“Market Timing, Selectivity and Alpha Generation: Evidence from Australian Equity Superannuation Funds”

AUTHORS	Michael E. Drew Madhu Veeraraghavan Vanessa Wilson
ARTICLE INFO	Michael E. Drew, Madhu Veeraraghavan and Vanessa Wilson (2005). Market Timing, Selectivity and Alpha Generation: Evidence from Australian Equity Superannuation Funds. *Investment Management and Financial Innovations*, *2*(2)
RELEASED ON	Friday, 27 May 2005
JOURNAL	"Investment Management and Financial Innovations"
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

Market Timing, Selectivity and Alpha Generation: Evidence from Australian Equity Superannuation Funds

Michael E. Drew, Madhu Veeraraghavan, Vanessa Wilson

Abstract

In this performance evaluation study, two questions are addressed. First, do active fund managers possess macro and micro forecasting skills that deliver superior risk-adjusted returns? Second, what is the nature of market timing/stock selectivity trade off in the generation of alpha? The answers from this study are as follows: as an industry, managers delivered inferior returns for superannuation investors for the period 1991 through 2000. The study provides little evidence that the Australian funds management industry holds sufficient macro and/or micro forecasting abilities to generate positive alpha. While previous research has found that inferior market timing decisions are compensated for by superior stock selection skills, this study finds no substantive inverse relationship between timing and selectivity.

Key words: Superannuation funds, Australia.
JEL Classification: G23; G15.

Introduction

The economic function of pension funds is to facilitate the transformation of retirement savings into retirement income. The efficiency with which fund managers execute this transformative function has received much attention from both academics and practitioners alike. The financial economics literature suggests that the performance of actively managed funds, on average, has been inferior to that of a passively managed alternative[1]. This has led researchers, such as Gruber (1996), to ask "why do investors buy actively managed mutual funds (p. 783)?" This paper investigates this question by examining the role of market timing and stock selectivity in the generation of alpha (α)[2].

In order for active managers to generate alpha, financial markets (at least in the short-run) must be predictable. Two possible methods used by managers to create value for investors are: superior market timing abilities (macro-forecasting); and/or, superior stock selection (micro-forecasting). Treynor and Mazuy (1966) argued that if managers could time the market they would hold a larger share of volatile (less volatile) securities in a bull (bear) market. Moreover, the documentation of anomalies relating to the size (Banz, 1981) and value (Rosenberg, Reid and Lanstein, 1985) premium may provide an opportunity for active managers to garner superior risk-adjusted returns from micro forecasting.

The breakdown of manager performance into macro and micro-forecasting decisions, formalised by Fama (1972), and the role of anomalies in the pricing of risk (Fama and French, 1996) have two important implications for the evaluation of manager performance. First, studies that fail to consider timing and selectivity simultaneously could lead to erroneous conclusions being made about the sources of alpha generation[3]. Second, multiple factors (apart from the overall

---

[1] See, for example, Gruber (1996), Sawicki and Ong (2000) and Wermers (2000).

[2] Following Warwick (2000), an investment manager is said to generate alpha (α) under the following circumstances: alpha is generated if investment returns exceed an appropriate benchmark, if the risk taken to achieve the return is similar to that of the benchmark; or, alpha is generated if managers' returns are equivalent to an appropriate benchmark, if the risk taken to achieve the return is less than that of the benchmark.

[3] Chen and Stockum (1986) note that the use of the traditional Sharpe-Linter-Mossin (SLM) model is likely to generate biased results as it treats the systematic risk level of a fund as a fixed coefficient rather than as a decision variable. The nonstationarity of a fund's systematic risk violates the basic assumption of an OLS regression model. Grant (1977) contends that this will result in a downwardly biased alpha coefficient. Treynor (1966) also argues that such measures do not capture the share of fund variability due to a lack of diversification, resulting in the possibility that managers could improve their ratings without improving the quality of their skills via security selection by giving up more diversification benefits.

market factor) such as firm size and the ratio of book-equity to market-equity are required to explain the cross-section of returns in an economically meaningful manner.

The pioneering contribution of Treynor and Mazuy (henceforth TM) (1966) assumed that portfolio returns would be a non-linear function of market returns. The TM quadratic-regression model permitted researchers to investigate the behaviour of systematic risk decisions made by managers. A second parametric test of selectivity and timing, developed by Henriksson and Merton (henceforth HM) (1981), used a different interpretation of market timing ability. In the spirit of TM, funds may alter portfolio composition subject to market movements, but HM also incorporated the idea that managers can elect the level of market risk. The up and down-market beta model of HM provides a useful confirmatory measure to test timing performance[1].

International evidence reports that an inverse relationship exists between market timing and stock selection. Fund managers typically have negative or 'perverse' market timing skills when evaluated by the TM and HM models. However, the poor market timing decisions of managers appear to be somewhat offset by superior stock selection skill. This negative relationship has been consistently demonstrated in US (Coggin, Fabozzi and Rahman, 1993; and Bollen and Busse, 2001), UK (Fletcher, 1995) and international (Cumby and Glen, 1990) mutual and pension fund returns.

However, for the Australian setting, the relationship between market timing and stock selectivity skills is less clear. The preliminary findings of Sinclair (1990) using a sample of 16 pooled superannuation funds over the period 1981 through 1987 found that 5 out of the 16 funds exhibited significant risk level changes, consistent with the proposition that managers were attempting to time the market. Moreover, all funds showed significant negative market timing ability and significant positive security selection ability, with timing dominating overall performance.

The small sample size investigated by Sinclair (1990) and use of a five-year sample period (which included the 1987 stock market crash) motivated Hallahan and Faff (1999) to undertake a detailed investigation of the timing and selectivity skills of 65 Australian equity trusts[2]. Hallahan and Faff (1999) selected a post-crash observation period from 1988 through 1997 using the TM and HM models[3]. Unlike previous research, the contribution of Hallahan and Faff (1999) provided two interesting results: first, some evidence of positive timing coefficients was evident; and, second, negative selectivity coefficients (although not always significant) were obtained by managers. While there remained a negative correlation between the timing and selectivity variables, Hallahan and Faff (1999) found that where there was evidence of market timing ability, this was being offset by poor stock selection ability.

Sawicki and Ong (2000) undertook a third major study considering the behaviour of marketing timing and stock selectivity in Australia. Using Ferson and Schadt's (1996) lagged information framework, the study examined the performance of 97 domestic managed funds over the period 1983 through 1995. Sawicki and Ong (2000) reported that conditional alphas were higher and positive (with the number of significant negative market timing coefficients greatly reduced) under conditioned information. At first glance, the results appeared to provide support to the status quo of negative market timing and positive selectivity.

However, Sawicki and Ong (2000) noted that the improvement in performance using the conditional model was counter-intuitive. The negative covariance found between fund beta and market return (resulting in improved performance) should have been controlled for by the conditioning information. However, a negative correlation would imply fund managers reduced their exposure to market movements when market returns were high and vice versa. Ferson and Warther (1996) suggest that the negative correlation may be partly the result of mutual fund cash flows.

