic CAPM ^C	-2.008	-3.371 (-4.721)	0.732 (-0.585)	0.00391 (1.335)	0.679 (0.522)	-0.065 (-0.573)	-0.046 (-1.901)	0.532	34	74	14719		
Frequency Analysis of Parameter Estimates	Sig $\alpha > 0$ (Total $\alpha > 0$)	Sig $\alpha < 0$ (Total $\alpha < 0$)	Sig $d_{2p} > 0$ (Total $d_{2p} > 0$)	Sig $d_{2p} < 0$ (Total $d_{2p} < 0$)	Sig $d_{3p} > 0$	Sig $d_{3p} < 0$	Sig $d_{4p} > 0$	Sig $d_{4p} < 0$	Sig $d_{5p} > 0$	Sig $d_{5p} < 0$			
TM Quadratic CAPM ^{UC}	23 (87)	19 (111)	10 (80)	15 (118)									
Multi-Factor Quadratic CAPM ^{UC}	25 (101)	19 (97)	11 (89)	20 (109)									
TM Quadratic CAPM ^C	17 (84)	22 (114)	19 (97)	13 (101)	11	39	25	17	3		37		

where $H_0: a = 0, H_1: a \neq 0, H_0: b_p = 1, H_1: b_p \neq 1$, and $H_0: b_b, d_i = 0, H_1: b_b, d_i \neq 0$

* p-values are for a two-tailed test

Table IX
Performance
Market-timing Estimates Applying Treynor and Mazuy's (1966) Unconditional Quadratic CAPM and Treynor and Mazuy's (1966) Conditional Quadratic CAPM
Active Institutional Fund Population

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of institutional funds, from January 1st 1988 to December 31st 1998. The unconditional (conditional) market-timing coefficient is the coefficient on the squared excess market return deriving from the following time-series regressions:

(i) Treynor and Mazuy's (1966) Unconditional Quadratic CAPM $r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + e_{pt}$
(ii) Multi-Factor Unconditional Quadratic CAPM $r_{pt} - r_{ft} = a_p^{4uc} + b_p(r_{mt} - r_{ft}) + b_{isp}(r_{it} - r_{st}) + b_{vsgp}(r_{vt} - r_{gt}) + b_{ap}(r_{dt} - r_{ft}) + d_p(r_{mt} - r_{ft})^2 + e_{pt}$
(iii) Treynor and Mazuy's (1966) Conditional Quadratic CAPM $r_{pt} - r_{ft} = a_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + d_{3p}(r_{mt} - r_{ft}, TB_{t-1}) + d_{4p}(r_{mt} - r_{ft}, DY_{t-1}) + d_{5p}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}$

where $r_{pt} - r_{ft}$ is the excess return of a fund (relative to the 30-day treasury bill yield); $r_{mt} - r_{ft}$ is the excess return on the All Ordinaries Accumulation Index; and where the coefficient, d_{2p} , measures a portfolio manager's unconditional market-timing ability; (ii) where $r_{it} - r_{st}$ is the differential return between a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index), $r_{vt} - r_{gt}$ is the differential return between growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index), $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index); and where d_p , measures a portfolio manager's unconditional multi-factor market-timing ability; and (iii) where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute lagged vectors of public-information proxies available at $t-1$ for predicting future market risk premia, viz., TB_{t-1} is the 30-day treasury bill yield; DY_{t-1} is the dividend yield on the All Ordinaries Accumulation Index, TS_{t-1} is the term structure (treasury yield spread) reflecting the relationship between the interest rate and the term to maturity for securities of similar risk (long less short-term bonds); and where the coefficient, d'_{5p} , measures a portfolio manager's conditional market-timing ability. The institutional fund return series is calculated on a pre-fees basis. The time-weighted average α 's assign a weight to each product according to the number of periods for which it was alive. ARsq is the adjusted correlation coefficient. White's (1980) heteroskedastic consistent t-ratios are reported in parentheses. The number of positive (negative) and statistically significant (at the 5% level) coefficients are depicted as Sig $d_{2p} > 0$ (Sig $d_{2p} < 0$). The non-parametric Wilcoxon Matched Pairs test (WMPT) and the standard Student's- t-test statistically distinguish between conditional and unconditional alphas and market-timing coefficients. The null suggests that the population distribution of the paired differences is symmetric and hence that the center of the distribution is zero.

Performance-evaluation Model	Time-Weighted α	Average α	d_p	d_{2p}	d_{3p}	d_{4p}	d_{5p}	ARsq	F-Value	Mean Age (months)	Monthly Obs	d_{2p} WMPT (t-test)	α WMPT (t-test)
TM Quadratic CAPM ^{UC}	2.869	3.075 (8.154)	0.940 (-6.388)	-0.00422 (-3.354)				0.861	488	78.8	9539	0.000* (0.000)*	0.041* (0.004)*
Multi-Factor Quadratic CAPM ^{UC}	2.792	2.782 (6.774)	0.975 (-1.698)	0.00270 (0.689)				0.877	261	78.8	9539		
TM Quadratic CAPM ^C	2.553	2.817 (7.601)	1.566 (2.988)	0.00106 (0.589)	0.941 (2.407)	-0.258 (-3.653)	-0.039 (-3.329)	0.865	254	78.8	9539		
Frequency Analysis of Parameter Estimates	Sig $\alpha > 0$ (Total $\alpha > 0$)	Sig $\alpha < 0$ (Total $\alpha < 0$)	Sig $\delta_{2p} > 0$ (Total $\delta_{2p} > 0$)	Sig $\delta_{2p} < 0$ (Total $\delta_{2p} < 0$)	Sig $\delta_{3p} > 0$	Sig $\delta_{3p} < 0$	Sig $\delta_{4p} > 0$	Sig $\delta_{4p} < 0$	Sig $\delta_{5p} > 0$	Sig $\delta_{5p} < 0$			
TM Quadratic CAPM ^{UC}	47 (109)	0 (12)	7 (41)	17 (80)									
Multi-Factor Quadratic CAPM ^{UC}	45 (98)	4 (23)	12 (49)	14 (72)									
TM Quadratic CAPM ^C	40 (106)	0 (15)	11 (61)	14 (60)	17	12	6	24	10	18			

Table X
Benchmark Inefficiency and Passive Investment Strategies
Passive Institutional Fund Population

This table depicts annualised monthly time-series statistics averaged cross-sectionally across the population of passive funds from January 1st 1988 to December 31st 1998. The following time-series estimations were conducted in order to verify the mean-variance efficiency of the benchmarks employed and to facilitate quantification of the risk-adjusted returns realised by passive participants:

