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# Do Derivatives Have a Role in the Risk-Shifting Behaviour of Fund Managers?

*by*
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***Abstract:***

*In this paper we examine the extent to which derivatives are used to affect the risk-shifting behaviour of Australian equity fund managers. We find, after periods of good and poor performance, the risk-shifting behaviour of fund managers is different between derivative users and non-users. Our results support the gaming and active competition hypotheses but there is little support for the cash flow hypothesis. The study also allows for a complex reporting environment by analysing data across three alternate time periods: the calendar year, financial year and quarterly frames. Given that our results are not consistent across time periods for users and non-users of derivatives, some caution in interpretation is required.*

***Keywords:***

*DERIVATIVE USE; MANAGED FUNDS; RISK-SHIFTING BEHAVIOUR; TOURNAMENT BEHAVIOUR.*

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The authors gratefully acknowledge the Russell Investment Group for supplying part of the data used in this study.

*Australian Journal of Management, Vol. 32, No. 2 December 2007, © The University of New South Wales*

## 1. Introduction

The performance of the investment fund industry is carefully monitored by a variety of interest groups including investors, financial advisors and financial consulting firms who collect and report outcomes. The competitive nature of the industry leads to agency pressures as the managers seek to maximize their compensation and vie for investment funds, thereby inducing behaviour that is not likely to be fully congruent with investor wealth maximization. Past returns and risk are the key measures in the assessment of managed funds. Managers have incentives to engage in 'tournament' behaviour and a change in risk in the underlying portfolio can potentially quickly impact on the fund return and, hence, tournament outcome. Derivative users may have an advantage in the risk-shifting process as the inclusion of derivatives in the portfolio allows for a low cost adjustment to the risk/return profile of the fund.

In this paper we examine the risk-shifting behaviour across a sample of Australian investment fund mangers, who are users and non-users of derivatives. We develop and test predictions with respect to the change in risk in response to past performance and derivative use. Two alternative risk measures are used: total risk (standard deviation) and downside risk. Past performance is dichotomized into good and poor outcomes.

The investment fund manager may be motivated by various performance criteria and/or reward outcomes. Brown, Harlow and Starks (1996) portray the industry as a tournament. They argue that manager behaviour will be motivated by their compensation plans that reward high performance at the end of the year.[1] Hence, managers who have performed poorly in the first half of the year will attempt to increase their performance by increasing the risk of their portfolio. The basic prediction of this 'gaming' hypothesis is that the increase in risk by the interim 'losers' will be greater than the increase in risk undertaken by the interim 'winners'. In contrast, Taylor (2003) proposes that managerial risk-shifting behaviour for interim losers and winners will be reversed when active managers are competing against each other in the tournament, as opposed to a competition against a predefined benchmark. Managers may also be motivated to attract high cash inflows. The past performance of funds is relevant in attracting new investment (Sirri & Tufano 1998). Compensation plans can also be dependent on

1. Obtaining hard 'evidence' on annual performance compensation in Australia is difficult due to confidentiality. Anecdotal evidence suggests that it is a strong feature of the industry. This is backed up by indirect evidence relating to the existence of a range of annual awards and annual 'league' tables that provide public rankings of funds. Most notable among these in Australia are those produced by the two major ratings agencies: Morningstar and S&P (e.g Morningstar see http://www.morningstar.com.au/). As one recent example, of how seriously fund managers treat these annual awards consider the case of the fund manager Tyndall. Tyndall proudly publicise the range of 'annual best of' awards that the fund has achieved in the recent past. For example, their website (accessed: 21 November, 2006) boasts: 2005 S&P Fund Manager of the Year; 'Best Australian Share Funds 2006' in Money Magazine's Best of Best Awards; AFR Smart Investor Blue Ribbon 2006—Australian Bonds Sector; 2005 Morningstar Fixed Interest Fund Manager of the Year—Australia; Income Fund of Year—Fixed Interest, and Income Fund of the Year—International Fixed Interest, in Personal Investment Magazine's Awards for Excellence in Financial Services 2005. (http://www.tyndall.com.au/dirt/tyndall/tyndallpublishv3.nsf/Content/BreakingNews-2005September12-Tyndall+wins+the+Standard+&+Poor's+Global+Fixed+Income+2006+award)

the net asset value of the fund (Chevalier & Ellison 1997), again supporting the competitive interpretation of manager activity.

These studies of manager motivations have focused on the performance/risk relationship of the fund. Integral to the risk profile of a fund is the portfolio composition and the inclusion of derivatives in the portfolio could theoretically allow managers to (more) quickly adjust fund risk and expected payoffs. Koski and Pontiff (1999) extend the tournament concept to consider how behaviour differs between managers who use derivatives and those who do not. Investment in derivatives provides an opportunity to hedge risks or to engage in speculative, higher-risk activities. Hence, the inclusion of derivatives in the fund portfolio allows a fund manager to adjust the risk of the fund portfolio with a relatively small initial outlay. Risk-shifting behaviour is potentially less costly for derivative users and, therefore, likely to be more evident within this group of fund managers.

We formulate and test three competing hypotheses: (a) gaming hypothesis (Brown, Harlow & Starks 1996); (b) cash flow hypothesis (Koski & Pontiff 1999); and, (c) active competition hypothesis (Taylor 2003). There is some evidence in the literature to support one or more of the hypotheses. However, individual studies tend to take a narrow perspective and the results in general are conflicting. In our view, it is now time to consolidate these different strands of the literature. Accordingly, one of our key contributions is the direct comparison of these hypotheses, within a single research setting.

We establish clear predictions of the expected change in risk for prior good and poor performers and for derivative users and non-users. We measure risk using symmetric risk (standard deviation) and downside risk. This distinction is important particularly in the context of derivative users, since this group is able to effectively avoid downside volatility but maximise the upside. Our classification of predictions for alternate hypotheses allows for an understanding of wherein lies the weight of evidence. Our analysis of the predictions for dichotomous performance and for users versus non-users of derivatives varies depending on the hypothesis and the risk measures.

We contribute to the literature in two main ways. First, we jointly examine each of the competing tournament hypotheses. This allows us to compare the hypotheses using the same data in the same setting. The prior literature has examined each hypothesis in isolation. Second, we consider the possibility that alternate reporting dates may give rise to multiple tournaments. In Australia the key reporting dates are the calendar year-end and the end of the financial year, June 30. Each date could create incentives for tournament behaviour. Additionally, regular reporting on a monthly basis by rating agencies such as ASSIRT and Morningstar ensures that retail investors have timely access to very recent performance results. Hence we incorporate a quarterly analysis. The prior literature has generally focused on the calendar year. We expect tournament behaviour to be occurring both within financial and calendar years and on an on-going basis in Australia.

Overall, the results indicate that the risk-shifting behaviour of fund managers, after periods of good and poor performance, is different between derivative users and non-users. The calendar year and financial year results indicate that derivative users are actively competing and that non-users are gaming. However, when we examine this behaviour on an on-going basis. there is no difference between users and non-users but both groups are actively competing, especially after periods of good performance. In an Australian context it appears that risk-shifting behaviour not only occurs both within calendar years and financial years, but also on an on-going basis. The alternate time period results are in some cases conflicting across derivative uses and non-users and, thus, some caution is warranted regarding the interpretation of our results. Nevertheless, despite the mixed results, it appears that derivatives are not being used aggressively by fund managers to manage their fund risk.