International evidence suggests that active fund managers face a trade-off between timing and selectivity in the generation of alpha. Specifically, this inverse relationship has predominantly taken the form of negative timing decisions being somewhat compensated for by positive selectiv-

[1] Dybvig and Ross (1985) argue that the HM model only tests if the fund manager had access to special information. Moreover, the HM model is not as sophisticated as the model of Jensen (1968) as it does not forecast the magnitude of the superior performance, only the direction of the performance.

[2] The sample investigated by Hallahan and Faff (1999) included diversified growth trusts (37), diversified income equity trusts (8), property equity trusts (9), diversified resources equity trusts (6), and other equity trusts (5).

[3] Hallahan and Faff (1999) also employed the specification tests of Jagannathan and Korajczyk (1986).

ity skills. However, the Australian setting provides an interesting case study, with Hallahan and Faff (1999) reporting contrary findings. The controversy surrounding the relationship between timing and selectivity in Australia has important implications for the performance of Australian equity superannuation funds. Superannuation is currently the second most important asset for Australians (after the home), with assets totalling AUD 495.3 billion in 2001 (APRA, 2001). The retail funds management industry, the focus of this study, managed a total of AUD 205 billion of these assets as at the end of fiscal 2000 (APRA, 2001)[1].

The primary concern for the fund manager is to maximise returns for their constituents, in this case, the superannuation fund member. In generating returns on retirement savings, it is important to ascertain the role of market timing and stock selectivity. Moreover, given the controversy surrounding the nature of the trade-off between timing and selectivity (and the issue of sample period selection) it is time to undertake a further investigation of the Australian setting. The rest of the paper is organised as follows. Section I outlines the performance evaluation models and tests of timing and selectivity used in the study. Section II describes the data. Section III presents the empirical analysis, with Section IV providing concluding remarks.

I. Tests of Timing, Selectivity and Performance

Fund manager skill is evaluated through an analysis of the alpha generated over a given period. This study is concerned initially with manager skill against benchmark performance and, primarily, with the ability for active managers to forecast market movements and to select undervalued stocks to create value for superannuation investors. In achieving the research objective, the analysis commences with the excess return from a single index model.

$$R_{it} - R_{ft} = \alpha_i + \beta_i \, (R_{mt} - R_{ft}) + \varepsilon_i \, , \tag{1}$$

where α_I = risk adjusted abnormal return from the single index model;
R_{ft} = return on the Reserve Bank of Australia 13 week T-note in month t;
R_{mt} = return on the Australian Stock Exchange Top 100 accumulation index in month t;
β_i = factor sensitivity of difference in fund return and the risk free rate; and,
ε_i = random error term.

Jensen's (1968) single index model, posits that the security's return should be linearly related to its risk, as measured by beta. The intercept term detects whether managers have superior forecasting abilities, with alpha generated by selecting securities resulting in $\varepsilon_i > 0$[2]. As Equation (1) is a single-period model, estimating the regression over time should allow investors to have heterogeneous investment horizons. Furthermore, returns are assumed to be independently and identically distributed (IID) through time and jointly multi-variate normal.

Recent advances in the asset pricing literature suggest that single index models are unable to capture the cross-section of expected stock returns, especially those anomalies relating to the size and value premium, in an economically meaningful manner. The selection of factors to be included in any multi index model has been a controversial subject in the evaluation literature. Gruber (1996) suggests that the selection of factors should include indices that span the major types of securities held by funds, that failure to do so will "make performance estimates more a matter of how the excluded categories of stocks did than how well management could select securities (p.787)." This study therefore employs a four-factor model, including factors relating to the market, size, style and bond indices of funds. Again, it is assumed returns conditional on factor realisations are IID through time and jointly multi-variate normal.

[1] Superannuation is the Commonwealth Government's preferred system for the provision of retirement savings for Australians. The importance of superannuation for the real sector cannot be underestimated. Superannuation is now the second most important asset (after the home) for Australians, with an average aggregated superannuation membership balance of AUD 60,000.

[2] Alpha generation will be significantly positive if the fund manager has the ability to forecast future security prices. Alpha will be zero if the manager mimics the composition of a reference benchmark. Finally, alpha will be significantly negative if the find manager performs worse than a naive strategy of random selection.

$$R_{it} - R_{ft} = \alpha_i + \beta_{mt}(R_{mt} - R_{ft}) + \beta_{si}(R_{st} - R_{lt}) + \beta_{gi}(R_{gt} - R_{vt}) + \beta_{di}(R_{dt} - R_{ft}) + \varepsilon_i , \quad (2)$$

where:

$R_{st} - R_{lt}$ = the size effect captured by the difference in return between a small market capitalisation portfolio and a large market capitalisation portfolio based on Australian Stock Exchange Frank Russell Company indices in month *t*;

$R_{vt} - Rg_t$ = the value premium effect captured by the difference in return between a value portfolio and a growth portfolio[1] based on the Australian Stock Exchange Frank Russell Company indices in month *t*;

$R_{dt} - R_{ft}$ = the bond indices effect captured by the difference in return on a bond index representing the Commonwealth, semi-government and corporate bonds with all maturities;

β_{ki} = factor sensitivity of difference in return on fund *i* to portfolio *j* (which represents the market, size, or value premium effect); and

ε_i = random error term.

As with the single index model, the manager's ability to generate alpha is indicated by a significant positive result. While general criticisms can be made of single and multi index models, one specific criticism is that both Equations (1) and (2) assume that a fund's systematic risk is stationary over time. The inability of such tests to incorporate dynamic risk strategies by managers may result in a regression estimate of α_i that may be significantly biased downward (Grant, 1977; and Lee and Rahman, 1990).

TM (1966) addressed this concern with the development of a quadratic market model. Through the addition of a quadratic term to Equation (1), portfolio returns are a non-linear function of the market return. This provides a measure of the timing abilities of fund managers.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + \varepsilon_i , \quad (3)$$

where γ_i = risk adjusted measure of market timing ability of fund *i*.

The following two hypotheses are tested with this model:

Hypothesis I:

H_0: $\alpha_i = 0$

H_a: $\alpha_i \neq 0$

Hypothesis II:

H_0: $\gamma_i = 0$

H_a: $\gamma_i \neq 0$

Hypothesis I is concerned with testing for the presence of abnormal performance as mentioned in the models specified previously, but is measured net of the manager's timing ability. Hypothesis II is concerned with measuring the market timing ability of fund managers. Market timing ability will be reflected by greater market exposure when the excess market returns are higher and vice versa. A significantly positive value of gamma would indicate superior market timing ability. If gamma does not deviate significantly from zero, the manager cannot outguess the market. If gamma is significantly negative, there has been perverse market timing undertaken by the manager.

HM (1981) took an alternative approach to the incorporation of timing ability into the traditional single index model. They assumed managers could elect the level of market risk they wished to encounter, incorporating an up-market beta (β_{1i}) and a down-market beta (β_{1i} - β_{2i}) in the analysis.

$$R_{it} = \alpha_i + \beta_{1i} R_{mt} + \beta_{2i} DR_{mt} + \varepsilon_i , \quad (4)$$

[1] This is the same as a portfolio of high book-to-market equity firms minus a portfolio of low book-to-market portfolio equity firms.

where:
α_I = risk adjusted abnormal return from dual-beta model or the fund's selectivity ability;
D = dummy variable that takes on a value of –1 for months when R_{mt} is negative, and zero otherwise; and,
β_{2i} = risk adjusted measure of market timing ability of fund i.