(i)	Unconditional CAPM	$r_{pt} - r_{ft} = \alpha_p^{1uc} + \beta_p(r_{mt} - r_{ft}) + e_{pt}$
(ii)	Conditional CAPM	$r_{pt} - r_{ft} = \alpha_p^{1c} + \beta_p(r_{mt} - r_{ft}) + d_{pTB}(r_{mt} - r_{ft}, TB_{t-1}) + d_{pDY}(r_{mt} - r_{ft}, DY_{t-1}) + d_{pTS}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}$
(iii)	Unconditional Four-Factor Attribution Model	$r_{pt} - r_{ft} = \alpha_p^{4uc} + \beta_p(r_{mt} - r_{ft}) + \beta_{lsp}(r_{lt} - r_{st}) + \beta_{vgp}(r_{vt} - r_{gt}) + \beta_{dp}(r_{dt} - r_{ft}) + e_{pt}$
(iv)	Treynor and Mazuy's (1966) Unconditional Quadratic CAPM	$r_{pt} - r_{ft} = \alpha_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + e_{pt}$
(v)	Multi-Factor Unconditional Quadratic CAPM	$r_{pt} - r_{ft} = \alpha_p^{4uc} + \beta_p(r_{mt} - r_{ft}) + \beta_{lsp}(r_{lt} - r_{st}) + \beta_{vgp}(r_{vt} - r_{gt}) + \beta_{dp}(r_{dt} - r_{ft}) + d_p(r_{mt} - r_{ft})^2 + e_{pt}$
(vi)	Treynor and Mazuy's (1966) Conditional Quadratic CAPM	$r_{pt} - r_{ft} = \alpha_p + d_{1p}(r_{mt} - r_{ft}) + d_{2p}(r_{mt} - r_{ft})^2 + d_{3p}(r_{mt} - r_{ft}, TB_{t-1}) + d_{4p}(r_{mt} - r_{ft}, DY_{t-1}) + d_{5p}(r_{mt} - r_{ft}, TS_{t-1}) + e_{pt}$

where $r_{pt} - r_{ft}$ is the excess return of a fund (relative to the 30-day treasury bill yield) and $r_{mt} - r_{ft}$ is the excess return on the All Ordinaries Accumulation Index; (ii), (v) where $(r_{mt} - r_{ft}, TB_{t-1})$, $(r_{mt} - r_{ft}, DY_{t-1})$, and $(r_{mt} - r_{ft}, TS_{t-1})$ constitute lagged vectors of public-information proxies available at $t-1$ for predicting future market risk premia, viz., TB_{t-1} is the 30-day treasury bill yield; DY_{t-1} is the dividend yield on the All Ordinaries Accumulation Index, TS_{t-1} is the term structure (treasury yield spread) reflecting the relationship between the interest rate and the term to maturity for securities of similar risk (long less short-term bonds); and (iii) and (vi) where $r_{lt} - r_{st}$ is the differential return between a large 'cap' portfolio (proxied by the ASX 100 Leaders Accumulation Index) and a small 'cap' portfolio (proxied by the ASX Small Ordinaries Accumulation Index), $r_{vt} - r_{gt}$ is the differential return between growth and value portfolios (proxied by the ASX Russell All Growth Index and the ASX Russell All Value Index), and $r_{dt} - r_{ft}$ is the excess return on a bond index (proxied by the SBC Composite Bond Index). The passive fund return series is calculated on a pre-fees basis. ARsq is the adjusted correlation coefficient. t-ratios are reported in parentheses.

Performance-evaluation Model	Time-Weighted α	Average α	β_p / d_{1p}	d_{2p}	δ_{TBP} / d_{3p}	δ_{DVP} / d_{4p}	δ_{TSP} / d_{5p}	β_{lsp}	β_{vgp}	β_{dp}	ARsq	F-Value	Mean Age (months)	Monthly Obs
CAPM ^{UC}	0.070	0.106 (0.801)	0.999 (-0.326)								0.998	22031	59.3	593
CAPM ^C	0.0024	0.047 (0.280)	0.856 (-2.419)		0.070 (0.366)	0.029 (2.375)	0.008 (1.917)				0.998	9225	59.3	593
Attribution Model ^{4F UC}	-0.054	0.015 (0.060)	0.998 (-0.751)					0.020 (2.050)	0.008 (0.782)	0.019 (0.026)	0.998	9442	59.3	593
TM Quadratic CAPM ^{UC}	-0.069	-0.012 (0.099)	1.000 (0.065)	0.00026 (2.037)							0.998	14666	59.3	593
Multi-Factor Quadratic CAPM ^{UC}	-0.112	-0.014 (-0.066)	0.998 (-0.622)	0.00019 (0.606)				0.020 (1.984)	0.008 (0.824)	0.032 (0.044)	0.998	9131	59.3	593
TM Quadratic CAPM ^C	-0.057	0.018 (0.099)	0.895 (-1.027)	0.00026 (0.282)	0.030 (-0.322)	0.023 (0.476)	0.006 (0.811)				0.998	7504	59.3	593

where $H_0: \alpha = 0$, $H_1: \alpha \neq 0$, $H_0: \beta_p = 1$, $H_1: \beta_p \neq 1$, and $H_0: \beta_p, d_1, d_2, d_3, d_4, d_5 = 0$, $H_1: \beta_p, d_1 \neq 0$

*White's (1980) heteroskedastic consistent t-ratios

Appendix I

Table XI

Joint Cross-Sectional Regressions: The Individual and Institutional Performance-Flow Relation Active Institutional and Mutual Fund Populations

To discern statistical differentials in the nature of investor flows and the salience of particular evaluation techniques with respect to the preferences of individual and institutional investors, we also include a mutual fund dummy variable, DMF_t . The dummy is interacted with the various performance metrics, $(DMF_t, \sum_{k=1}^k d_{t-i}^k)$, and takes the value of one for funds that reside in the mutual fund sphere and zero otherwise (i.e., for institutional funds). Thus, throughout the sample period, 1988-1998, we jointly estimate the following (generic) cross-sectional regression on both the institutional and mutual fund populations,

$$CF_t^{n/a} = b_0 + \sum_{k=1}^k b_{kt} d_{t-i}^k + b_2 DMF_t + b_3 (DMF_t, \sum_{k=1}^k d_{t-i}^k) + e_t,$$

where CF_t^a denotes the absolute net flow in period t, assumed to occur in the middle of the month; δ_{t-i}^k is the performance proxy k, estimated over the monthly period t-i, and β_{kt} is the dependent variable's sensitivity to performance proxy k. The first column, 'Specific Estimation', depicts the particular model employed, where the performance proxy is defined as the unconditional four-factor alpha, α_t^4 , estimated during period t, the unconditional one-factor alpha, α_t^1 , excess returns relative to the risk-free rate, $(R_t - R_{ft})$, and excess returns relative to the market proxy, $(R_t - R_{mt})$. ARsq denotes the adjusted correlation coefficient. The parameter estimates are depicted in columns two to five. Given the potential for cross-sectional correlation amongst alphas and flows we use White's (1980) heteroskedasticity-consistent variances and standard errors. t-ratios are reported in parentheses.