The paper is structured as follows. Section 2 provides some regulatory background and a brief review of the literature and section 3 provides an outline of the data and methods including a summary of the hypothesised performance/risk relationships. Results are presented in section 4 and conclusions are provided in section 5.

## 2. Regulatory Background and Brief Literature Review

### *2.1 Regulatory Background*

At a general level, the Financial Services Reform Act 2001 provides for a uniform disclosure regime aimed at giving consumers ready access to adequate information regarding financial products. The broad ambit of this legislation captures managed investment schemes and it effectively creates a principles-based framework in relation to the content of disclosure documents. A key element of the law is the provision of a product disclosure statement (PDS) to retail clients and the main content requirements are set out in s1013D of the Act. Related to this is the requirement that Australian fund mangers have an Australian Financial Services Licence to offer investment products to retail customers. In granting the licence, the Australian Securities and Investment Commission (ASIC) requires the licence holder to demonstrate competence in managing derivatives. Specifically, in any offer to the public via a PDS the fund manager must explain the use of derivatives that will be employed in the delivery of the product.[2] Thus, the legislative framework is provided by the licensing regime concerned with demonstrated ability to deal with derivatives and to use the derivatives within the parameters as laid down in the PDS.[3]

### *2.2 Literature*

The literature review is divided into two sections. First, we examine the literature that focuses on risk shifting behaviour and tournament related activities. Second, we discuss Australian studies that address the use of derivatives by fund managers.

*2.2.1 Risk Shifting Behaviour* Risk shifting behaviour is examined by Brown, Harlow and Starks (1996) in a tournament setting. They focus on the reactions of fund managers to their most recent performance results. Fundamental to

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2. In late 2004, ASIC issued an Information Release on PDS disclosure that among other things issued guidance on the required disclosure regarding derivative use. Refer to: http://www.asic.gov.au/asic/asic_pub.nsf/byheadline/IR+0471+ASIC+issues+guidance+on+PDS+disclosure?openDocument
3. Fong, Gallagher and Ng (2005, p. 2) report that the Australian Prudential Regulation Authority (APRA) prescribe non-speculative use of derivatives which must be in accordance with the fund's trust deed.

management behaviour is the assumption that investors use prior period performance to determine future investments. The flow-performance relationship has been well documented (e.g. Sirri & Tufano 1992; Del Guercio & Tkac 2002) and extended to consider the impact of investor search costs and management advertising (Huang, Wei & Yan 2007). Tournament research focuses on the agency issues arising from these relationships.

Brown, Harlow and Starks find evidence to suggest that managers with unfavorable performance results mid-year, will adjust the risk of the portfolio in the second half of the year in a bid to lift their performance ranking by year end. The results show that risk shifting behaviour is more evident for losers than for winners consistent with managerial incentive gaming. Koski and Pontiff (1999) provide an alternative explanation for the Brown, Harlow and Starks results. They propose that managers are slow to respond to new cash flows. The prior good performance of a 'winning' manager, induces an increase in cash and, hence, a decrease in risk. For the 'losing' manager, investors accelerate redemptions and the risk of the fund increases as cash holdings are drawn down and/or borrowings are used to fund the outflow. However, they do not reconcile the asymmetry in fund flows. While winners indeed could expect high inflows, it is not likely that losers will have an expectation of a corresponding outflow (Sirri & Tufano 1998). Berkowitz and Kotowitz (2000) demonstrate the nonlinearity in the funds flow and performance relationship and argue that better performing managers have an incentive to increase risk.

Subsequent studies have not clearly supported the Brown, Harlow and Starks results. Chevalier and Ellison (1999) find that the risk taking behaviour of poorer performing funds differed from funds with higher performance but the timing of the outcomes was not necessarily consistent with the Brown, Harlow and Starks hypothesis. Busse (2001) re-examines the tournament analysis with daily data and cannot find evidence to support BHS. He argues that his more precise volatility estimates from the daily data are more reliable for testing the hypotheses.

*2.2.2 Derivative Use by Australian Fund Managers* There are limited studies on derivative use and risk shifting behaviour in the Australian fund management industry. Indeed, the use of derivatives is not extensive. Pinnuck (2004) finds that, although one-half of the managers sampled held exchange traded options, the percentage of the total portfolio value, represented by options, was less than 5%. The performance, risk and turnover for option users are not significantly different to non-users. Fong, Gallagher and Ng (2005) examine institutional funds and find no difference between users and non-users of derivatives in terms of their performance and risk characteristics. Their results show that options are used to gain exposure to momentum stocks. By examining derivative trading behaviour; Fong, Gallagher and Ng provide a motivation for derivative use by managers.

## 3. Data and Experimental Design

### *3.1 Data*

Information regarding the use of derivatives is required to be disclosed in the prospectuses and financial reports of Australian investment funds. We examine the use of derivatives by funds over the period 2002 to 2005. A fund is determined to be a derivative user if its prospectus indicates that the fund is authorized to use derivatives and its annual reports indicate that derivatives have been used.[4] Our initial analysis is conducted using a sample of 102 Australian retail domestic general equity funds. These funds were selected from the domestic equity category on the Morningstar database. Funds were only selected if monthly return data was available for the entire period from January 2002 to December 2005 and where derivative use could be determined. We also constructed weekly return data for these 102 funds over the same period.[5] To further extend our study we used an alternative data source which was available only for a limited number of funds. This sample (obtained from the Russell Investment Group) comprises 30 funds for the period from January 1994 to December 2003 where actual percentage derivative use was identified. The percentages are determined relative to the total fund assets at the beginning of each period.

Table 1 summarizes the derivative use, age and size of funds in the main sample and the actual derivative use sub-sample.[6] Panel A shows that of the 102 funds in the main sample, 34 (33.3%) are derivative users, while the remainder are not. The average fund age is 11.70 years and size is A$47.50 million. There are no significant differences in age and size between derivative users and non-users. In panel B, 20 of the funds are derivative users and 10 funds are non-users. Derivative use ranges from 0.06% to 6.27% of total funds assets. In the actual derivative use sub-sample, derivative users are bigger and older than non-users.

### *3.2 Hypothesized Relationships*

From the literature we extract three key hypotheses that portray the relationship between performance and risk: the ‘gaming’ hypothesis, the ‘cash flow’ hypothesis (CF), and Taylor’s (2003) ‘active competitors’ hypothesis (AC). The expected strategies of managers vary depending on the hypothesis adopted.

Under the gaming hypothesis, in a period following poor performance, we would expect to see an increase in risk as managers attempt to boost performance. Following good performance, risk is expected to remain stable in an attempt to maintain the current performance ranking. The manager’s motivation is to maximize payoffs from incentive compensation contracts.

Proponents of the cash flow hypothesis would argue that cash flows are insensitive to poor performance therefore there would be no risk impact. Further, recipients of cash inflows following good performance could be unable to invest these new contributions immediately resulting in an increase in the fund’s cash position leading to a decrease in risk.