Like the TM's quadratic market model, two hypotheses are tested with this model.
Hypothesis III:
H_0: $\alpha_i = 0$
H_a: $\alpha_i \neq 0$

Hypothesis IV:
H_0: $\beta_{2i} = \beta_{1i}$
H_a: $\beta_{2i} \neq \beta_{0i}$

Again, Hypothesis III considers superior selectivity skills net of timing ability. Hypothesis IV is concerned with the market timing abilities of fund managers, determining whether a manager's down-market beta is significantly different from the up-market beta.

A successful market timer will have a down-market beta greater than the up-market beta, $(\beta_{1i} - \beta_{2i}) > \beta_{1i}$, therefore the resultant estimate for β_{2i} is significantly positive. If the estimate is significantly negative, 'perverse' market timing decisions have been undertaken. If the manager's actual β_{2i} is not zero, deductions made from Jensen's (1968) basic model may be rendered invalid. Sinclair (1990) explains that alpha from a single index model would be overstated when β_{2i} is greater than zero (a superior market timer) and understated when β_{2i} is less than zero (an inferior market timer).

Prior to describing the sample investigated in this study, two issues regarding the estimation technique undertaken in this study are noteworthy. First, a correction for heteroskedasticity was necessary for both the TM and HM models. This is due to the error term demonstrating conditional heteroskedasticity as managers attempted to time market movements[1]. This occurs despite the assumption of security returns being independent and identically distributed through time. To correct for this, Breen, Jagannathan and Ofer (1986), and Lehman and Modest (1987) suggest the use of heteroskedasticity-consistent standard errors employed by White (1980), Hansen (1982), and Hsieh (1983). All tests for significance in this study will be based on heteroskedasticity-adjusted *t*-statistics.

Second, diagnostic tests (reported in Appendix I) reveal the problem of multicollinearity for both market timing models. Collinearity of the regressors yields imprecise parameter estimates, weakening hypothesis testing. Auxiliary regressions demonstrated that the squared excess market return variable and the excess market return variable with a dummy for the TM and HM models, respectively, is an approximate linear combination of the excess market return variable. The output from auxiliary regressions is provided in Appendix II. The *F*-statistics have *p*-values of zero under both market proxies used in this study and are less than the significance values of 5% and 10%. Therefore the null hypothesis of no multicollinearity is rejected, with the variables mentioned being collinear with the other explanatory variable[2]. Therefore, the empirical investigation has taken steps to correct for multicollinearity, as estimates without this correction will yield spurious results.

[1] Previous studies have demonstrated that ignoring heteroskedasticity often leads to the rejection of the null hypothesis of no market timing ability too often when the null is in fact true, and vice versa. Although Henriksson (1981) found that adjusting for heteroskedastic error terms did not alter their results, studies by Breen, Jagannathan, and Ofer (1986), and Lee and Rahman (1990) suggest the existence of non-homoskedastic residuals can significantly affect the power of tests for market timing. This is the result of OLS estimates being inefficient, as systematic risk is non-stationary.

[2] Appendix III shows that for the first market proxy, the ASX Top 100 Accumulation index, the squared excess market return variable and the excess market return variable with a dummy change from being significant variables when regressed against the excess fund return variable to insignificant variables when regressed with all explanatory variables. This is

Chapman and Pearson (2000) demonstrated that the problem of multicollinearity resulting from a model taking a non-linear functional form is resolved by the technique of orthogonalised polynomials[1]. This is achieved by transforming the squared excess market return variable and the excess market return variable with a dummy under both models, resulting in:

The transformed TM model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i p_i(R_{mt}) + \varepsilon_i . \qquad (5)$$

With the transformed HM model taking the form:

$$R_{it} = \alpha_i + \beta_{1i} R_{mt} + \beta_{2i} p_i(R_{mt}) + \varepsilon_i . \qquad (6)$$

The new regressor, p_i (R_{mt}), is formed as the regression residual of R_{mt}^2 and DR_{mt} (under separate equations) onto a constant. This is then scaled to have a standard deviation equal to the standard deviation of the dependent variable, R_{it}. These orthogonalised and scaled monomials have the incremental effect of adding the original terms in Equations (3) and (4). The parameter estimates from Equations (5) and (6) will be reported throughout the study.

II. Data

Morningstar Research Pty Ltd provided return data on retail 'Superannuation Funds Australian Equity – General' for the period of January 1991 through December 2000. Fund returns were net of management expenses but excluded entry and exit loads. To minimise the problem of survivorship bias, all funds in existence over the observation period were initially considered, including all terminated funds. The only exclusion from the sample were funds that did not have at least 30 months of data available. The population consisted of 142 funds, with 8 funds being excluded as the result of $n \geq 30$, resulting in a sample of 134 funds.

The funds are separated into three categories by Morningstar: open-end; closed-end; and, non-surviving or terminated funds. Open-end funds, commonly referred to as unit trusts, may issue or redeem additional units of the fund at net asset value. The retail funds considered in this study require a minimum initial investment of AUD 2,000 with minimum contributions of AUD 100. A total of 68 open-end funds are examined in this study.

Closed-end funds sell units to investors only once, at the time of offer. These funds do not issue additional units and may not redeem units on demand. A lack of liquidity may prevent an investor from exiting this fund. However, the effect of large capital inflows and outflows from contributors is minimal, giving managers some control over the assets under management. A total of 55 closed-end funds is examined in this study.

The non-surviving cohort includes funds that ceased operations over the observation period. Elton, Gruber and Blake (1996) suggest that fund attrition is the result of either poor fund performance over a period of time or because the total market value of the fund is sufficiently small that the management judges that it no longer pays to maintain the fund. The latter reason for closing a fund is associated with the former reason: poor performance. The exclusion of non-surviving funds therefore results in an overestimation of historical returns[2]. Over the observation period 13 retail funds were terminated, and are included in the pool of funds considered in the analysis.

Admati and Pfleiderer (1997) advocate the use of a benchmark proxy that reflects each fund's investment strategy to augment the precision of performance evaluations. One of the advantages of the sample investigated in this study is that the asset allocation parameters are known. To have membership in the category, funds are required to hold at least 80% of assets in a general portfolio of Australian equities, with a maximum of 20% in domestic fixed interest securities. After an investigation of the fund mandates, the Australian Stock Exchange (ASX) Top 100 Accumulation

---

usually seen to be evidence of multicollinearity. Although the confirmatory proxy, the ASX Top 20 Accumulation index still shows some significant results, its significance has been reduced dramatically.

[1] See Draper and Smith (1998) for a detailed discussion of orthogonalised polynomials.

[2] For estimates of survivorship bias, see Grinblatt and Titman (1989), Brown, Goetzmann, Ibbotson and Ross (1992), and Brown and Goetzmann (1994).

index has been selected as the benchmark market proxy. Given the large-capitalisation bias of managers, the ASX Top 20 Accumulation index is used as a confirmatory proxy. If managers have engaged in some strategic behaviour over the observation period (for instance, attempting to exploit the size and/or value premium), the multi index model is designed to capture these affects. The ability of active managers to generate alpha through superior macro forecasting abilities (for example, switching between equities and fixed interest), and/or the ability to exploit any deficiencies in the arbitrage function of markets through stock selection, will be captured by Equations (5) and (6).