Specific Estimation	Performance Proxy (δ_{t-i}^k)	($DMF_t, \sum_{k=1}^k d_{t-i}^k$)	b_0	Total No. Obs	F-Value	ARsq
$CF_{12}^a = b_0 + b_1 \alpha_{12}^4 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	8.959 (5.20)^	-8.837 (-5.13)^	1.855 (2.58)^	2140	47.830	0.069
$CF_{12}^a = b_0 + b_1 \alpha_{24}^4 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	24.197 (4.40)^	-23.897 (-4.35)^	-0.677 (-0.60)	866	36.570	0.135
$CF_{12}^a = b_0 + b_1 \alpha_{36}^4 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	28.708 (3.61)^	-28.208 (-3.55)^	-2.254 (-1.73)*	758	25.967	0.115
$CF_{12}^a = b_0 + b_1 (Ri-Rm)_{12} + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	16.673 (7.26)^	-16.403 (-7.14)^	0.920 (1.33)	2140	87.841	0.129
$CF_{12}^a = b_0 + b_1 (Ri-Rm)_{24} + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	29.339 (5.26)^	-28.951 (-5.19)^	-0.187 (-0.17)	866	45.701	0.166
$CF_{12}^a = b_0 + b_1 (Ri-Rm)_{36} + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	27.320 (3.38)^	-26.860 (-3.32)^	-1.761 (-1.53)	758	26.486	0.117
$CF_{12}^a = b_0 + b_1 \alpha_{12}^1 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	15.79 (7.31)^	-15.50 (-7.18)^	0.75 (1.09)	2140	91.87	0.13
$CF_{12}^a = b_0 + b_1 \alpha_{24}^1 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	27.68 (4.92)^	-27.32 (-4.85)^	-0.18 (-0.16)	866	45.75	0.17
$CF_{12}^a = b_0 + b_1 \alpha_{36}^1 + b_2 RetailDummy + b_3 (PM*RD)$ t-ratio	27.16 (3.87)^	-26.72 (-3.80)^	-1.64 (-1.45)	758	28.95	0.13

*Statistically significant at the 5% level

^ Statistically significant at the 1% level

¹ We assume that a risk-averse agent, when faced with a choice under conditions of uncertainty, acts in a manner consistent with the expected utility maxim. That is, the portfolio problem at any time t becomes the selection of a combination of investments that yield maximum expected utility (where the Von Neuman-Morgenstern utility function is monotone increasing and strictly concave in c_t and r_t). In order to satisfy such conditions it is assumed that the investor's utility function meets the condition that $U' > 0$ and $U'' < 0$ and that asset and portfolio returns are normally distributed. For the purposes of parsimony, we discard more sophisticated specifications such as recursive utility functions or those which assert that investors are concerned with a short-period distribution of return as opposed to the distribution of wealth at the horizon (see, for instance, Epstein and Sin (1989) and Benartzi and Thaler (1995)).

² An 'institution' is defined by the NYSE as a firm that employs professionals to manage money for the benefit of others. Many institutions do not manage the portfolio themselves (i.e., in-house management), rather they contract with outside portfolio managers specialising in particular asset classes and/or style(s).

³ Pension assets have been in the forefront of strategic targeting by all types of financial institutions, including banks, trust companies, broker-dealers, insurance companies, and independent asset management firms (Walter (1998)). Assets allocated to pension funds in 1995 were estimated to amount to approximately \$US8.2 trillion, roughly two-thirds of which covered private-sector employees with the balance pertaining to public-sector employees. This pool, which grew at a rate of 11% per annum during 1990-1995, is forecast to grow at roughly 9% per annum and to reach \$12.5 trillion by 2000. At the end of 1994, Western European pension assets had an estimated value of about \$1.6 trillion, with the United Kingdom accounting for almost half the total and the Netherlands second-largest with a 17% share.

⁴ It is important to differentiate between institutional fund managers who have been allocated funds by pension plans sponsors and the pension plans themselves. Brinson, Hood and Beebower (1986), Ippolito and Turner (1987) and Berkowitz, Finney and Logue (1988) evaluate the performance of a sample of large US pension plans which consist of a multitude of institutional fund managers acting in various asset classes and characterised by disparate investment styles.

⁵ Despite the abundance of timing-related studies, Becker, Ferson, Myers and Schill claim that the '*conditional* timing ability of market-timing mutual funds remains largely unexplored' (1999: 119).

⁶ Total capital allocated with investment managers was distributed as follows: domestic equities \$142 billion (27% of the market), international equities \$79 billion (15%), domestic fixed interest \$110 billion (22%), international fixed interest \$18 billion (3%), property \$56 billion (11%) and cash \$72 billion (14%). Other asset classes amounted to \$48 billion, or around 8%.

⁷ Similar to their US and UK counterparts, Australian pension plan sponsors do not exert a distinct influence on the investment opportunity set and/or trading activities of fund managers.

⁸ For example, one of the more complete samples, Sirri and Tufano (1998), contains only 87% of total assets or 71% of the number of funds. Another recent study, by Del Grucio and Tkac (1999), consists of just 55% of the 1994 US equity mutual fund industry assets.

⁹ Across the varying asset classes, there are more than 3,500 individual funds included in the Assirt database. Hence, we employ the Assirt data when constructing estimates of abnormal performance.

¹⁰ The generic method of calculating raw performance is consistent with the Dietz (1966) formulation. Dietz altered the industry's perception of portfolio performance. His introduction of a practical approximation for the general concept of time-weighted returns helped us distinguish the performance of the investment manager from the impact of cash-flows. Accordingly, raw monthly 'total' returns are calculated gross of all operating expenses and ongoing fees - typically

approximated by the Management Expense Ratio. However, returns are not adjusted for entry or exit fees as these may vary amongst investors. Naturally, the use of monthly data involves the implicit assumption that individual and institutional investors assess risk and return on a monthly basis. In determining the total return of each product the consultancies assume reinvestment of all cash and bonus distributions so as to account for variations in the size and timing of distributions. This assumption allows the measurement of all returns generated by the product and preserves the time value of money. Such an approach is also the method approved by the Association for Investment Management and Research (AIMR) and is most indicative of the manager's contribution to the fund or investor.

¹¹ For instance, Chevalier and Ellison (1995) eliminate funds with less than \$20 million in assets. Elton, Gruber and Blake (1996b) impose a minimum \$15 million net asset value.

¹² Examples of studies which do impose such restrictions include Hendricks, Patel and Zeckhauser (1993), Malkiel (1995), and Blake and Morey (1999). Hendricks, Patel and Zeckhauser restrict their sample to no-load, growth funds. Malkiel excludes all specialised funds that do not hold diversified equity portfolios. Blake and Morey (1999) only include 'growth' equity funds.

¹³ As at December 1998, our institutional population consisted of approximately \$38 billion dollars worth of assets under management. Yet by published accounts, the size of this asset class was around \$37 billion.

¹⁴ The Australian and US pension fund markets are quite similar in terms of industry concentration; both are characterised by a fairly decentralised distribution of assets. For example, domestically, the mean market-share of a top 25 fund complex is 3.25% which compares well with Lakonishok, Shleifer and Vishny's (1992) estimates. In contrast, the top five UK asset managers account for approximately 80% of the market (see Blake, Lehmann and Timmerman (1999) and Lambert (1998)).

¹⁵ Blake, Lehmann and Timmerman's (1998) study is not particularly relevant to this exercise since they do not examine 'specialist' pension fund managers. Rather, their analysis pertains to 'balanced' funds that invest across a multiplicity of asset classes, including UK equities, international equities, UK bonds, international bonds, UK indexed-linked bonds, cash, UK property and international property.

¹⁶ As far as we are aware, all prior pension fund studies have also employed returns gross of expenses (see, Lakonishok, Shleifer and Vishny (1992), Coggin, Fabozzi and Rahmann (1993), and Christopherson, Ferson and Glassman (1998)).