4. Annual reports we checked for derivative use at least every two years. The type of derivatives used by the funds could not be identified. The information regarding derivative use is for a particular fund not the manager or the family of funds.
5. Weekly return data were constructed from weekly fund exit prices adjusted for distributions. Only those funds with at least three weekly observations per quarter were included in the sample.
6. Descriptive statistics are for the year 2005 for panel A and 2003 for panel B. Derivative use varies over the sample period.

## Table 1
## Derivative Use, Age and Size of Sample Funds

The table provides a summary of derivative use and the age and size of the sample funds. Panel A covers our main sample of 102 Australian retail domestic equity funds. The data was obtained from Morningstar where monthly return observations were available for the entire period from January 2002 to December 2005. Derivative use was obtained from fund prospectuses and annual reports. Panel B covers the actual derivative use sub-sample of 30 funds. The data was obtained from Morningstar where monthly return observations were available for the period from January 1994 to December 2003 and actual percentage derivative use information was obtained from the Russell Investment Group. Derivative use is calculated as the proportion of fund assets held as derivatives.

| | All Funds | Derivative Users | Non-Users |
|---|---|---|---|
| *Panel A: Main Sample* | | | |
| N | 102 | 34 | 68 |
| Age (Avg) in years | 11.70 | 11.15 | 11.94 |
| Size (Avg) in A$ millions | 47.50 | 52.92 | 45.31 |
| *Panel B: Actual Derivative Use Sub-sample* | | | |
| N | 30 | 20 | 10 |
| Derivative Use (Avg) | 1.11% | 1.67% | 0.00% |
| Derivative Use (Min) | 0.00% | 0.06% | 0.00% |
| Derivative Use (Max) | 6.27% | 6.27% | 0.00% |
| Age (Avg) in years | 7.98 | 11.57 | 4.83 |
| Size (Avg) in millions | 63.40 | 96.97 | 43.72 |

Using an alternative framework Taylor (2003) models the risk shifting behaviour of fund managers. He proposes that managers who are ranked against an external benchmark, such as a market index, will follow the Brown, Harlow and Starks tournament behaviour. However, when the managers are actively competing against each other the winning manager is more likely to increase the portfolio risk in a response to his expectation of the losing manager's behaviour. Similarly the losing manager anticipates the winner's strategy and takes an opposing strategy. Taylor argues that in equilibrium the resulting probabilities of gambling are such that the winner will take more risk than the loser. Applying Taylor's active competitors hypothesis we expect poor performing managers to decrease their risk as the losing manager anticipates the winners' strategy and takes the opposing action. Winners will increase their risk in reaction to the anticipated gaming by the losers. The expectations following poor and good performance, for each of the hypotheses, are summarized in table 2, panel A.

## Table 2

## Summary of Risk Change Predictions for the ‘Gaming’, ‘Cash Flow’ and ‘Active Competitors’ Hypotheses

*Panel A: Basic Risk Change Predictions*

| Interim Performance | H1: Gaming Hypothesis Risk Change Prediction | Commentary | H2: Cash Flow Hypothesis Risk Change Prediction | Commentary | H3: Active Competitors Hypothesis Risk Change Prediction | Commentary |
|---|---|---|---|---|---|---|
| Poor | *Increase* | Attempt to boost performance | *Stable* | Cash flows are insensitive to poor performance, hence no risk impact | *Decrease* | Losing manager anticipates winners strategy and takes opposing action |
| Good | *Stable/ Decrease* | Attempt to maintain performance/risk ranking | *Decrease* | Good performance induces new cash inflows that are difficult to place quickly | *Increase* | Active competition sees winners reacting to anticipated gaming by losers |

*Panel B: Total Risk—Risk Change Predictions for Derivative Users versus Non-users*

| H1: Gaming Hypothesis | Risk Change Prediction | | |
|---|---|---|---|
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Increase* | *Increase* | Risk increase for DU > DNU |
| Good | *Stable/ Decrease* | *Stable/ Decrease* | If risk decreases, decrease for DU > DNU |
| **H2: Cash Flow Hypothesis** | Risk Change Prediction | | |
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Stable* | *Stable* | Cash flows are insensitive to poor performance, hence no risk impact. No difference between DU and DNU |
| Good | *Stable* | *Decrease* | DU can (DNU can’t) mitigate impact of difficult to place new cash inflows by derivative actions |
| **H3: Active Competitors Hypothesis** | Risk Change Prediction | | |
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Decrease* | *Decrease* | Risk decrease for DU > DNU |
| Good | *Increase* | *Increase* | Risk increase for DU > DNU |

**Table 2 Continued**

*Panel C: Downside Risk—Risk Change Predictions for Derivative Users versus Non-users*

| H1: Gaming Hypothesis | Risk Change Prediction | | |
|---|---|---|---|
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Stable* | *Increase* | DU can (DNU can't) maintain downside risk while increasing upside risk |
| Good | *Stable* | *Stable/ Decrease* | DU can (DNU can't) maintain downside risk while increasing upside risk |
| H2: Cash Flow Hypothesis | Risk Change Prediction | | |
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Stable* | *Stable* | Cash flows are insensitive to poor performance, hence no risk impact. No difference between DU and DNU |
| Good | *Stable* | *Decrease* | DU can (DNU can't) mitigate impact of difficult to place new cash inflows by derivative actions |
| H3: Active Competitors Hypothesis | Risk Change Prediction | | |
| Interim Performance | Derivative Users (DU) | Derivative Non-users (DNU) | Commentary |
| Poor | *Stable* | *Decrease* | DU can (DNU can't) maintain downside risk while increasing upside risk |
| Good | *Stable* | *Increase* | DU can (DNU can't) maintain downside risk while increasing upside risk |

Complicating the performance/risk relationship is the potential inclusion of derivatives in the portfolio. A derivative user has an advantage in that it is cost effective to shift the risk of the portfolio and they can do so in a timely manner. We expect to see a difference between managers who do and do not use derivatives. Moreover, any changes in risk to the portfolio are expected to be greater for derivative users. To summarize the expected relationship between performance and risk for derivative users and non-users we present panel B of table 2. Change in risk is stated relative to the alternate performance group. Further, for the gaming and cash flow hypotheses, we can specify that derivative users are expected to change their total risk by a greater amount than the non-derivative users.

Fundamental to testing these hypotheses is the measurement of risk. There are a number of alternative risk measures available. Koski and Pontiff examine changes in total risk, beta and idiosyncratic risk. Reference to the typical fund managers' performance tables and key reporting figures indicates that the most relevant measure of risk is total risk. Accordingly, we adopt this measure. In addition, given the asymmetric nature of the payoff from derivatives, we also consider downside risk which is simply the lower bound of the standard deviation measure.[7] We consider total risk (standard deviation) and downside risk to be the most relevant in a risk behaviour study as our hypotheses focus on the behaviour processes of managers as portrayed to the investing public.[8] For a derivative user the expected change in downside risk will be different to the expected change in total risk since a derivative user can minimize downside risk while maximizing the upside return. Panel C of table 2 shows the impact of these differences on performance-risk predictions for each of the three hypotheses.