III. Empirical Analysis

Active fund managers engage in macro and/or micro forecasting to generate alpha. Alpha generation results in value being created for clients, with the manager garnering returns that exceed the cost of becoming informed. Hence, the economics of active management requires that the marginal benefit of active management exceeded its marginal costs. Initial studies of manager performance focussed on the ability of managers to generate superior risk-adjusted returns through active stock selection. The analysis of selectivity ability commences with the single index model of Equation (1).

Table 1

Cohort Single Index Performance Estimates

Listed are the average realised monthly percentage returns and coefficients, net of management expenses, from a pooled regression of excess returns against the single index model of the form:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_i$$

The adjusted R-squared and Durbin-Watson statistics are also reported. The ASX Top 100 (Panel A) and ASX Top 20 (Panel B) Accumulation indices provide a proxy for benchmark returns. The sample consists of 68 open-end funds, 55 closed-end funds, and 13 finalised funds (136 retail funds in total).

Cohort	α_i	Stand. Error	β_i	Stand. Error	R^2 adj	DW
Panel A: R_{mt} = ASX Top 100 accumulation index						
Retail open-end	-0.16817 (t = -0.95)	0.21363	0.87319 (t = 19.73)	0.06061	0.78961	2.1776
Retail closed-end	-0.16600 (t = -1.38)	0.16091	0.79995 (t = 22.77)	0.04638	0.72639	2.1815
Retail non-surviving	-0.24824 (t = -0.99)	0.33924	0.55988 (t = 8.35)	0.08842	0.49093	2.1703
All retail funds	- 0.17495 (t = -1.13)	0.20408	0.81362 (t =19.87)	0.05745	0.7389	2.1779
Basis Points (per annum)	- 210					
Panel B: R_{mt} = ASX Top 20 accumulation index						
Retail open-end	-0.25077 (t = -1.08)	0.24999	0.80066 (t = 13.24)	0.07463	0.71408	2.1086
Retail closed-end	-0.21665 (t = -1.39)	0.18507	0.73141 (t = 15.78)	0.05354	0.66745	2.1197
Retail non-surviving	-0.24279 (t = -0.85)	0.35093	0.50762 (t = 7.18)	0.08701	0.44012	2.1493
All retail funds	-0.23621 (t = -1.19)	0.23313	0.74464 (t = 13.69)	0.06722	0.6759	2.1174
Basis Points (per annum)	- 283					

Table 1 shows that the average manager underperformed by -0.1749% per month, equivalent to –210 (-283) basis points p.a., using the broad ASX Top 100 (Top 20) Accumulation as the reference rate. The negative result was evident across all cohorts, with the retail non-surviving category (as expected) providing the greatest level of alpha destruction. However, the cohort alphas are all insignificant from zero at both the 5% and 10% levels. The funds management industry was unable to predict security prices with sufficient accuracy to outperform a naive strategy per unit of systematic risk. Therefore, alpha generation was not sufficient to recover management expenses.

Table 2 provides estimates of the single-factor model on an individual fund basis. Of the 136 funds, 109 (94) funds were characterised by alphas that were insignificant from zero against the Top 100 index at the 5% (10%) significance level. In only 27 (42) cases there was evidence of abnormal performance at the 5% (10%) level. Out of the significant cases, only 1 (1) fund had a significantly positive alpha while 26 (41) funds had significant negative alphas[1].

Table 2

Individual Single Index Performance Estimates

Listed are the number of alphas that are insignificant (Zero), and significantly different from zero (Positive/Negative) from a single index model. Also reported are the number of betas insignificant (Unity), significantly different from unity (Greater than unity/Less than unity). The results are considered at the 5% and 10% significance levels for both market proxies. Finally, the mean alpha and beta terms for the sample are also shown.

	Significance	α = Zero	α > Zero	α < Zero	Total	Mean α
Panel A: Single Index Alphas for Individual Funds						
Top 100	5 %	109	1	26	136	-0.17
	10 %	94	1	41	136	
Top 20	5 %	110	0	26	136	-0.23
	10 %	93	1	42	136	
	Significance	β = Unity	β >Unity	β < Unity	Total	Mean β
Panel B: Single Index Betas for Individual Funds						
Top 100	5 %	3	8	133	136	0.81
	10 %	1	8	135	136	
Top 20	5 %	3	6	133	136	0.74
	10 %	1	6	135	136	

The evidence provided in Table 2 raises some important concerns regarding the overall level of systematic risk adopted by managers. On an individual fund basis, only 3 funds reveal a beta estimate that is insignificant from unity at the 5% level. Only 8 funds exhibited beta estimates that were significantly greater than unity using the Top 100 index, with 6 funds demonstrating this characteristic against the Top 20 index.

Prior to drawing strong conclusions from the estimation of Equation (1), it is important to acknowledge that the model has a number of limitations. These include a heavy reliance on the ability for equity risk premium to capture fund return and Roll's (1977, 1978) concerns regarding the observability of the market portfolio. Recent advances in the asset pricing literature, led by Fama and French (1996), have allowed researchers to resolve some of these concerns. Table 3 provides estimates of the multi index model of Equation (2).

[1] However, the hypothesis that fund alphas are jointly equal to zero cannot be rejected at the 95% and 90% confidence levels as more than half of the sample had alphas that were not significantly different from zero.

Table 3

Cohort Multi Index Performance Estimates

Listed are the average realised monthly percentage returns, from a pooled regression of excess percentage returns against the multi index model of the form:

$$Rit - Rft = \alpha i + \beta mt\ (Rmt - Rft) + \beta si\ (Rst - Rlt) + \beta gi\ (Rgt - Rvt) + \beta di\ (Rdt - Rft) + \varepsilon i$$

The intercept, α, is a measure of selectivity ability and the coefficients βs, βg, and βd represent the size, style and bond portfolios respectively.

Cohort	α_i	β_i	β_{si}	β_{gi}	β_{di}	R^2 adj	DW
Panel A: R_{mt} = ASX Top 100 accumulation index							
Retail open-end	0.02799 (t = 0.11)	0.85203 (t = 19.62)	0.17979 (t = 2.57)	0.07957 (t = 1.04)	0.32387 (t = 2.63)	0.82406	2.2698
Retail closed-end	-0.06153 (t = -0.63)	0.79131 (t = 23.43)	0.13933 (t = 2.68)	-0.02903 (t = -0.02)	0.35698 (t = 3.65)	0.77440	2.2069
Retail non-surviving	-0.16470 (t = -0.71)	0.56949 (t = 7.99)	0.22297 (t = 2.47)	0.04483 (t = 0.29)	0.61133 (t = 3.66)	0.62034	2.0439
All retail funds	-0.03810 (t = -0.29)	0.80047 (t = 20.06)	0.16756 (t = 2.61)	0.03233 (t = 0.54)	0.36474 (t = 3.14)	0.78828	2.2144
Basis Points (per annum)	- 46						
Panel B: R_{mt} = ASX Top 20 accumulation index							
Retail open-end	-0.02466 (t = -0.11)	0.83152 (t = 15.68)	0.33443 (t = 3.76)	0.03847 (t = 0.55)	0.31686 (t = 2.08)	0.79127	2.2651
Retail closed-end	-0.08859 (t = -0.68)	0.77407 (t = 19.56)	0.27836 (t = 4.38)	-0.04212 (t = -0.19)	0.33079 (t = 2.88)	0.74720	2.1926
Retail non-surviving	-0.17033 (t = -0.58)	0.55813 (t = 7.68)	0.31253 (t = 3.15)	0.06729 (t = 0.40)	0.61173 (t = 3.62)	0.60504	2.0487
All retail funds	-0.06444 (t = -0.39)	0.78216 (t = 16.49)	0.30966 (t = 3.96)	0.00863 (t = 0.24)	0.35068 (t = 2.55)	0.75922	2.2080
Basis Points (per annum)	- 77						