¹⁷ While UK fund managers tend to offer 'balanced' multiple-asset-class portfolios with an aversion to particular style categorisations (Blake, Lehmann and Timmerman (1999)), Australian and US institutional participants are normally defined by a specific investment philosophy (e.g., growth, value or growth at reasonable price (GARP)) to which they are held.

¹⁸ In order to preserve the stability of the estimated alpha and beta coefficients, we require funds to have a minimum 12 month price history. This particular threshold was selected to minimise the look-ahead bias inherent in such procedures. We also estimate the models with minimum 24 and 36 month price histories, the results of which are not reported. Suffice is to say that the conclusions are quantitatively and qualitatively similar, irrespective of time-series threshold imposed.

¹⁹ This is not a novel interpretation; Jensen (1972) recognised the possibility of confounding variation in portfolio risk and risk premia with abnormal performance (see also Grant (1977)). Time-varying systematic risk derives from a number of sources; for example, the betas of the underlying assets may change or the participant may actively alter the portfolio weights by materially departing from a buy-and-hold strategy (see Ferson and Harvey (1991), Ferson and Korajczyk (1995), and Braun, Nelson and Sunier (1995)).

²⁰ Consistent with Ferson and Schadt (1996), we may articulate the conditional variant of the CAPM as follows,

$$\begin{aligned}
r_{it} &= b_i(Z_{t-1})r_{mt} + u_{it}, \\
E(u_{it} | Z_{t-1}) &= 0, \\
E(u_{it}r_{mt} | Z_{t-1}) &= 0,
\end{aligned}$$

where r_{it} is the excess return of fund i ; Z_{t-1} is a vector of predetermined public instruments available at time $t-1$; r_{mt} is the excess return realised by the market proxy; and $b_i(Z_{t-1})$ are the time $t-1$ conditional market betas. The conditional CAPM is operationalised by assuming that the portfolio's beta is a linear function of the lagged macroeconomic predictor variables, Z_{t-1} ,

$$b_p(Z_t - 1) = b_{1p} + b_{2p}z_{t-1},$$

where b_{1p} is the unconditional mean of the conditional beta $E[b_p(Z_{t-1})]$; b_{2p} is a beta response coefficient vector that monitors variation in systematic risk with respect to the innovation of the conditioning variable vector, $z_{t-1} = Z_{t-1} - E(Z_{t-1})$.

²¹ Elton, Gruber, Das and Hlavka note that studies which apply multiple index models may fail to attribute to management the element of abnormal performance associated with superior *sector* selection. This is true of Elton, Gruber, Das and Hlavka's study as well as those of Lehmann and Modest (1987), Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989) and Conner and Korajczyk (1991).

²² Given the strong correlation between the growth less value index and portfolios dissected by their book-to-market ratios, we selected only one of the factors.

²³ Elton, Gruber and Blake (1997) examine the efficacy of employing a number of alternative indices and find that while momentum does account for part of the covariance among funds, its importance is essentially attributable to the effect of capturing common holdings. In their comparative analysis of the various factors, Elton, Gruber and Blake conclude that 'a four index model based on widely available indexes of securities with different characteristics explains a great deal of the correlation between mutual funds' (1997: 33).

²⁴ It is exceedingly difficult to estimate conditional variants of the multi-factor model as this would require 16 independent variables and thus impose an untenable look-ahead bias.

²⁵ Elton, Gruber and Blake (1997) find that the four-index model significantly reduces residual correlation relative to a model using any possible combination of subsets of the indexes.

²⁶ For further evidence of these biases, see Grant (1977), Dybvig and Ross (1985), and Grinblatt and Titman (1989a).

²⁷ Both Fama (1972) and Jensen (1972) recognised the importance of distinguishing between selectivity and timing strategies when evaluating performance.

²⁸ Merton and Henriksson (1981) also provide a joint test of market-timing and stock-selection abilities. In their model it is assumed that managers target two levels of systematic risk: one in which participants forecast the riskless asset to yield returns in excess of the market proxy and an alternative in which converse is true. However, Merton and Henriksson do not attempt to quantify the magnitude of the return differential between the risky and riskless assets, rather they predict the direction of the forecast used to re-balance the portfolio between the two asset classes. Hence, one particular limitation associated with this model is that it does not evaluate the precision with which investment managers use their 'private information', rather, it only tests whether managers are endowed with such information (see also Dybvig and Ross (1985)).

²⁹ We estimate Treynor and Mazuy's model applying White's (1980) heteroskedastic consistent standard errors, given the possibility that non-stationary systematic risk may cause inefficient OLS estimates. In the Treynor and Mazuy model, the error term may exhibit conditional heteroskedasticity arising from the fund manager's attempt to time the market, despite the assumption that the returns are i.i.d random variables (see Coggin, Fabozzi and Rahmann (1993)).

³⁰ According to the 1999 Pension Fund Consultant Survey, more than 50% of all plan sponsors employ asset consultants.

³¹ The institutional agent fundamentally differs in its financial needs and sophistication from the individual agent. Whereas mutual fund investors make financing decisions on their own behalf, the capital-allocation strategies of institutional investors are comparatively complex. Plan sponsors are fiduciaries acting on behalf of others. Significantly, they are often finance professionals with expertise in the area of asset management. They are also accountable to senior management and plan members in the event of inferior fund performance, with their responsibilities in the capacity of trustee legally mandated through the Trust Investment Law. It is reasonable to presume, therefore, that the sophistication of the institutional agent's information set dominates that of the individual. Asset consultancies such as The Frank Russell Company, William M. Mercer, and Wilshire Associates advise plan sponsors on manager selection and the allocation of capital amongst classes of assets and differing investment styles. Selecting a manager is an exhaustive process often incurring fees of up to \$100,000. Indeed, 53.1% of plan sponsors investors evaluate the performance of their managers at monthly or quarterly frequencies applying quite sophisticated techniques (Nelson/Wilshire Survey (1997)). Conversely, the evidence of autocorrelation in mutual fund flows suggests that individuals refrain from regularly scrutinising their portfolio manager's performance (see Joye, da Silva Rosa, Jarnećić and Walter (2000c)). This is in part an artefact of the individual investor's primitive information set, which consists of crudely adjusted performance figures, popular publications, and mutual fund advertising. Capon et al. (1996) find that 75% of recent mutual fund purchasers surveyed did not know the investment style of their funds, and only 19% consult a rating service such as Morningstar or Lipper. The 1995 Money Magazine poll of mutual fund investors found that only 26.7% said they compared their fund's return to a benchmark. Certainly, the institutional investor's style-analysis, risk-adjustment and benchmarking do not appear to proliferate in the individual universe.

³² There has been a generic downward trend in expense ratios through time; intense competition for institutional 'mandates' has resulted in a dramatic fall in pension fund fees. As at September 1999, the mean active institutional equity MER was 54 basis points whereas the mean passive MER was just 10 basis points. Thus, currently the fee spread accounts for 49 basis points. For mandates in excess of \$50m institutional clients across the majority of asset classes are now paying fees 5-10 basis points less than that paid two years ago. With a greater percentage of managers offering to negotiate fees for mandates in excess of \$100 million, these falls are likely to have been even larger. Similarly, the expense ratios associated with mutual funds have declined to approximately 188 basis points, as at December 1998. These figures compare well with those evidenced in US and European markets (see, for instance, Coggin, Fabozzi and Rahmann (1993) and Otten and Schweitzer (1999)).

