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Quality investing in an Australian context

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Abstract
This study extends an examination of Quality investing in the US to the Australian market. Specifically, a Quality score is computed as the aggregate of eight fundamental accounting metrics. An investment strategy investing in the highest (lowest) quality stock quintile, that is, Quintile 5 (1) generates an average annual Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted alpha of 6.37% (−7.98%), which is significant at the 5% level over April 2000–March 2010. A two-way segmentation based on size first, and quality second, reveals that the strong positive quality effect is primarily driven by small stocks, as the average DGTW-alpha for the top-quality tercile of small stocks is 14.02%, significant at the 5% level. Statistically significant positive DGTW-alphas are also determined for quality micro and large stocks. The quality analysis is also applied to a sample of Active Equity Mutual Funds' stock holdings. Weak evidence of the quality return premium is detected at the fund level.

Keywords
Active management, investment performance, fundamental analysis, mutual funds, quality, stock holdings

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1. Introduction

This study extends a US analysis (Gallagher et al., 2013) of quality as an investment style into the Australian market. The US research indicates that an asymmetric relationship between the Daniel, Grinblatt, Titman and Wermers (DGTW)[1]-adjusted performance of high- and low-quality stocks (and funds) exists on average. Specifically, low-quality stocks/funds (i.e. those in decile 10) significantly underperform their characteristic-matched benchmarks, although high-quality stocks/funds do not generate outperformance on average. However, high-quality stocks/funds outperform low-quality stocks/funds during times of market stress. This paper investigates these issues in an Australian context using a similar definition of quality and data from 2000 to 2010.

There are a number of reasons why an Australian application is fruitful. Firstly, given an ageing population who will need stable investments to fund their retirement, an understanding of suitable post-retirement equity products is important. Secondly, Doran et al. (2012) suggest that ‘a single, poorly-timed negative return event (of around −20%) can raise the probability of [financial] ruin [of one’s superannuation] from 33% to 50% for average life expectancy’ (pp.5–6). Thus, research into equities with a focus on downside protection is important. Thirdly, Money Management (2013) states that investors are moving away from the traditional defensive investment options such as cash and Government bonds due to declining interest rates and bond yields. As a result, Equity-Income funds have emerged as a viable defensive investment option. This study investigates the role that active equity funds focusing on ‘quality’ investments could play in the construction of post-retirement products. Moreover, if a portfolio of high-quality stocks outperforms a portfolio of low-quality stocks in general then the fundamental variables included in the Quality score (hereafter Q-Score) are important measures for the Australian market. Furthermore, if high-quality funds provide downside protection, then funds exhibiting the characteristics that give rise to a high Q-Score (e.g. profitability, operating efficiency and financial stability) are of interest when (i) identifying funds to invest in post-retirement, and (ii) when constructing a fund-of-funds to meet post-retirement objectives.

There is a limited body of Australian literature pertaining to accounting ratios and the usefulness of Financial Statement Analysis (e.g. Habib, 2010; Houghton and Woodliff, 1987; Worthington, 1998; Worthington and West, 2004). The literature evaluates accounting metrics individually such as the asset growth effect (Bettman et al., 2011; Dou et al., 2012), profitability (Dou et al., 2012), leverage and liquidity effect (Gharghori et al., 2009). The use of a composite score to assess the quality of stocks (recognising that many financial ratios are correlated), and their performance, is therefore valuable. There is a limited literature that investigates accruals quality and earnings management (e.g. Coulton et al., 2005; Gray et al., 2009; Kent et al., 2010; Oei et al., 2008). Furthermore, there are only a handful of papers that explicitly consider the relationship between earnings/accruals and stock returns (Chia et al., 1997; Clinch et al., 2012; Cotter, 1996; Hodgson and Stephenson-Clarke, 2000; Loftus and Sin, 1997; Taylor and Wong, 2012). Hence, exploration of quality as an investment style is of interest. The Australian equity fund literature has also not investigated ‘quality’ as an investment style; its focus has been on; (i) manager trading (Fong et al., 2011; Pinnuck, 2003); (ii) performance persistence (Humphrey and O’Brien, 2010) and (iii) performance evaluation (Fong et al., 2008; Ghaghori et al., 2009; Heaney, 2008). Furthermore, the quality characteristics of fund managers’ holdings have not been analysed.