The analysis presented in Table 3 provides corroborating evidence of the results from the single index model, with one notable exception. As an industry, funds underperformed the market by a range of –46 (–77) basis points per annum, using the ASX Top 100 (Top 20) accumulation index as a proxy for passive returns. However, unlike the previous analysis, all cohorts do not destroy value for investors. Managers in the retail open-end category generated a positive alpha of around 34 basis points per annum (net of the cost of becoming informed) against the Top 100 index[1]. While this result is encouraging for those investors skilled enough (or lucky enough) to hold only surviving funds over the observation period, a complete discussion of performance requires acknowledgment of any survivorship bias. Inclusion of terminated funds reverses this result, confirming that any analysis ignoring fund termination will dramatically overstate the industry's stock selectivity skills. Finally, all reported alpha estimates are insignificant from zero at both 5% and 10% levels, so the hypothesis that alpha is equal to zero cannot be rejected.

[1] However, this result reverses when the ASX Top 20 Accumulation index is used as the market proxy, with the industry destroying around –30 basis points in value per annum. This highlights, out of sample, the concerns of Lehmann and Modest (1987) regarding the issue of benchmark selection in performance evaluation.

Table 4

Individual Multi Index Performance Estimates

Listed are the number of alphas that are insignificant (Zero), and significantly different from zero (Positive/Negative) from a multi index model. Also reported are the number of betas insignificant (Unity), significantly different from unity (Greater than unity/Less than unity). The results are considered at the 5% and 10% significance levels for both market proxies. Finally, the mean alpha and beta terms for the sample are also shown.

	Significance	α = Zero	α > Zero	α < Zero	Total	Mean α
Panel A: Multi Index Alphas for Individual Funds						
Top 100	5 %	111	5	20	136	-0.038
	10 %	102	10	24	136	
Top 20	5 %	117	3	16	136	-0.064
	10 %	107	5	24	136	
	Significance	β = Unity	β >Unity	β < Unity	Total	Mean β
Panel B: Multi Index Betas for Individual Funds						
Top 100	5 %	3	10	133	136	0.80
	10 %	2	10	134	136	
Top 20	5 %	2	10	134	136	0.78
	10 %	2	10	134	136	

Turning to the role of the explanatory variables in Equation (2), the average fund beta ranged from 0.78 to 0.80, implying that managers adopted a portfolio composition less risky than the general market. These values are significant at both the 5% and 10% levels under both market proxies. The individual fund analysis indicated that 133 (134) betas were significant at the 5% (10%) level against the Top 100 index. To provide some guide to the range of systematic risk decisions made by managers, the highest beta recorded beta by any fund was 1.32 (Top 100 index), with the lowest estimated at 0.51.

The size factor, β_{si}, is positive and highly significant under both market proxies, ranging from 0.17 to 0.33. The results provide some support to the notion that managers are attempting to exploit the size anomaly. Moreover, the evidence highlights the limitations of using single index models of Equation (1) to analyse the cross-section of fund returns. The regression coefficient relating to size was positive and significant for 88 (94) of the funds at the 5% (10%) level under the Top 100 index.

The style factor, β_{gi}, is positive but insignificant under both market proxies significance levels. This is in contrast to the findings of Gruber (1996) who reported a significant negative coefficient for the style variable. Only 39 (48) funds were statistically significant at the 5% (10%) level under the Top 100 index. In further contrast to Gruber's (1996) results from US mutual funds, 32 (33) were positive estimates. This raises some important issues for superannuation investors regarding the consistency of the manager's asset selection style (value or growth). Moreover, research across a variety of international markets reports the existence of a 'sweet spot' for investors who hold small capitalisation stocks with a value bias[1]. Such opportunities appear to remain largely unexploited by the majority of managers investigated in this study.

Turning to the final explanatory variable, the bond factor (β_{di}), plays an important role in capturing the return behaviour of managers. Managers appear to be investing in a portfolio that has a significant holding of returns provided by less volatile, fixed interest securities. Moving to the individual fund level, 98 (113) funds had significant coefficients at the 5% (10%) level under the Top 100 proxy. Moreover, these estimates were all positive. We now turn to another important

[1] This finding is confirmed by Fama and French (1996) for the US stock market, Halliwell, Heaney, and Sawicki (1999) for Australia, and Drew and Veeraraghavan (2001) for the emerging markets in Asia.

aspect of fund performance – market timing. The issue often examined is how successful have funds been in timing market movements and more importantly how is timing measured?

Underlying the estimates from Equations (1) and (2) is the assumption that a funds' systematic risk remains constant over time. Relaxing this assumption, thereby decomposing the role of market timing from stock selection, requires regression models to take a non-linear form. The evaluation of market timing commences with the augmented TM model of Equation (5). The TM approach adds a quadratic term to Equation (1) in an attempt to incorporate the dynamism of a fund's systematic risk.

Table 5

TM Performance Estimates

Listed are the average realised monthly percentage returns, net of expenses, from a pooled regression of excess percentage returns against TM's quadratic market model of the form:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i (R_{mt} - R_{ft})^2 + e_I$$

The ASX Top 100 (Panel A) and ASX Top 20 (Panel B) accumulation indices are the proxy for benchmark returns. The intercept term, α_i measures selectivity skill with the coefficient γ_i measuring market timing ability.