³³ The advantages afforded to institutional investors doubtlessly facilitate more efficient consumption-allocation decisions. An example of such is the significant negative relationship between the size of institutional investments and the fee paid; lower expense ratios may be negotiated for larger mandates. Whereas the mean fee charged on a \$25 million investment is 58 basis points, capital injections exceeding \$250 million incur just 46 basis points. Passive participants offer even more attractive terms; for allocations in excess of \$200m institutions are charged merely 7 basis points. Interviews with institutional fund managers also reveal that higher pay-for-performance sensitivities proliferate this sphere. And this propensity to offer fees based on investment performance has increased rapidly through time. Such explicit incentive structures serve to mitigate agency conflicts and closely align the interests of the portfolio manager and his/her institutional clientele. In contrast, the flat-fees structures that prevail in the mutual fund sphere place a premium on asset growth - irrespective of the consequences for investment performance.

³⁴ According to Carhart (1997), 44% of US mutual funds ceased to exist over the 1962-1993 period.

³⁵ To discuss performance on a comparable basis, we assume that institutional participants levied the mean MER, 0.84%.

³⁶ The kurtosis statistics of 2.16 and 3.17 for the excess return distributions in the institutional and mutual fund universes indicate that the institutional excess returns are more tightly clustered around their mean. It is also apparent that the excess return distributions of both populations are far less negatively skewed than that of the market proxy (the latter's skewness is not reported). Where the average security held by portfolio managers has less option-like characteristics relative to that of the market portfolio, Treynor and Mazuy's (1966) selectivity (timing) coefficients will be asymptotically biased downwards (upwards) (see Jagannathan and Korajczyk (1986)).

³⁷ Whilst a primitive measure, the information ratios (which reflect the ability of each participant to convert risk - defined as the standard deviation of the excess returns - into return) also convey the relative inefficiency of mutual fund managers: a 10% increase in annual tracking error contributed to a 62 basis point decline in performance.

³⁸ See Otten and Schweitzer (1999) for evidence of European mutual fund underperformance.

³⁹ Note that the time-weighted alpha is analogous to an 'equally-weighted' portfolio of managers. Where the time-weighted alphas exceed the individual averages, we may infer that managers with longer return series have delivered superior performance relative to the more youthful funds.

⁴⁰ It is pertinent to digress for a moment and consider the explanatory power of estimates in the prior literature. For instance, in the context of the Elton, Gruber and Blake (1996b) survivorship paper, a number of factors may have perturbed the integrity of their computations. First, the analysis is premised upon the Wiesenberger cohort of funds and may not be truly representative of the population of products. Particularly, mutual fund disappearance in their sample arises only through merger. That is, liquidated funds were excluded from the experimental design. Carhart (1997) finds that liquidated products exhibit exceptionally poor performance relative to the sample of all non-survivors. Thus, their estimates of attrition may be, by virtue of their construction, quite conservative and thus their r-squares artificially inflated. Second, while Elton, Gruber and Blake (1996b) do not explicitly articulate the minimum time-series threshold imposed, we demonstrate that adopting the method of Elton, Gruber and Blake (1996a) - ie, a 36 month minimum price history - results in the removal of 36% of all non-surviving funds. Hence, the strong correlation between fund age and the incidence of attrition suggests that researchers should seek to minimise look-ahead-biases in order to mitigate the effects of conditioning upon survival. Yet Elton, Gruber and Blake (1997), when attempting to control for survival-induced biases, require that the non-surviving sample of funds exist for a minimum of five-years. Third, Elton, Gruber and Blake (1996b) exclude all funds with less than \$15m in assets which results in the omission of 154 products. This is a particularly curious method to employ, considering the robust correlation between asset size and the probability of failure, and moreover, their appreciation of such. One might, therefore, call into question the exceptionally high r-squares associated with prior mutual fund analyses.

⁴¹ Edelen (1999) finds that performance-evaluation methods that do *not* account for a fund's 'flow-induced' tracking error may result in biased inferences with respect to a manager's information processing skills; that is, his or her ability to identify mispriced securities.

⁴² This marked effect of introducing conditional methods of evaluation contrasts the results of Carhart (1995) who finds that such dynamic performance measurement models do not significantly alter his estimates of performance.

⁴³ The size of the left tail is considerably larger than that anticipated under a t-distribution, which with more than 200 degrees of freedom should roughly approximate the normal.

⁴⁴ For instance, Edelen finds that the median fund's abnormal return is positive. He concludes, that 'fund managers...fit the profile of informed traders in a market in Grossman and Stiglitz informational equilibrium...[specifically] when the costs

associated with providing liquidity to investors are controlled for... fund managers' portfolio-choice decisions add about 1.5% per year to the value of the fund.' (1999: 441).

⁴⁵ To explore this further we conducted sub-period analyses, the results of which are not reported. These experiments tend to corroborate the latter explanation.

⁴⁶ In private correspondence with Professor Wayne Ferson we subsequently confirmed these suspicions.

⁴⁷ Interviews with institutional portfolio managers substantiate this claim, to quote one, 'cash-flows can have a big impact on performance' (Macquarie Investment Management (1999)).

⁴⁸ The negative covariance between the conditional (institutional) betas and the excess return on the market portfolio, $cov(r_m, d_{2p}z)$, is also confirmed by F (Wald) statistics where the null of a constant conditional beta is frequently rejected.

⁴⁹ Another possible explanation for this disparity is the institutional fund large 'cap' bias. The changes in institutional systematic risk are consistent with the time-varying nature of large 'cap' betas which, as suggested by Chan and Chen (1988), Ferson and Harvey (1991) and Jagannathan and Wang (1996), are negatively correlated with expected market returns.

⁵⁰ It is important to assess the marginal explanatory power of the conditioning macroeconomic predictor variables. It appears that there is some time-variation in the agent's systematic risk not captured by the unconditional models. In both universes, the adjusted coefficients of determination increase subsequent to the introduction of the additional lagged public-information proxies. From the right hand column of Tables II and III - which depict the results of the non-parametric Wilcoxon Matched-Pairs test and the Student's t-test - it is evident that the conditional and unconditional alphas are statistically distinct. Indeed, the relative significance of the conditioning factors substantiates the proposition that institutional investors place greater emphasis on macroeconomic predictor variables. In the mutual fund sphere, the lagged interaction factor relating to the slope of the term structure is the only statistically significant public-information proxy. However, both the shape of the term structure and the lagged dividend yield are statistically significant at the 1% level in estimations conducted on the individual institutional funds. There is, therefore, a trade-off between the use of the public-information proxies and the influence of flow on abnormal performance.

⁵¹ While this evidence does lend support to the findings of Gompers and Metrick (1998), it is worth noting that we present a somewhat finer categorisation of institutional preferences, differentiating between the portfolio-choice decisions of both institutional and mutual funds.

⁵² Interestingly, Blake, Lehmann and Timmerman (1999) also find a remarkably low cross-sectional variation in pension fund returns. They note that their range is small when compared with those observed in analyses of US equity mutual funds.