### *3.3 Models*

The literature identifies age and size to be important explanatory variables in fund activities (e.g. Chevalier & Ellison 1997; Sirri & Tufano 1998). Chevalier and Ellison find that the cash flows of older funds are less sensitive to recent performance. Therefore managers of older funds have less incentive to engage in risk shifting behaviour. Larger funds have lower growth and again have less incentive to adjust the riskiness of the portfolio to attract new money. Therefore, we include age and size as variables to control for these relationships.

We begin our analysis by considering the basic risk/performance relationship of managed funds. The base case model to assess risk shifting behaviour is expressed in Equation 1.

$$\Delta Risk = \alpha + \beta PERF + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \qquad (1)$$

where *ΔRISK*: change in the risk variable between periods; *PERF:* difference between the fund return and the benchmark return in the previous period, where the

7. Our focus on these two risk measures is supported by two common performance measures applied to fund managers—namely, the Sharpe ratio and the Sortino ratio. The denominator of each of these ratio-based measures use standard deviation and downside risk, respectively.
8. For completeness and consistency we also estimate the initial model for beta and idiosyncratic risk. These results contributed little to our focus on management behaviour in response to investor demands. Further, management of beta and idiosyncratic risk involves an assessment of the market timing measure. This variable is not relevant in the context of gaming.

benchmark return is the return on the All Ords Accumulation Index;[9] *LagRisk* : value of the risk variable during the previous period; *Age* is the age in months for the fund at the beginning of the period; *Size*: natural logarithm of Total Net Assets at the beginning of the period; $Dummy_j$: dummy variables for sub-periods. Two measures of risk are examined: (a) Standard deviation (STD) is the standard deviation of fund returns over the period; and, (b) Downside risk (DOWN) is the downside standard deviation calculated as the square root of the average square of the maximum of zero and the fund return less the market return.

We then extend Model 1 to incorporate derivative users and non-users as in Equation 2, similar to Koski and Pontiff.

$$\Delta Risk = \alpha_N D_N + \alpha_U D_U + \beta_N [D_N * PERF] + \beta_U [D_U * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \tag{2}$$

where $D_N$ = 1 if Non-derivative user; $D_U$ = 1 if Derivative user; both zero otherwise.

Given the asymmetric nature of the cash flow reaction to good and poor performance we extend the model further by dichotomising the performance measures. Specifically, we examine two additional models: Equation 3 allows us to identify the performance effect and Equation 4 jointly incorporates derivative users and the performance effect.

$$\Delta Risk = \alpha_{Poor} D_{Poor} + \alpha_{Good} D_{Good} + \beta_{Poor} [D_{Poor} * PERF] + \beta_{Good} [D_{Good} * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \tag{3}$$

where $D_{\text{Poor}}$ = 1 if poor interim performance; $D_{\text{Good}}$ = 1 if good interim performance; both zero otherwise. A good (poor) performer has a return, in the previous period, greater than (less than) the return on the All Ords Accumulation Index for the same period.

$$\Delta Risk = \sum_{\substack{PN,PU,\\ GN,GU}} \alpha_i D_i + \sum_{\substack{PN,PU,\\ GN,GU}} \beta_i [D_i * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \tag{4}$$

where $D_{PN}$ = 1 if Poor/Non-user; $D_{PU}$ = 1 if Poor/User; $D_{GN}$ = 1 if Good/Non-user; $D_{GU}$ = 1 if Good/User; all zero otherwise.

The expected sign/direction of the coefficients depends on the hypothesis being tested. In table 3 we summarise our expectations with respect to the coefficients, mapping directly from the hypothesised relationships in table 2. The hypothesised relationships will vary for derivative users where downside risk is measured. This variation is attributed to the ability of derivative users to minimise their downside risk through hedging strategies without affecting their upside potential. In panel A of table 3 we summarise the expected sign/direction of the coefficients for the gaming, cash flow and active competitors' hypotheses as

9. The models were also run using the difference between the fund return and the average return of all funds in the sample. The results are consistent with those using the market return as the benchmark. The correlation between the sample average return and the All Ords return is 0.97.

relevant to equations 1, 2 and 3. In panel B we summarise the expected sign/direction of the coefficients on equation 4 where total risk is tested. Panel C shows the expected sign/direction of the coefficients in model 4 when the downside risk measure is employed.

All regressions are analysed using weighted least squares regression (WLS). Weights for the WLS are computed by running a first-pass ordinary least squares regression. The residual terms from this regression are then used to compute a fund-specific standard deviation, the inverse of which is used as the weight in the second-pass weighted least squares regression. The procedure is designed to control for fund-specific heteroskedasticity.

### *3.4 Measurement Periods*

Consistent with Koski and Pontiff we run each of the models within a calendar year. However, we also examine the relationship between past performance and change in risk within financial years. The financial year performance is regarded in Australia as equally, if not more, important than calendar year performance. The financial year is the key reporting date for investors and managers alike, both for taxation and accounting purposes. The performance tables at this time of year are deemed to have at least the same market 'prominence' compared to those published at the calendar year end. Thus, we argue that there are strong incentives for managers to manipulate their fund performance during financial years and calendar years.

Further in Australia, two key assessment agencies—ASSIRT and Morningstar—provide monthly updates in a timely manner to investors. These updates include key performance measures. The information allows for the assessment of managed funds on an ongoing basis which could in fact increase/complicate the risk shifting behaviour of fund managers. As such, the risk adjustments may not be purely played within the confines of the annual timeframe but on a more regular basis. In a further extension of our analysis, we therefore switch to three-month intervals and use weekly returns so that we can obtain meaningful standard deviation measures. Models 1 to 4 are re-estimated using this more finely sampled data.

## 4. Results

### *4.1 Descriptive Statistics*

Table 4 shows the means and standard deviations of the return and risk measures for the entire sample period and by year for derivative users and non-users. In specific years, such as 2003, derivative users had a lower average return than non-users, and in 2002 and 2005 derivative users had lower downside risk than non-users. However, over the entire sample period there are no significant differences between derivative users and non-users. These results are consistent with Koski and Pontiff (1999), Fong, Gallagher and Ng (2005) and Pinnuck (2004) who find no significant differences in risk and performance measures between users and non-users of derivatives.