Cohort	α_i	β_I	γ_I	R^2	DW
		Panel A: R_{mt} = ASX Top 100 accumulation index			
Retail open-end	-0.16406 (t = -0.95)	0.86145 (t = 19.97)	-0.04916 (t = -1.12)	0.78479	2.1545
Retail closed-end	-0.16604 (t = -1.40)	0.79752 (t = 24.62)	-0.04239 (t = -1.36)	0.72671	2.1644
Retail non-surviving	-0.31028 (t = -1.16)	0.60908 (t = 8.84)	-0.11427 (t = -1.16)	0.49264	2.1870
All retail funds	-0.17884 (t = -1.15)	0.81147 (t = 20.79)	-0.05265 (t = -1.22)	0.74000	2.1621
Basis Points (per annum)	-215				
		Panel B: R_{mt} = ASX Top 20 accumulation index			
Retail open-end	-0.24361 (t = -1.11)	0.77429 (t = 14.36)	-0.12806 (t = -2.30)	0.72806	2.0979
Retail closed-end	-0.21950 (t = -1.48)	0.72647 (t = 18.17)	-0.10525 (t = -2.59)	0.67694	2.1144
Retail non-surviving	-0.31019 (t = -1.05)	0.54704 (t = 7.78)	-0.13714 (t = -1.41)	0.4480	2.1659
All retail funds	-0.24023 (t = -1.26)	0.73323 (t = 15.27)	-0.11970 (t = -2.33)	0.68737	2.1122
Basis Points (per annum)	-288				

The results reported in Table 5 further support the conclusion that on average, active managers have limited stock selection abilities, consistent with the findings of Hallahan and Faff (1999) for Australian unit trusts. However, this is contrary to the findings of accretive selection skills by Coggin, Fabozzi and Rahman (1993), Fletcher (1995) and Bello and Janjigian (1997) amongst others, and Sawicki and Ong (2000) for Australia. The alpha coefficients reported in Table 5 using both market proxies are slightly greater compared to the coefficients obtained from the single-factor model shown in Table 1, a result consistent with Grant's (1977) contention that single index performance measures will have a downward bias if market timing effects are ignored.

A total of 28 (45) funds exhibited significant abnormal performance against the Top 100 index at the 5% (10%) level. Of the funds with significant alphas, just one generated a positive alpha, with the remaining 27 managers recording negative performance. With approximately three-quarters of the sample portraying no significant evidence of selection ability (and those with a significant result demonstrating poor selectivity skills), the null hypothesis of no stock selection skill across the industry is not rejected.

The beta estimates provided in Table 5 reinforce the finding that Australian superannuation funds took relatively low risks over the sample period. However, the linear combination of an industry beta less than unity combined with negative selectivity estimates violates the received finding of a perverse relationship between timing and selectivity. Specifically, this violates the widely cited findings of Black, Jensen, and Scholes (1972), and Kon and Jen (1978) who provide evidence that low-risk portfolio compositions tend to result in positive selectivity performance estimates and vice versa[1]. Interestingly, over 90% of the funds that exhibited significant negative selectivity ability had systematic risk levels less than unity. This raises the issue of whether the industry's inferior performance was a result of generally poor micro forecasting ability by managers or some, as yet unidentified, features of portfolio composition.

Equation (5) provides gamma estimates as a measure of market timing ability. Against both market proxies, all cohorts showed negative macro forecasting skill. The problem of benchmark selection is again highlighted, with all results being insignificant at the 5% and 10% levels against the Top 100, but significant at the both levels for the Top 20 index. Hence, it again appears that selection of the market proxy may significantly alter performance evaluation results. However, some consensus is reached with the estimated regression coefficients from both proxies being negative, leading to a broad non-rejection of the null hypothesis[2].

The evidence listed in Table 5 finds both support and controversy with previous studies examining the Australian market. The findings are consistent with preliminary findings of perverse market timing by Sinclair (1990) and the recent contribution of Sawicki and Ong (2000). However, the results do not reflect Hallahan and Faff's results, of limited, mainly positive market timing skills of the managers of Australian unit trusts.

Individual fund gammas were significant in 31 (51) cases at the 5% (10%) level under the Top 100 proxy. All of the estimated coefficients were significantly negative under both market proxies, equating to approximately 23% (38%) of the sample having significant perverse market timing abilities against Top 100 (Top 20). The implication of this result is that around a quarter of managers tend to increase (decrease) their equity exposure as the market falls (rises). To sum it up, we do not reject the null of hypothesis of no timing ability for the industry at both significance levels.

Finally, it is important to comment on the nature of the relationship between timing and selectivity. Against the Top 100 index, there is a negative, but very low correlation found between the two coefficients, with a reported value of –0.232[3]. The Top 20 index corroborates this result, with an estimated value of –0.069. These low values would support Lehman and Modest's (1987) finding of 'no substantive' correlation. This is in contrast to a large body of research reporting a large negative correlation between timing and selectivity (Henriksson, 1984; Chang and Lewellen, 1984; Connor and Korajcyzk, 1991; Fletcher, 1995; and Bello and Janjigian, 1997). These results are also in contrast to previous Australian studies of Sinclair (1990), Hallahan and Faff (1999) and Sawicki and Ong (2000). Therefore, given these controversial findings, we turn to an alternative market-timing model, the HM model to further investigate the validity of the results.

---

[1] Moreover, Kon and Jen (1978) note that engaging in portfolio re-balancing (to maintain a target beta) will result in a transaction cost bias in favour of low beta portfolios.

[2] This poor performance is also evident where funds having the same selectivity and timing coefficients under TM generate an alpha of –0.255 (-0.247) at the 5% (10%) level under the Top 100 index.

[3] This is significant at the 5% and 10% levels with a t-statistics of –2.760.

Table 6

HM Performance Estimates

Listed are the average realised monthly percentage returns, net of expenses, from a pooled regression of excess percentage returns against HM's dual-beta model of the form:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i} (R_{mt} - R_{ft}) + \beta_{2i} D (R_{mt} - R_{ft}) + e_I$$

The ASX Top 100 (Panel A) and ASX Top 20 (Panel B) accumulation indices are the proxy for benchmark returns. The intercept term, α_i is a measure of selectivity ability, and the coefficients β_{1i}, and (β_{1i} - β_{2i}) represent the up and down-market betas respectively. A successful market timer will have a down-market beta greater than the up-market beta. Therefore, β_{2i} should be significantly positive for a successful market timer.

Cohort	α_i	β_{1i}	β_{2I}	R^2	DW
		Panel A: R_{mt} = ASX Top 100 accumulation index			
Retail open-end	-0.17340 (t = -0.98)	0.86823 (t = 19.85)	-0.03620 (t = -0.72)	0.78290	2.1678
Retail closed-end	-0.16819 (t = -1.40)	0.79851 (t = 23.97)	-0.03115 (t = -0.94)	0.72599	2.1728
Retail non-surviving	-0.27349 (t = -1.01)	0.58139 (t = 8.94)	-0.06706 (t = -0.88)	0.48959	2.2077
All retail funds	-0.18086 (t = -1.51)	0.81262 (t = 20.48)	-0.03710 (t = -0.82)	0.73863	2.1736
Basis Points (per annum)	-217				
		Panel B: R_{mt} = ASX Top 20 accumulation index			
Retail open-end	-0.26753 (t = -1.18)	0.78369 (t = 14.28)	-0.12343 (t = -2.05)	0.72573	2.0883
Retail closed-end	-0.22379 (t = -1.49)	0.72813 (t = 17.67)	-0.09485 (t = -2.20)	0.67474	2.1122
Retail non-surviving	-0.28914 (t = -0.94)	0.53557 (t = 7.79)	-0.11158 (t = -1.25)	0.44525	2.1860
All retail funds	-0.25190 (t = -1.28)	0.73750 (t = 15.03)	-0.11074 (t = -2.04)	0.68509	2.1092
Basis Points (per annum)	-302				

Similar to the results reported earlier in this study, the returns are largely negative but insignificant from zero at the 5% and 10% levels. Again, one fund generated a significant positive alpha for investors (the same fund found using the TM technique) with 28 funds having significant estimates under the Top 100 index. As with all of the tests undertaken in this study, we do not reject the null hypothesis of no selectivity ability. The trend of managers having a relatively low risk appetite is confirmed by using Equation (6). A total of 7 (6) funds had beta coefficients significantly greater than unity against the Top 100 (Top 20), at both the 5% and 10% levels. This small group of relatively high-risk funds has remained the same for all of the models estimated.