⁵³ The benefits of doing so are obviously more statistically robust estimates of the alpha and beta coefficients.

⁵⁴ Elton, Gruber and Blake (1997) employ a five-year minimum price history.

⁵⁵ This is consistent with the findings of Blake, Lehmann and Timmerman (1999), who document mean reversion in UK pension fund portfolio weights toward a common, time-varying strategic asset allocation. Also in accordance with the analysis above, they evidence 'surprisingly little cross-sectional variation in the average *ex post* returns arising from the strategic-asset-allocation, market-timing and security-selection decisions of fund managers' (1999: 429).

⁵⁶ The high pay-for- (relative) performance sensitivities proliferating in the institutional universe provide strong disincentives to deviations from peer-group performance. Conversely, where the mutual fund manager's remuneration is premised purely upon asset growth, and asymmetric performance-flow relations propagate call-option like incentives structures (see Joye et al. (2000c)), participants will be motivated to deliver significant outperformance. This incentive exists irrespective of the returns realised by contemporaries and may engender loadings of diversifiable risk.

⁵⁷ Joye et al.'s (2000c) concurrent examination of persistence and the performance-flow relation in the institutional and mutual fund spheres reveals welfare-decreasing asymmetries in the individual investor's response to past performance.

⁵⁸ Joye et al.'s (2000c) exploration of both persistence and the institutional investor's non-linear response to past performance intimates toward an astonishingly sophisticated institutional clientele.

⁵⁹ It is important to note that such sophistication need not be manifest in the form a linear performance-flow relation, as suggested by Del Grucio and Tkac (1999).

⁶⁰ Grinblatt and Titman (1989a) assert that small mutual funds have an advantage over larger ones insofar as they can more easily buy and sell securities without altering prices. This is congruous with the notion that large asset managers incur market impact costs that inhibit the efficacy of their selectivity strategies. Alternatively, it is also possible that small funds are more susceptible to survivorship bias and experience higher transaction costs relative to larger funds where they cannot exploit certain economies of scale. To empirically assess these conjectures we examined the performance of four equally-weighted institutional and mutual fund portfolios, sorted according to the value of assets at the beginning of each year. The first quartile consists of the ranking period's smallest funds whilst the fourth is composed of that period's largest funds. The performance of each portfolio is subsequently estimated over [0,+12], [0,+24] and [0,+36] month 'evaluation' periods applying excess returns relative to the market proxy and the unconditional four-factor alpha. Irrespective of the performance-evaluation technique, small mutual funds outperform their larger counterparts. This performance differential is non-trivial. Over the period [0, +12] months, the funds in the first quartile outperform the funds in the fourth quartile by 1.68% on a market-adjusted basis, and by 5.90% when applying the four-factor model. Similar findings obtain for the institutional universe. The quartiles comprising the smaller funds outperformed other quartiles over [0,+12] months, [0,+24] months and [0,+36] months on both a market-adjusted return basis and when one employed the more rigorous four-factor method. Again, the differences are non-trivially large. Over the period [0,+12] months, first quartile institutional funds outperform their fourth quartile counterparts by 0.97% on a market-adjusted basis, and by 1.00% premised upon the four-factor formulation.

⁶¹ It is conceivable that asset growth actually enhances the selectivity strategies of active participants. For example, large capital inflows might enable smaller managers to obtain interests in assets that would have otherwise been excluded from the investment opportunity set. From this perspective, insufficient investor flows, and hence fund size, impede the successful deployment of a manager's (private) informational assimilation advantage and thus the acquisition of the idealised portfolio. Further, in discussions with practitioners it has been asserted that significant asset growth presents participants with 'demonstrable pricing power'. It remains, therefore, an empirical question as to whether capital-flows contribute to or detract from the efficacy of active investment strategies.

⁶² The favourable conclusions of Grinblatt and Titman (1989a, 1993) might also be attributed to the fact that they examine, through direct portfolio-holdings data, ex ante performance as opposed to realised, ex post performance. Hence, Grinblatt and Titman implicitly control for the impact of flow-induced noise trade.

⁶³ We first consider the absolute new cash-flow into and out of a fund, specifically, $CF_{it}^a = NAV_{it} - NAV_{it-1}$ where CF_{it}^a is fund i 's absolute flow in month t and where NAV_{it-i} denotes fund i 's net asset value in the months t and $t-i$. Unlike Smith (1970), earnings reinvestments are not deemed to be voluntary new share purchases. That is, automatic reinvestments are not perceived as conscious consumer decisions to allocate capital. This avoids observing a spurious positive correlation between asset growth and prior period performance. In operationalising this procedure, all dividends and capital gains are assumed to be reinvested in the fund from which they originate, and the originating fund's net absolute flow is adjusted by

the amount of the reinvestment. Given that NAV is a stock measure, an assumption must also be made about the ‘incidence’ of the net flows. For the purposes of this exercise, we assume that the incidence of flows occur in the middle of the month:

$$CF_{it}^a = \frac{NAV_{it} - (NAV_{it}(1+r_{it}))}{(1+r_{it})^2}$$

Thus, for every institutional and mutual fund product, we calculate, on a monthly basis, the absolute cash-flows premised upon the timing assumption articulated above. To verify the robustness of these results we also employ normalised estimates of flow. This divides the absolute monthly flow by the net asset value of the fund at the beginning of the each month and measures new flow as a proportional growth rate, viz., $CF_{it}^n = CF_{it}^a / NAV_{it-1}$.

⁶⁴ Blake, Lehmann and Timmerman (1999) find that in the UK the mean pension fund holds around \$110 million in assets.

⁶⁵ The 36 month selection period and the use of the one-factor formulation were arbitrary choices and do not influence the results. The reader is referred to Joye et al. (2000c) for a more comprehensive analysis of the performance-flow relation.

⁶⁶ Persistence in performance intimates toward the possibility that past alpha may be an omitted explanatory variable.

⁶⁷ Alternatively, this evidence may lend credence to the proposition that asset growth facilitates the acquisition of the idealised investment opportunity set (i.e., target efficient portfolio) and/or presents participants with ‘demonstrable pricing

⁶⁸ Specifically, in both universes we estimate a past performance proxy for every individual product, say, the [-12,0] month unconditional four-factor alpha, on January 1st of each year. We also concurrently compute a subsequent cash-flow, say, the ‘absolute’ [0,+12] month flow. We then roll forward on an arbitrary (12, 24 and 36 month) basis and repeat the process through time (where possible, we preserve the independence of the observations). At the end of the sample period, we pool the data and cross-sectionally regress capital-flows against the contemporaneous performance proxies.

⁶⁹ The time horizon over which investors evaluate performance is an important issue that has to be taken into account when evaluating the impact of performance on capital-flows. It is significant because if performance is estimated over a shorter or longer horizon than the typical horizon used by investors when allocating capital, the regression will yield a downwardly biased estimate of the association between fund performance and capital-flows. To mitigate the impact of this bias, fund performance is estimated over three horizons or event-windows, [-36,0] months, [-24,0] months and [-12,0] months.

⁷⁰ Note that our conditional benchmarks already control for the relation between aggregate investor flows and time-varying expected returns.