# Table 3

## Coefficient Predictions in the Context of Dummy Variable-based Regression Models

$$\Delta Risk = \alpha + \beta PERF + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (1)$$

where Δ RISK is the change in the risk variable between the first six-months and the second six-months in a year. Alternate measure of risk are standard deviation (STD) and downside risk (DOWN); PERF is the difference between the fund return and the benchmark return in the first six-months of the year; LagRisk is the value of the risk variable during the first six-months of the year; Age is the age in months for the fund at the beginning of the period; Size is the natural logarithm of Total Net Assets at the beginning of the period; $Dummy_j$ represents a range of dummy variables for sub-periods and fund types.

$$\Delta Risk = \alpha_N D_N + \alpha_U D_U + \beta_N [D_N * PERF] + \beta_U [D_U * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (2)$$

where $D_N = 1$ if Non-derivative user; $D_U = 1$ if Derivative user

$$\Delta Risk = \alpha_{Poor} D_{Poor} + \alpha_{Good} D_{Good} + \beta_{Poor} [D_{Poor} * PERF] + \beta_{Good} [D_{Good} * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (3)$$

Where $D_{Poor} = 1$ if poor interim performance; $D_{GOOD} = 1$ if good interim performance

$$\Delta Risk = \sum_{\substack{PN,PU,\\GN,GU}} \alpha_i D_i + \sum_{\substack{PN,PU,\\GN,GU}} \beta_i [D_i * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (4)$$

where $D_{PN} = 1$ if Poor/Non-user; $D_{PU} = 1$ if Poor/User; $D_{GN} = 1$ if Good/Non-user; $D_{GU} = 1$ if Good/User

| | Model (1) | Model (2) | | | | | Model (3) | |
|---|---|---|---|---|---|---|---|---|
| | | Total Risk | | | Downside Risk | | | |
| *Panel A: Base Models* | | | | | | | | |
| Hypothesis | $\beta$ | $\beta_N$ | $\beta_U$ | Supp. Test | $\beta_N$ | $\beta_U$ | $\beta_{Poor}$ | $\beta_{Good}$ |
| H1: Gaming | – | – | – | $\beta_N > \beta_U$ | – | 0 | – | –/0 |
| H2: CF* | –/0 | – | 0 | | – | 0 | 0 | – |
| H3: AC** | + | + | + | $\beta_N < \beta_U$ | + | 0 | + | + |

*Panel B: Model (4): Conditional Derivative Use Model—Total Risk*

| Hypothesis | $\beta_{PN}$ | $\beta_{PU}$ | $\beta_{GN}$ | $\beta_{GU}$ | Supplementary Tests | |
|---|---|---|---|---|---|---|
| H1: Gaming | – | – | –/0 | –/0 | $\beta_{PN} > \beta_{PU}$ | $\beta_{GN} > \beta_{GU}$ |
| H2: CF* | 0 | 0 | – | 0 | | |
| H3: AC** | + | + | + | + | $\beta_{PN} < \beta_{PU}$ | $\beta_{GN} < \beta_{GU}$ |

*Panel C: Model (4): Conditional Derivative Use Model—Downside Risk*

| Hypothesis | $\beta_{PN}$ | $\beta_{PU}$ | $\beta_{GN}$ | $\beta_{GU}$ |
|---|---|---|---|---|
| H1: Gaming | – | 0 | –/0 | 0 |
| H2: CF* | 0 | 0 | – | 0 |
| H3: AC** | + | 0 | + | 0 |

Note: * CF: 'cash flow' hypothesis; ** AC: 'active competitors' hypothesis.

## Table 4

## Return and Risk Characteristics—Derivative Users versus Non-Users

The table reports means and standard deviations of return and risk measures for all funds, derivative users and non-users. Results are based on monthly returns over the period from January 2002 to December 2005. Tests of differences are t-tests of the null hypothesis that mean variable estimates are equal for derivative users and non-users.

| | All Funds | | Derivative Users | | Non-Users | | Tests of Differences |
|---|---|---|---|---|---|---|---|
| | Mean | Std | Mean | Std | Mean | Std | p-value |
| *Return* | | | | | | | |
| All years | 0.0097 | 0.0020 | 0.0095 | 0.0018 | 0.0098 | 0.0021 | 0.45 |
| 2002 | –0.0086 | 0.0054 | –0.0082 | 0.0046 | –0.0087 | 0.0057 | 0.69 |
| 2003 | 0.0116 | 0.0029 | 0.0106 | 0.0017 | 0.0119 | 0.0031 | 0.01 |
| 2004 | 0.0195 | 0.0038 | 0.0192 | 0.0021 | 0.0196 | 0.0044 | 0.58 |
| 2005 | 0.0164 | 0.0038 | 0.0165 | 0.0022 | 0.0163 | 0.0044 | 0.75 |
| *Standard deviation* | | | | | | | |
| All years | 0.0288 | 0.0047 | 0.0288 | 0.0028 | 0.0288 | 0.0054 | 0.98 |
| 2002 | 0.0259 | 0.0047 | 0.0256 | 0.0022 | 0.0260 | 0.0053 | 0.57 |
| 2003 | 0.0310 | 0.0052 | 0.0315 | 0.0029 | 0.0308 | 0.0057 | 0.43 |
| 2004 | 0.0187 | 0.0040 | 0.0182 | 0.0029 | 0.0189 | 0.0045 | 0.37 |
| 2005 | 0.0312 | 0.0067 | 0.0301 | 0.0041 | 0.0317 | 0.0076 | 0.17 |
| *Downside risk* | | | | | | | |
| All years | 0.0024 | 0.0022 | 0.0021 | 0.0014 | 0.0025 | 0.0025 | 0.29 |
| 2002 | 0.0032 | 0.0037 | 0.0022 | 0.0026 | 0.0035 | 0.0040 | 0.05 |
| 2003 | 0.0018 | 0.0016 | 0.0016 | 0.0011 | 0.0019 | 0.0017 | 0.29 |
| 2004 | 0.0020 | 0.0024 | 0.0018 | 0.0012 | 0.0021 | 0.0027 | 0.36 |
| 2005 | 0.0025 | 0.0032 | 0.0019 | 0.0017 | 0.0028 | 0.0037 | 0.07 |

### *4.2 Main Regression Results*

The results for Model 1 are reported in table 5. The final column provides an indication as to their consistency with the hypotheses. Both panels A and B show a non-significant relationship between past performance and change in total risk. This is generally consistent with the cash flow hypothesis. However, panel C indicates a significant positive relationship between past performance and change in total risk, consistent with the active competition hypothesis. All panels reveal a significant positive relationship between past performance and change in downside risk, consistent with the active competition hypothesis. While these results must be interpreted with caution as they are at the aggregate level, there appears to be support for the active competition hypothesis, especially in panel C, when using weekly data and three-month time periods in assessing the risk-performance relationship.

## Table 5
## Regression of Change in Risk on Past Performance—Model 1

$$\Delta Risk = \alpha + \beta PERF + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \qquad (1)$$