The beta$_2$ results from Table 6 provide a measure of market timing ability. Successful market timing by the manager results in positive beta$_2$ coefficient being significantly different from zero. As an industry, the estimates corroborate the result of no timing ability using both market proxies. Moving to an individual fund analysis, 8 (26) funds showed significant timing skill at the 5% (10%) level using the Top 100 index[1]. Finally, the HM measure confirms a marginal nega-

[1] This poor performance is also evident where the number of funds having the same selectivity and timing coefficients under HM generate an alpha of –0.209 (-0.227) at the 5% (10%) level under the Top 100 proxy.

tive relationship between macro and micro forecasting ability, with a correlation of –0.252[1] using the Top 100, and –0.086 against the Top 20 index. The international and domestic phenomenon of significant but perverse market timing decisions, typically offset by significant accretive stock selection skill, is not supported in this study. This study provides little evidence that the Australian funds management industry has sufficient macro and/or micro forecasting abilities to generate positive alpha for superannuation investors.

IV. Concluding Remarks

The performance evaluation literature has long debated the relationship between macro and micro forecasting skill. Elton and Gruber (1995) point out that the acceptance of modern portfolio theory has changed the evaluation process from crude calculations to detailed explanations of risk and return. While the evidence has largely found that inferior market timing decisions are compensated for by superior stock selection skills, the recent contribution by Hallahan and Faff (1999) reported contrary behaviour for Australia. However, regardless of whether timing skills are positive or negative, previous studies have reported the existence of a significant negative relationship with a manager's selection ability. The consensus view posits a situation where managers face a trade-off between timing and selectivity when generating alpha.

As Australia moves towards a full choice regime in superannuation, permitting investors to move superannuation savings with freedom among different investment alternatives, the findings of this study question the ability for the funds management industry to create value for constituents through alpha generation. Moreover, the findings of limited macro or micro forecasting skill question the ongoing role of dedicated, single-sector funds (such as the actively managed Australian equity funds investigated in this study) in the transformation of retirement savings into retirement income. One legitimate economic function for such intermediaries would be to provide a diversification facility for unit-holders, in this case, superannuation contributors.

The study has been unsuccessful in unifying the literature regarding the timing and selectivity performance of the Australian funds management industry by Sinclair (1990), Hallahan and Faff (1999) and Sawicki and Ong (2000). Previous research shows that the relationship between timing/selectivity trade-off, is a negative one. The findings of this study are consistent with the work of Lehman and Modest (1987), in that no substantive inverse relationship exists between timing and selectivity. The evidence suggests that managers did not try to significantly alter their systematic risk levels, resulting in largely fixed coefficients over the sample period. Our findings are also consistent with Fabozzi and Francis's (1979) observation that managers in the US do not try to alter their systematic risk to exploit market movements. Possible reasons offered as to why this phenomenon occurs include the manager's inability to time market movements and/or costs of such timing being prohibitive. It is our conjecture that two important areas lead the agenda for future research on the role of timing and selectivity in the generation of alpha. The first area relates to the definition of style for Australian superannuation fund managers. An investigation into the style of asset selection decisions made by the Australian funds management industry is required to permit a deeper understanding of alpha that is consumed by poor selectivity.

A fruitful area of research may relate to the issue of style drift over the observation period. Second, future research may consider the incorporation of multi index models with traditional selectivity and timing technology, in a conditional setting, to further decompose alpha generation by managers. These issues are left to future work.

References

1. Admati, A.R., and S.A. Pfleiderer, 1997, 'Does It All Add Up? Benchmarks and the Compensation of Active Portfolio Managers', *Journal of Business*, Vol. 70, pp. 323-350.
2. Banz, R.W., 1981, 'The Relation between Return and Market Value of Common Stocks', *Journal of Financial Economics*, Vol. 9, pp. 3-18.

[1] This is significant at the 5% and 10% levels with a t-statistics of –3.009.

3. Bello, Z.Y., and V. Janjigian, 1997, 'A Reexamination of the Market-Timing and Security-Selection Performance of Mutual Funds', *Financial Analysts Journal*, Vol. 53, pp. 24-30.
4. Black, F., M.C. Jensen, and M. Scholes, 1972, 'The Capital Asset Pricing Model: Some Empirical Tests', M.C. Jensen (ed*.), Studies in the Theory of Capital Markets*, (Praeger Publishers: New York).
5. Bollen N.P.B., and J.A. Busse, 2001, 'On the Timing Ability or Mutual Fund Managers', *Journal of Finance*, Vol. 56, pp. 1075-1094.
6. Breen, W., R. Jagannathan, and A.R. Ofer, 1986, 'Correcting for Heteroscedasticity in Tests for Market Timing Ability', *Journal of Business*, Vol. 59, pp. 585-598.
7. Brown, S., and W. Goetzmann, 1995, 'Performance persistence', *Journal of Finance*, Vol. 50, pp. 679-698.
8. Brown, S., W. Goetzmann, R. Ibbotson, and S. Ross, 1992, 'Survivorship bias in performance studies', *Review of Financial Studies*, Vol. 5, pp. 553-580.
9. Chapman, D.A., and N.D. Pearson, 2000, 'Is the Short Rate Drift Actually Nonlinear?', *Journal of Finance*, Vol. 55, pp. 355-388.
10. Chen, C.R., and S. Stockum, 1986, 'Selectivity, Market Timing, and Random Beta Behavior or Mutual Funds: A Generalized Model', *Journal of Financial Research*, Vol. 9, pp. 87-96.
11. Coggin, T.D., F.J. Fabozzi, and S. Rahman, 1993, 'The Investment Performance of U.S. Equity Pension Fund Managers: An Empirical Investigation', *Journal of Finance*, Vol. 48, pp. 1039-1055.
12. Cumby, R.E., and J.D. Glen, 1990, 'Evaluating the Performance of International Mutual Funds', *Journal of Finance*, Vol. 45, pp. 497-521.
13. Draper, N.R., and H. Smith, 1998, *Applied Regression Analysis*, (John Wiley & Sons: New York).
14. Drew, M.E., and M. Veeraraghavan, 2001, 'Explaining the cross-section of stock returns in the Asian region', *International Quarterly Journal of Finance*, Vol. 1, pp. 205-221.
15. Elton, E., M. Gruber, and C. Blake, 1996, 'Survivorship bias and mutual fund performance', *Review of Financial Studies*, Vol. 9, pp. 133-157.
16. Fabozzi, F.J., and J.C. Francis, 1979, 'Mutual Fund Systematic Risk for Bull and Bear Markets: An Empirical Examination', *Journal of Finance*, Vol. 34, pp. 1243-1250.
17. Fama, E.F., 1972, 'Components of Investment Performance', *Journal of Finance*, Vol. 27, pp. 551-567.
18. _____ and K.R. French, 1996, 'Mulitfactor Explanations of Asset Pricing Anomalies', *Journal of Finance*, Vol. 51, pp. 55-84.
19. Ferson, W.E., and R.W. Schadt, 1996, 'Measuring Fund Strategy and Performance in Changing Economic Conditions', *Journal of Finance*, Vol. 51, pp. 425-461.
20. _____ and V.A. Warther, 1996, 'Evaluating Fund Performance in a Dynamic Market,' *Financial Analysts Journal*, Vol. 52, pp. 20-28.
21. Fletcher, J., 1995, 'An Examination of the Selectivity and Market Timing Performance of UK Unit Trusts', *Journal of Business Finance and Accounting*, Vol. 22, pp. 143-156.
22. Grant, D., 1977, 'Portfolio Performance and the Cost of Timing Decisions', *Journal of Finance*, Vol. 32, pp. 837-846.
23. Grinblatt, M., and S. Titman, 1989, 'Portfolio performance: Old issues and new insights', *Review of Financial Studies*, Vol. 2, pp. 393-421.
24. Gruber, M., 1996, 'Another Puzzle: The Growth in Actively Managed Mutual Funds', *Journal of Finance*, Vol. 51, pp. 783-810.
25. Hallahan, T.A., and R.W. Faff, 1999, 'An Examination of Australian Equity Trusts for Selectivity and Market Timing Performance', *Journal of Multinational Financial Management*, Vol. 9, pp. 387-402.
26. Halliwell, J., R.A. Heaney, and J. Sawicki, 1999, 'Size and Book to Market Effects in Australian Share Markets: A Time Series Analysis', *Accounting Research Journal*, Vol. 12, pp. 122-137.