⁷¹ Specification issues could arise because of the potential for dual-causality. While significant current-period inflows might negatively impact on future alpha there is also a great deal of evidence which suggests that past alpha strongly affects future flows (see, for example, Gruber (1996), Goetzmann and Peles (1997), Sirri and Tufano (1998) and Joye, da Silva Rosa, Jarnećic and Walter (2000c)). Accordingly, we employ a lagged flow variable that ameliorates the impact of reverse-causality (where current-period returns cannot have influenced past capital-flows). Note, however, that this argument becomes quite nebulous if, consistent with Gruber (1996) and Zheng’s (1998) smart money effect, investors employ persistence-based capital-allocation strategies.

⁷² Specifically, we employ lagged [-3,0], [-6,0], and [-12,0] month capital-flows to proxy for a fund’s future noise-trade.

⁷³ Migrating to the use of a lagged [-12,0] month flow proxy has little effect on the predictive capacities of the performance-evaluation technique, with the capital-flow regressor statistically indistinguishable from zero.

⁷⁴ Kon (1983) and Henriksson (1984) document an inverse cross-sectional relation between measures of mutual fund timing and selectivity. Henriksson conjectures that this phenomenon may arise from either a mean-variance inefficient market

proxy, the use of a single-factor rather than a multi-factor asset-pricing model, and/or errors-in-variables bias. Jagannathan and Korajczyk (1986) suggest that if managers acquire stocks with option-like characteristics (e.g., highly levered firms), or use derivative strategies such as written call or put options, mutual fund portfolios might spuriously exhibit positive timing performance and negative security selection; viz., artificial timing ability is obtained at the cost of poor measured security selectivity. However, no such explication exists for a representative sample of *institutional* investment vehicles. In unreported analysis, we explore the cross-sectional relation between institutional and mutual fund selectivity and timing strategies from two perspectives. Firstly, we regress the unconditional and conditional (one and multi-factor) timing coefficients on the corresponding selectivity estimates (i.e., the intercepts). Secondly, we compute a Spearman's rank correlation coefficient to non-parametrically assess the relation between the two data series. Regardless of the one or multi-factor point estimates used, the negative relation between the selectivity and timing coefficients is a pervasive phenomenon across both the institutional and mutual fund spheres. In the parametric analysis, the independent variables are statistically significant at the 1% level. The non-parametric Spearman's correlation coefficients are also highly significant. It appears that the ability to add value through stock selection comes at a cost - a diminished aptitude for forecasting the future trajectory of equity markets. An examination of the coefficients on the independent variables provides an economic interpretation of this effect. For instance, in the case of the (institutional) multi-factor timing model a 50% increase in annual selectivity performance results in a 12.3 basis point (0.123%) decline in annual macro-forecasting performance. Patently, this is not an economically significant relation, particularly given the aforementioned insignificant contributions of macro-forecasting activities to total portfolio performance. Two noteworthy observations are made: (i) the coefficients reveal that this effect is most apparent in the institutional universe; and (ii) migrating to the conditional models greatly attenuates the statistical significance of the relation. Specifically, the point estimates, rank correlations, t-ratios, and the adjusted R-squares all fall dramatically upon introducing the conditioning information. For example, the unconditional one-factor alphas explain 43% of the cross-sectional variation in the contemporaneous timing coefficients. However, the explanatory power of the conditional one-factor alphas is significantly less, with an adjusted R-square of just 6%. This latter result, proliferating across both spheres, has not been noted in the extant literature and may be worthy of further exploration. Suffice is to say that where conditional methods propagate a rightward shift in the distribution of market-timing coefficients, one would anticipate an erosion of the inverse relation between selectivity and timing abilities. The former revelation most probably derives from the propensity of institutional participants to engage in macroeconomic investment strategies. It is not unreasonable to presume that where institutional funds commit resources to 'top-down' investment strategies they would be less inclined to participate in 'bottom up' security selection.

⁷⁵ The explanatory power of each model with respect to the time-series variation in mutual fund returns is not particularly high, intimating toward the aforementioned possibility of residual risk captured by the stochastic error term. Further, it is apparent upon examining the distribution of the conditional one-factor and unconditional multi-factor macro-forecasting t-ratios that there exists no overwhelming evidence suggestive of a systematic inability to forecast future market risk premia, with the preponderance of t-ratios distributed normally with a mean of zero.

⁷⁶ Over the sample period, the skewness of the market, large 'cap', and small 'cap' proxies was -0.071 , -0.076 and 0.091 respectively. Interestingly, this contradicts the direction of the bias anticipated by Jagannathan and Korajczyk (1986).

⁷⁷ One particularly interesting dynamic is noted; in contrast to the mutual fund sphere, the macro-forecasting abilities of institutional agents have resulted in an incremental elevation in the estimates of abnormal performance.

⁷⁸ See, for example, Treynor and Mazuy (1966), Kon (1983), Henriksson (1984), Lehmann and Modest (1987), Lee and Rahmann, (1990), Coggin, Fabozzi and Rahmann (1993), Cai, Chan and Yamada (1997), and Bollen and Busse (1999).

⁷⁹ Potentially, one might rationalise our conclusions with the inherently small, incremental and continuous nature of individual capital-flows. Edelen (1999) asserts that if investor flows are sufficiently large they may propagate negative market-timing in fund returns. Edelen finds that when a second market-timing variable is interacted with a fund's realised flow all of the negative market-timing falls on the interactive regressor: funds exhibit negative market-timing when and only when they experience flow. He concludes that absent flow, the inferred market-timing ability of the fund manager is positive.

⁸⁰ A recent survey of portfolio managers corroborates this claim: most participants expressed an aversion to predicting the trajectory of volatile capital markets. Rather, they appear to be predisposed to individual or sector selection strategies (Investor Weekly (1999)).

⁸¹ The above finding is also manifest in the cross-sectional consistency of the parameter estimates. Where the CAPM presumes stationary portfolio risk through time, the influence of macro-forecasting strategies should propagate an upward (downward) bias into conventional estimates of systematic risk (abnormal performance) (See Grant (1977), Dybvig and Ross (1985), and Grinblatt and Titman (1989a)). Yet in the mutual fund market we observe very little difference between the Jensen one-factor and Elton, Gruber and Blake four-factor estimates of systematic risk (0.68 and 0.75 respectively) and those deriving from the unconditional one- and multi-factor Treynor and Mazuy market-timing models (0.694 and 0.747 respectively). Likewise, given the similarities between the two sets of intercepts there appears to be virtually no timing induced biases in our prior assessment of mutual fund selectivity strategies. Specifically, there is an 11 (21) basis point differential between the one- (multi-) factor models. The relative congruence among the timing and selectivity coefficients in the institutional sphere also suggests an absence of macro-forecasting activities.

⁸² The comparative distributions of all coefficients also corroborates this. Subsequent to the inclusion of the predetermined predictor variables, the distribution of positive and negative coefficients is equalised. Whereas 80 (118) of the unconditional timing estimates are positive (negative), 97 conditional coefficients are positive and 101 negative. Likewise, the distribution of all positive and negative timing values is also equilibrated; where 41 (80) of all unconditional one-factor point estimates are negative (positive), of the 121 conditional coefficients 60 (61) are positive (negative).