Results of regressions testing the relation between the change in risk variable and prior period fund performance as expressed in model 1. Alternate change in risk variables are: STD—standard deviation and DOWN—downside risk. The independent variables are: PERF—the difference between the fund return and the benchmark return in the previous period, and LagRisk—the value of the risk variable during the previous period, Age—the age in months of the fund at the beginning of the period and Size—the log of total net assets at the beginning of the period. Each regression also includes dummy variables (not reported) for sub-periods. Values in parentheses are p-values for tests of the null hypothesis that the coefficient equals zero. Results are reported for weighted least squares (WLS), where the inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

| Risk Measure | α | β | γ | $\lambda_1$ | $\lambda_2$ | Consistency with Hypothesis |
|---|---|---|---|---|---|---|
| | | | *Panel A: Calendar Year Results* | | | |
| Δ STD | 0.0163<br>(0.00) | –0.0059<br>(0.27) | –0.4419<br>(0.00) | –0.000002<br>(0.08) | 0.00004<br>(0.53) | CF* |
| Δ DOWN | 0.0008<br>(0.14) | 0.0161<br>(0.00) | –0.5383<br>(0.00) | 0.000001<br>(0.15) | –0.00002<br>(0.59) | AC** |
| | | | *Panel B: Financial Year Results* | | | |
| Δ STD | 0.0232<br>(0.00) | 0.0092<br>(0.18) | –0.6285<br>(0.00) | –0.0000004<br>(0.80) | –0.00002<br>(0.78) | CF* |
| Δ DOWN | 0.0002<br>(0.81) | 0.0399<br>(0.00) | –0.3472<br>(0.00) | 0.0000<br>(0.99) | –0.00004<br>(0.26) | AC** |
| | | | *Panel C: Weekly Data Results* | | | |
| Δ STD | 0.0104<br>(0.00) | 0.0300<br>(0.00) | –0.9097<br>(0.00) | 0.000005<br>(0.70) | –0.0001<br>(0.09) | AC** |
| Δ DOWN | 0.0047<br>(0.00) | 0.0099<br>(0.00) | –0.8720<br>(0.00) | 0.0000002<br>(0.81) | –0.00004<br>(0.16) | AC** |

Note: * CF: 'cash flow' hypothesis; ** AC: 'active competitors' hypothesis.

These results provide preliminary evidence that active competition between funds exists and is continuously managed in response to the frequent reporting of performance information. In short, the results from the baseline Model 1 provide sufficient encouragement to explore our more elaborate models which consider the use of derivatives and the dichotomisation of performance.

The results for Model 2 are presented in table 6. These results separate the risk-performance relationship for derivative users and non-users. The calendar year and financial year results show a significant negative relationship between past performance and change in total risk for non-users. For derivative users, a significant positive relationship is reported. This suggests that users and non-users of derivatives respond to past performance differently in changing their total risk.[10]

10. A Walt test is performed to determine if there is a significant difference between $\beta_N$ and $\beta_U$. The test statistic is significant at the 5% level for all equations reported Table 6.

The results in panel C are different, with a significant positive relationship for non-users and no relationship for derivative users. The risk-performance relationship is not consistent over different time intervals.

**Table 6**

**Regression of Change in Risk on Past Performance, Derivative Users and Non-Users—Model 2**

$$\Delta Risk = \alpha_N D_N + \alpha_U D_U + \beta_N [D_N * PERF] + \beta_U [D_U * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (2)$$

Results of regressions testing the relation between the change in risk variable and prior period fund performance as expressed in model 2. Alternate change in risk variables are: STD—standard deviation and DOWN—downside risk. The independent variables are: $D_N = 1$ if Non-derivative user; $D_U = 1$ if Derivative user, PERF—the difference between the fund return and the benchmark return in the previous period, and LagRisk—the value of the risk variable during the previous period, Age—the age in months of the fund at the beginning of the period and Size—the log of Total Net Assets at the beginning of the period. Each regression also includes dummy variables (not reported) for sub-periods. Values in parentheses are p-values for tests of the null hypothesis that the coefficient equals zero. Results are reported for weighted least squares (WLS), where the inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

| Risk Measure | $\alpha_N$ | $\alpha_U$ | $\beta_N^{\#}$ | $\beta_U^{\#}$ | $\gamma$ | Consistency with Hypothesis |
|---|---|---|---|---|---|---|
| *Panel A: Calendar Year Results* | | | | | | |
| Δ STD | 0.0171<br>(0.00) | 0.0166<br>(0.00) | –0.0158<br>(0.01) | 0.0206<br>(0.08) | –0.4553<br>(0.00) | N:Gaming/CF*<br>U: AC** |
| Δ DOWN | 0.0006<br>(0.25) | 0.0011<br>(0.05) | 0.0199<br>(0.00) | 0.0002<br>(0.97) | –0.5379<br>(0.00) | AC** |
| *Panel B: Financial Year Results* | | | | | | |
| Δ STD | 0.0247<br>(0.00) | 0.0228<br>(0.00) | –0.0204<br>(0.00) | 0.0405<br>(0.00) | –0.6738<br>(0.00) | N:Gaming/CF*<br>U: AC** |
| Δ DOWN | 0.0012<br>(0.08) | 0.0005<br>(0.43) | 0.0155<br>(0.00) | 0.0401<br>(0.00) | –0.5229<br>(0.00) | N:AC** |
| *Panel C: Weekly Data Results* | | | | | | |
| Δ STD | 0.0106<br>(0.00) | 0.0095<br>(0.00) | 0.0354<br>(0.00) | 0.0092<br>(0.37) | –0.9143<br>(0.00) | N:AC**<br>U: CF* |
| Δ DOWN | 0.0047<br>(0.00) | 0.0045<br>(0.01) | 0.0137<br>(0.00) | –0.0017<br>(0.74) | –0.8716<br>(0.00) | AC** |

Note: *CF: 'cash flow' hypothesis ** AC: 'active competitors' hypothesis

# Results from a Wald test shows that there is a significant difference, at the 5% level of significance, between $\beta_N$ and $\beta_U$ in all equations.

For conciseness the coefficients on the age and size variables are not reported. Coefficients on these variables are in general consistent with table 5.

There is more consistency for the downside risk results, with a significant positive relationship for non-users across all panels. For derivative users, a positive relationship is reported in the financial year results and insignificant results are reported elsewhere. This could reflect that derivative users are better able to control their downside risk than non-users. Overall, the results show that there are significant differences in how derivative users and non-users change their fund risk in response to past performance.

Model 3 accommodates a dichotomisation of performance. In this model we can determine if changes in risk are consistent after periods of good and poor past performance. This is important for the cash flow hypothesis given the asymmetric nature of the performance-flow relationship. It may also be important if funds respond differently to good and poor performance. The results are presented in table 7. In the calendar year results (panel A) there is evidence of gaming after both poor and good performance on the total risk measure and after poor performance on the downside risk measure. There is also evidence of gaming after poor performance in the financial year results (panel B). In both the financial year and weekly data results (panel C), there is evidence of active competition after good performance on the total risk measure. In all three panels there is evidence of active competition after good performance on the downside risk measure. There is also some support for the cash flow hypothesis in the weekly data results after poor performance in both the total risk and downside risk measures and in the financial year results after poor performance in the downside risk measure.

Overall, there is little consistent support for any one hypothesis. The results suggest that funds tend to increase their risk after poor performance and also tend to increase their risk after good performance. As this is an unusual result, we move on to Model 4 to see if further insights can be gained from this more fine-tuned model.

Model 4 completes our modelling process, bringing together the dichotomy of performance and the delineation between derivative users and non-users. The results are presented in table 8. The calendar year results in panel A indicate that after poor performance, non-users increase their total risk (gaming), but derivative users decrease their total risk (active competition). There are no significant changes after good performance (gaming). In the financial year results in panel B, non-users increase their total risk after poor performance (gaming) but users do not (cash flow). After good performance, non-users don't see a change in risk (gaming), while derivative users increase their total risk (active competition). In panel C, both non-users and users increase their total risk after good performance (active competition), but do nothing following poor performance (cash flow). These results suggest that on an ongoing basis, both derivative users and non-users are actively competing by boosting their risk after good performance. However, in the financial year and calendar year tournaments, the results indicate that derivative user behaviour is consistent with the active competition hypothesis, while non-user behaviour is consistent with the gaming hypothesis. There is little consistent support for the cash flow hypothesis.