27. Hansen, L., 1982, ‘Large Sample Properties of Generalised Method of Moments Estimators’, *Econometrica*, Vol. 50, pp. 1029-1054.
28. Henriksson, R.D., 1984, ‘Market Timing and Mutual Fund Performance: An Empirical Investigation’, *Journal of Business*, Vol. 57, pp. 73-96.
29. _____ and R.C. Merton, 1981, ‘On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills’, *Journal of Business*, Vol. 54, pp. 513-533.
30. Hsieh, D., 1983, ‘A Heteroskedasticity-Consistent Covariance Matrix Estimator for Time Series Regressions’, *Journal of Econometrics*, Vol. 22, pp. 281-290.
31. Jagannathan, R., and R. Korajczyk, 1986, ‘Assessing the Market Timing Performance of Managed Portfolios’, *Journal of Business*, Vol. 59, pp. 217-235.
32. Jensen, M., 1968, ‘The Performance of Mutual Funds in the Period 1945-1964’, *Journal of Finance*, Vol. 23, pp. 389-416.
33. Kon, S.J., and F.C. Jen, 1978, ‘The Investment Performance of Mutual Funds: An Empirical Investigation of Timing, Selectivity, and Market Efficiency’, *Journal of Business*, Vol. 52, pp. 263-289.
34. Lee, C.F., and S. Rahman, 1990, ‘Market Timing, Selectivity, and Mutual Fund Performance: An Empirical Investigation’, *Journal of Business*, Vol. 63, pp. 261-278.
35. Lehmann B.N., and D.M. Modest, 1987, ‘Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons’, *Journal of Finance*, Vol. 42, pp. 233-265.
36. Rosenberg, B., K. Reid, and R. Lanstein, 1985, ‘Persuasive Evidence of Market Inefficiency’, *Journal of Portfolio Management*, Vol. 11, pp. 9-17.
37. Sawicki, J., and F. Ong, 2000, ‘Evaluating Mutual Fund Performance using Conditional Measures: Australian Evidence’, *Pacific-Basin Finance Journal* Vol. 8, pp. 505-528.
38. Treynor, J., 1965, ‘How to Rate Management of Mutual Funds’, *Harvard Business Review*, Vol. 43, pp. 63-75.
39. _____ and K. Mazuy, 1966, ‘Can Mutual Funds Outguess the Market’, *Harvard Business Review*, Vol. 44, pp. 131-136.
40. Warwick, B., 2000, Searching for Alpha: The Quest for Exceptional Investment Performance, (John Wiley & Sons: New York).
41. Wermers, R., 2000, ‘Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs and expenses’, *Journal of Finance*, Vol. 55, pp. 1655-1695.
42. White, H., 1980, ‘Heteroskedasticity-Consistent Covariance Matrix Estimators and a Direct Test for Heteroskedasticity’, *Econometrica*, Vol. 48, pp. 817-838.

Appendix I

Diagnostic Tests

Listed are the diagnostic tests for each model used in the study. Durbin Watson and Jarque Bera test statistics (and probability values) are reported. The data set employed is largely clean, as the diagnostic tests reveal that the models employed do not suffer from any of the common ailments of first-order serial correlation, or non-normality of the residuals. All results have used White's (1980) option for heteroskedasticity-consistent variance and standard errors.

Diagnostic Test	Market Proxy	Single-index	Multi-index	Quadratic	Dual-Beta
Durbin-Watson	Top 100	2.1779	2.2144	2.1621	2.1736
	Top 20	2.1174	2.2080	2.1122	2.1092
Jarque Bera	Top 100	15.11 (p = 0.45)	25.45 (p = 0.42)	15.27 (p = 0.44)	14.61 (p = 0.43)
	Top 20	13.24 (p = 0.33)	10.86 (p = 0.43)	13.62 (p = 0.34)	12.05 (p = 0.35)

Appendix II

Tests for Multicollinearity

Listed are the diagnostic checks for multicollinearity for the market timing models, TM and HM. The results demonstrate that the R2 values (and the corresponding F-statistic) for the auxiliary regressions estimated on the variables suspected to cause multicollinearity. The probability values given are less than the significance levels at the 5% and 10% level, resulting in a rejection of the null hypothesis of no multicollinearity.

Model	Market Proxy	Variable	R^2	F-stat (p-value)
Treynor and Mazuy (1966)	Top 100	$\gamma_i R_{mt}^2$	0.13	7.37 (p = 0.00)
	Top 20	$\gamma_i R_{mt}^2$	0.06	3.11 (p = 0.00)
Henriksson and Merton (1981)	Top 100	$\beta_{2i}DR_{mt}$	0.69	110.81 (p = 0.00)
	Top 20	$\beta_{2i}DR_{mt}$	0.72	128.37 (p = 0.00)

Appendix III

Additional Tests for Multicollinearity

Listed are additional diagnostic checks for multicollinearity for the two market timing models. It shows regression estimates for the variables responsible for the collinearity problem. This is achieved by: first, regressing these variables alone against the original dependent variable, excess fund returns; and, second regressing them with the other explanatory variable against excess fund returns.

Model	Market Proxy	Variable	Estimate when regressed alone	Estimate when regressed with other explanatory variables
Treynor and Mazuy (1966)	Top 100	γi Rmt2	-0.0705 (t = -3.79)	-0.0106 (t = -1.22)
	Top 20	γi Rmt2	-0.0659 (t = -2.58)	-0.0234 (t = -2.33)
Henriksson and Merton (1981)	Top 100	β2iDRmt	1.2885 (t = 8.39)	-0.1244 (t = -0.82)
	Top 20	β2iDRmt	1.0834 (t = 7.58)	-0.3551 (t = -2.04)