⁸³ A potential criticism might arise from the skewness of the excess return distributions relative to that of the market proxy. Jagannathan and Korajczyk (1986) demonstrate, both empirically and theoretically, that mutual funds holding stocks with option-like payoffs generate potentially spurious performance results (similar problems arise with the use of dynamic trading strategies, such as portfolio insurance, and if the frequency of trade occurs more often than the conventional (monthly) return measurement interval). Where the average security held by portfolio managers has less option-like characteristics relative to that of the market portfolio, Treynor and Mazuy's (1966) selectivity (timing) coefficients will be asymptotically biased downwards (upwards). Indeed Jagannathan and Korajczyk assert that the propensity of mutual funds to invest in 'higher quality' (i.e., less option-like) securities may explain the preponderance of negative timing coefficients evidenced in the literature. They assume here that larger securities are characterised by less risky debt and lower leverage. Given the aforementioned skewness statistics, one might therefore anticipate an upward bias in the coefficients (on the squared excess market return), thus providing an explanation for the absence of perverse market-timing; a small fall in the returns realised by a fund might be correlated with appreciable falls in equity market returns. Consequently, we would also expect the influence of the conditioning information on the option-like nature of the RHS variables to induce an upward (downward) bias into the conditional selectivity (timing) coefficients. However, this is not the case. We find, contrary to Bollen and Busse (1999), quite the opposite: conditional timing (selectivity) point estimates are greater (less) than unconditional estimates. Moreover, when we examine the relative skewness of the market, large 'cap' and small 'cap'

proxies, it becomes apparent that that smaller (larger) securities have more put (call) option-like characteristics relative to that of the market portfolio. Considering the relative size and style biases of institutional and mutual funds (articulated upon in Section V), portfolio composition should have, in aggregate, propagated spurious evidence of perverse market-timing; that is, exacerbated the effect. Exposures to smaller (larger) securities with more put (call) option-like characteristics relative to the market proxy, should upwardly (downwardly) bias market-timing estimates. The absence of such further substantiates the notion that exposures to derivative strategies and/or highly levered firms have not perturbed our macro-forecasting results.

⁸⁴ The ignorant and uninformed individual investor is also a common theme in the herding literature where individuals are often depicted as trading purely on sentiment. Shiller (1984) and Delong, Shleifer, Summers and Waldman (1990) claim that the influences of fad and fashion are likely to impact on the investment decisions of individual agents. Similarly, Shleifer and Summers (1990) maintain that individual investors may herd if they follow the same signals (broker recommendations, popular market gurus and forecasters) or place greater importance on recent news (overreact). Lakonishok, Shleifer and Vishny (1994) argue that individual investors engage in irrational positive feedback trading because they extrapolate past growth rates. Indeed, Odean (1999) finds that the individual investor's overconfidence results in a tremendous performance penalty. His message is simple: trading is hazardous to your wealth.

⁸⁵ Participants employed three primary indexed investment techniques: full replication, stratification and optimisation.

⁸⁶ Often this involves employing a passive core augmented by an active periphery. Value is added through exploiting apparent 'index inclusion effects', participation in initial public offerings, and the use of exotic derivative strategies.

⁸⁷ We are eager to confirm that our empirical results, with respect to selectivity and timing strategies, are *not* an artefact of a mean-variance inefficient benchmark. The use of an inefficient benchmark may result in spurious conclusions with respect to the existence of abnormal performance. This point was first noted by Roll (1978), who cautioned against the use of the CAPM as a benchmark for performance, stressing that it is difficult to distinguish between investment performance and benchmark inefficiency. Ross's (1976) discovery of APT has led to further questions concerning the appropriate proxies against which to judge abnormal performance. Recently, Lehmann and Modest (1987), Grinblatt and Titman (1990, 1993) and Elton, Gruber, Das and Hlvtka (1993) have documented the extent to which measured US equity mutual fund performance can depend critically on the benchmark used in the analysis. In particular, Lehmann and Modest (1987) emphasised the sensitivity of performance to the benchmark chosen and the need to find a set of benchmarks that represent the common factors determining security returns.

⁸⁸ In addition, we attempt to verify the integrity of the various performance-evaluation techniques. For example, we are keen to ensure that the timing abilities evidenced are not artefacts of a spurious return generating process, in the Jagannathan and Korajczyk (1986) sense, or model misspecification. Similar problems arise with the use of dynamic trading strategies, such as portfolio insurance, and if the frequency of trade takes place more often than the conventional (monthly) return measurement interval. Accordingly, we examine the performance of the population of passive (i.e., naïve) investment strategies relative to the six unconditional (conditional) one and multi-factor timing and selectivity models. Under the null, all estimates of abnormal performance should be statistically indistinguishable from zero.

⁸⁹ In his sample, the mean active mutual fund outperformed the Wilshire 5000 by approximately 0.18% per annum. He also documents the efficacy of persistence-based capital-allocation strategies. Post-fees, it is not therefore clear whether individual agents would be better served by investing in a market-linked equity index fund.

⁹⁰ Adopting a somewhat different perspective, we consider the implications of this analysis for the internal validity of the evaluation techniques. Observe in Table X that the statistical insignificance of every (individual) alpha point estimate

across the six performance-evaluation models substantiates the robustness of our prior selectivity analysis. The maximum (minimum) mean risk-adjusted excess return realised by any naïve portfolios is just 0.106% (-0.012%) per annum. And the maximum (minimum) t-ratio is 0.280 (-0.326). Our estimates of the stock selection abilities of active participants did not therefore arise as an artefact of model misspecification. The statistical insignificance of the passive fund population's performance also verifies the mean-variance efficiency of the market proxy. It is also important to note that (i) the statistical significance of the lagged public-information vectors is consistent with their explanatory power with respect to market risk premia; and (ii) the significance of the size factor in the four index formulation reflects the market proxy's large 'cap' bias. The specification of the macro-forecasting models does prove somewhat problematic. The unconditional one-factor Treynor and Mazuy model results attribute statistically significant market-timing abilities to naïve investment strategies, with the t-statistic on the timing coefficient equal to 2.037. This casts doubt on the integrity of the unconditional one-factor timing estimates. On the other hand, the conditional Treynor and Mazuy model appears to mitigate the misspecification evident in its unconditional counterpart: none of the naïve portfolios have statistically significant conditional timing coefficients. This set of results is entirely consistent with the findings of Ferson and Schadt (1996). Our additional multi-factor market-timing model also appears to be robustly specified. All selectivity and timing estimates are statistically indistinguishable from zero. In sum, our analysis of the efficacy of market-timing strategies remains relatively unperturbed by the biases induced by one-factor model misspecification. Indeed, the frailties of the latter are well appreciated by the literature

⁹¹ Exceptions will however exist. For example, Blake, Lehmann and Timmerman find that the institutional arrangements in the UK present pension fund managers with a 'weak incentive to add value', resulting in an absence of extensive attempts at active management (1999: 433).

⁹² In addition, this analysis may have implications for the role of investor clienteles in influencing our understanding of asset-pricing. For example, Brennan (1995) contends that much richer asset price dynamics are generated in a model with heterogeneous investors: for e.g., these models generate time variation in riskless interest rates and the market risk premium, both of which phenomena are observed empirically.