## Table 7

## Regression of Change in Risk on Past Performance Dichotomised for Good and Poor Performance—Model 3

$$\Delta Risk = \alpha_{Poor} D_{Poor} + \alpha_{Good} D_{Good} + \beta_{Poor}[D_{Poor} * PERF] + \beta_{Good}[D_{Good} * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (3)$$

Results of regressions testing the relation between the change in risk variable and prior period fund performance as expressed in model 3. Alternate change in risk variables are: STD—standard deviation and DOWN—downside risk. The independent variables are: $D_{Poor}$ = 1 if poor interim performance and $D_{Good}$ = 1 if good interim performance, PERF—the difference between the fund return and the benchmark return in the previous period, and LagRisk—the value of the risk variable during the previous period, Age—the age in months of the fund at the beginning of the period and Size—the log of total net assets at the beginning of the period. Each regression also includes dummy variables (not reported) for sub-periods. Values in parentheses are p-values for tests of the null hypothesis that the coefficient equals zero. Results are reported for weighted least squares (WLS), where the inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

| Risk Measure | $\alpha_{poor}$ | $\alpha_{good}$ | $\beta_{poor}$ | $\beta_{good}$ | $\gamma$ | Consistency with Hypothesis |
|---|---|---|---|---|---|---|
| | | | *Panel A: Calendar Year Results* | | | |
| Δ STD | 0.0163<br>(0.00) | 0.0160<br>(0.00) | –0.0389<br>(0.08) | 0.0110<br>(0.15) | –0.5715<br>(0.00) | Gaming |
| Δ DOWN | –0.0004<br>(0.50) | 0.0006<br>(0.26) | –0.0502<br>(0.00) | 0.0195<br>(0.00) | –0.6282<br>(0.00) | Poor: Gaming<br>Good: AC** |
| | | | *Panel B: Financial Year Results* | | | |
| Δ STD | 0.0236<br>(0.00) | 0.0248<br>(0.00) | –0.1528<br>(0.00) | 0.0397<br>(0.00) | –0.7619<br>(0.00) | Poor: Gaming<br>Good: AC** |
| Δ DOWN | 0.0002<br>(0.76) | 0.0005<br>(0.50) | –0.0121<br>(0.52) | 0.0311<br>(0.00) | –0.6281<br>(0.00) | Poor: CF*<br>Good: AC** |
| | | | *Panel C: Weekly Data Results* | | | |
| Δ STD | 0.0096<br>(0.00) | 0.0086<br>(0.00) | 0.0044<br>(0.64) | 0.1356<br>(0.00) | –0.9386<br>(0.00) | Poor: CF*<br>Good: AC** |
| Δ DOWN | 0.0045<br>(0.00) | 0.0040<br>(0.00) | 0.0041<br>(0.33) | 0.0469<br>(0.00) | –0.8894<br>(0.00) | Poor: CF*<br>Good: AC** |

Note: *CF: 'cash flow' hypothesis ** AC: 'active competitors' hypothesis.

For conciseness the coefficients on the age and size variables are not reported. Coefficients on these variables are in general consistent with table 5.

The downside risk measure provides similar results. In panel A, non-users increase downside risk after poor performance and increase downside risk after good performance. In panel B, derivative users decrease downside risk after poor performance and increase downside risk after good performance. Non-users also increase downside risk after good performance. In panel C, both users and non-users increase their downside risk after good performance. These results are generally consistent with the total risk results and provide little indication that derivative users are better able to manage downside risk than non-users.

## Table 8
## Regression of Change in Risk on Past Performance Dichotomised for Good and Poor Performance and Derivative Users and Non-Users—Model 4

$$\Delta Risk = \sum_{\substack{PN,PU,\\GN,GU}} \alpha_i D_i + \sum_{\substack{PN,PU,\\GN,GU}} \beta_i [D_i * PERF] + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (4)$$

Results of regressions testing the relation between the change in risk variable and prior period fund performance as expressed in model 4. Alternate change in risk variables are: STD—standard deviation and DOWN—downside risk. The independent variables are: $D_{PN}$ = 1 if Poor performer and Non-user of derivatives, $D_{PU}$ = 1 if Poor performer and User of derivatives, $D_{GN}$ = 1 if Good performer and Non-user of derivatives, $D_{GU}$ = 1 if Good performer and User of derivatives, PERF—the difference between the fund return and the benchmark return in the previous period, and LagRisk—the value of the risk variable during the previous period, Age—the age in months of the fund at the beginning of the period and Size—the log of total net assets at the beginning of the period. Each regression also includes dummy variables (not reported) for sub-periods. Values in parentheses are p-values for tests of the null hypothesis that the coefficient equals zero. Results are reported for weighted least squares (WLS), where the inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

| Risk Measure | $\alpha_{PN}$ | $\alpha_{PU}$ | $\alpha_{GN}$ | $\alpha_{GU}$ | $\beta_{PN}$ | $\beta_{PU}$ | $\beta_{GN}$ | $\beta_{GU}$ | $\gamma$ | Consistency with hypothesis |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | *Panel A: Calendar Year Results* | | | | | |
| Δ STD | 0.0173<br>(0.00) | 0.0193<br>(0.00) | 0.0170<br>(0.00) | 0.0171<br>(0.00) | –0.0594$^{\#}$<br>(0.02) | 0.1207$^{\#}$<br>(0.02) | 0.0056<br>(0.50) | 0.0234<br>(0.17) | –0.4742<br>(0.00) | PoorN: Gaming<br>PoorU: AC**<br>Good: Gaming |
| Δ DOWN | –0.0005<br>(0.34) | 0.0002<br>(0.77) | 0.0003<br>(0.47) | 0.0014<br>(0.01) | –0.0538<br>(0.00) | –0.0337<br>(0.22) | 0.0263$^{\#\#}$<br>(0.00) | –0.0122$^{\#\#}$<br>(0.17) | –0.6299<br>(0.00) | Poor: Gaming<br>Good: AC** |
| | | | | | *Panel B: Financial Year Results* | | | | | |
| Δ STD | 0.0247<br>(0.00) | 0.0244<br>(0.00) | 0.0269<br>(0.00) | 0.0248<br>(0.00) | –0.1815$^{\#}$<br>(0.00) | –0.0537$^{\#}$<br>(0.38) | 0.0076$^{\#\#}$<br>(0.34) | 0.0700$^{\#\#}$<br>(0.00) | –0.7727<br>(0.00) | PoorN: Gaming<br>PoorU: CF*<br>GoodN: Gaming<br>GoodU: AC** |
| Δ DOWN | 0.0005<br>(0.53) | 0.0001<br>(0.85) | 0.0007<br>(0.32) | 0.0006<br>(0.44) | –0.0321$^{\#}$<br>(0.19) | 0.0360$^{\#}$<br>(0.04) | 0.0223$^{\#\#\#}$<br>(0.00) | 0.0380$^{\#\#\#}$<br>(0.00) | –0.6267<br>(0.00) | PoorN: CF*<br>GoodN: AC** |
| | | | | | *Panel C: Weekly Data Results* | | | | | |
| Δ STD | 0.0100<br>(0.00) | 0.0092<br>(0.00) | 0.0090<br>(0.00) | 0.0082<br>(0.00) | 0.0138<br>(0.24) | –0.0059<br>(0.70) | 0.1271<br>(0.00) | 0.1355<br>(0.00) | –0.9377<br>(0.00) | Poor: CF*<br>Good: AC** |
| Δ DOWN | 0.0046<br>(0.00) | 0.0044<br>(0.03) | 0.0040<br>(0.00) | 0.0039<br>(0.02) | 0.0083<br>(0.09) | –0.0051<br>(0.49) | 0.0470<br>(0.00) | 0.0429<br>(0.00) | –0.8890<br>(0.00) | Poor: AC**<br>GoodN: AC** |

Note: * 'cash flow' hypothesis ** AC: 'active competitors' hypothesis
# A Wald test shows that there is a significant difference, at the 1% level of significance, between βPN and βPU for these equations.
##A Wald test shows that there is a significant difference, at the 1% level of significance, between βGN and βGU for these equations.
### A Wald test shows that there is a significant difference, at the 10% level of significance, between βGN and βGU for these equations.
For conciseness the coefficients on the age and size variables are not reported. Coefficients on these variables are in general consistent with table 5.

Overall, the results suggest that the risk shifting behaviour of fund managers is not consistent between derivative users and non-users and after periods of good and poor performance. The calendar year and financial year results are consistent with derivative users actively competing, while non-users are gaming. However, when we examine this behaviour on an on-going basis we find that both users and non-users are actively competing, especially after periods of good performance. In an Australian context it appears that risk shifting behaviour not only occurs both within calendar years and financial years, but also on an ongoing basis. Finally, the results do not indicate that derivatives are being used aggressively by fund managers to manage their fund risk. However, we now examine this in more detail using our sub-sample with actual derivative use.

### *4.3 Model Extension—Actual Derivative Use*

The same methodology was employed for the actual derivative use sub-sample—where actual derivative use data was available for 30 of the sample funds. We replace the dummy variable for derivative use in equation 1 with a continuous variable measuring the percentage of the value of the portfolio that is comprised of derivatives. Equation 5 is estimated using combined calendar and financial year data:

$$\Delta Risk = \beta_1 AvgDUse + \beta_2 PERF + \beta_3 AvgDUse \times PERF + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (5)$$

where AvgDUse: average value of derivatives divided by total fund value in the period; AvgDUse*PERF: interaction between average derivative use and past performance.

The results are presented in table 9. There is a significant negative relation between past performance and change in total risk (STD) and the relationship is weaker, but not significantly so, as the level of derivative use increases. There is a significant positive relation between past performance and change in downside risk, which is also weaker as the use of derivatives increases. While the results here are not strong, they tend to indicate that derivatives are being used to reduce rather than increase risk.

## 5. Conclusions

This study compares the risk-performance relationship of Australian managed funds that include derivatives in their portfolios with those that do not, in the context of tournament behaviour. We tested three tournament-based hypotheses: (a) gaming hypothesis (Brown, et al. 1996), (b) cash flow hypothesis (Koski and Pontiff, 1999), and (c) active competition hypothesis (Taylor, 2003).

Modelling the behaviour of fund mangers in a complex economy is indeed an ambitious task. Potentially there are a complicated set of behavioural and economic factors compounding into a performance outcome. However, our study consolidates three competing hypotheses, extends them to incorporate both total and downside risk and a dichotomy of performance outcomes. We then focus on the use of derivatives as a key tool to orchestrate risk shifts. Our conclusions are reviewed below.

## Table 9

## Regression of Change in Risk on Past Performance for Actual Derivative Use—Model 5

$$\Delta Risk = \beta_1 AvgDUse + \beta_2 PERF + \beta_3 AvgDUse \times PERF + \gamma LagRisk + \lambda_1 Age + \lambda_2 Size + \sum \delta_j Dummy_j + \varepsilon \quad (5)$$

Results of regressions testing the relation between the change in risk variable and prior period fund performance as expressed in model 5. Alternate change in risk variables are: STD—standard deviation and DOWN—downside risk. The independent variables are: AvgDUse—the annual average percentage of derivatives held in the portfolio, PERF—the difference between the fund return and the benchmark return in the previous period, and LagRisk—the value of the risk variable during the previous period, Age—the age in months of the fund at the beginning of the period and Size—the log of total net assets at the beginning of the period. Each regression also includes dummy variables (not reported) for sub-periods. Values in parentheses are p-values for tests of the null hypothesis that the coefficient equals zero. Results are reported for weighted least squares (WLS), where the inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

| Risk Measure | Intercept | AvgDUse | PERF | AvgDUse*PERF | LagRISK |
|---|---|---|---|---|---|
| Δ STD | 0.0327 | 0.0121 | –0.0421 | 1.1583 | –1.5053 |
| | (0.00) | (0.64) | (0.06) | (0.19) | (0.00) |
| Δ DOWN | 0.0027 | 0.0335 | 0.0890 | –0.6656 | –0.5221 |
| | (0.25) | (0.01) | (0.00) | (0.15) | (0.00) |

Note: For conciseness the coefficients on the age and size variables are not reported. Coefficients on these variables are in general consistent with table 5.

Although it appears that derivative users and non-users have similar risk and performance characteristics, their risk-shifting behaviour after periods of good and poor performance differs in direction and magnitude. It is therefore not surprising that our results do not find consistent support for any one hypothesis. We do find support for the gaming and active competition hypotheses but little support for the cash flow hypothesis. The calendar year and financial year results suggest that derivative users are actively competing and that non-users are gaming. However, when we examine this behaviour on an on-going basis we find that both users and non-users are actively competing, especially after periods of good performance. The conflict in results across alternate reporting periods suggests some caution in interpretation is warranted. It also suggests the need for further research in understanding the motivations and timing of investment decisions by fund managers.

Despite the conflicting results across time periods, we can conclude that in an Australian context tournament behaviour is occurring during calendar years, financial years and on an on-going basis. This is possibly in response to the publication of performance results at the end of both the years as well as on a monthly basis. Finally, the results do not indicate that derivatives are being used aggressively by fund managers to shift their fund risk. While fund managers are not extensively using derivatives to manage their downside risk, there are indications that derivatives are being used to maintain total risk positions.

Overall, our evidence is suggestive that there is a difference between how users and non-users of derivatives react to good and poor performance outcomes. Any model which doesn't separate these effects will be measuring a muddled aggregate relation between past performance and changes in risk. Further, our results using weekly data show that in Australia tournament behaviour is occurring on an on-going basis, perhaps as part of an on-going management strategy to remain on the top of performance tables.

(Date of receipt of final transcript: March 9, 2007.
Accepted by David Gallagher & Garry Twite, Area Editors.)

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