A Q-Score is constructed for the Australian market in a similar vein to Gallagher et al. (2013). Specifically, the Q-Score is an aggregate of eight fundamental accounting ratios: Return on Equity (ROE), ΔROE, Return on Assets (ROA), ΔROA, Operating Cash Flow (OCF), Δ Asset Turnover (ATO), Δ Shares Outstanding (SH) and Δ Total Equity (TE). These metrics are selected based on a review of the Australian and international literature on accounting ratios and stock returns (see Gallagher et al., 2013: 5–8 for a detailed discussion of academic papers supporting the inclusion of each metric).

The universe of stocks for which the required accounting and stock return data are available is divided into quintile portfolios. In contrast to the US analysis, a symmetric return relationship is identified whereby high (low) quality stocks outperform (underperform) on average.[2] Specifically, the average DGTW-adjusted return to the portfolio of stocks containing the highest quality stocks (i.e. Quintile 5) is 6.37%, significant at the 5% level. Conversely, the lowest quality stocks underperform by 7.98%; this is also significant at the 5% level. The analysis is also repeated on a subset of stocks held by at least one mutual fund at the time of portfolio formation (March year *t*). The results are similar overall, although mutual funds appear to avoid the lowest quality stocks with an insignificant DGTW-adjusted return of −2.00% identified for Quintile 1. Furthermore, low-quality stocks are smaller, more volatile and more sensitive to market movements.

Upon conducting a two-way sort by first dividing stocks into one of three size groups (micro, small and large) and then on the basis of quality, it becomes clear that the result is primarily caused by small stocks. In particular, the highest quality tercile of small stocks generates a statistically significant average DGTW-alpha of 14.02%, while the high-quality micro and large stocks generate average returns of 5.04% and 5.72%, which are significant at the 5% and 10% levels, respectively. If stocks are first sorted on size, the strong negative performance for the low-quality stocks is not identified. Specifically, small and statistically insignificant positive alphas are determined for the low-quality micro, small and large stocks.

Using a unique sample of stock holdings from Russell Investments for long-only Active Australian Equity Mutual Funds, the quality analysis is applied to the funds' portfolios. A weighted-average Q-Score is calculated for each fund in March of year *t*. On an equal-weighted basis, the top tercile of funds generates an average annual DGTW-alpha of 2.09%, which is weakly significant over April 2000–March 2010. Similarly, the bottom tercile of funds generates an average DGTW-alpha of 2.17%, which is significant at the 10% level. Statistically significant equally weighted capital asset pricing model (CAPM)-adjusted returns of approximately 3–5% are also determined for all three fund terciles. However, no statistically significant adjusted performance is detected when asset-weighting is used. This indicates that it is the smaller/boutique funds that are driving the outperformance within the terciles. Overall, performance is comparable across the terciles, thus weak evidence of the quality return premium is identified at the fund level.

Furthermore, the size and style characteristics of the funds do not differ substantially across the Q-Score sorted fund terciles. Specifically, the average Asset and DGTW[3] size, book-to-market and momentum values determined are similar. This is not surprising given that the overall level of quality of the sample of funds does not differ dramatically; for example, the average Q-Score for Tercile 1 (3) is 4.60 (8.29). Nonetheless, the results for the fund sample are interesting in the sense that, contrary to the US, statistically significant outperformance is generated by high-quality funds in Australia. In the US, poor-quality funds underperform; however, high-quality funds do not outperform.

The remainder of this paper is structured as follows: the next section discusses the extant literature, followed by the data and methodology sections, the results and finally the conclusion.

2. Literature

There are a limited number of studies in Australia that focus on Financial Statement Analysis and the use of accounting ratios. Recently, the emphasis has been on investigating which line items on the financial statements are the most informative (Barton et al., 2010; Habib, 2010). Earnings before Tax (EBT) and Net Income (NPAT) are determined to have the highest explanatory power in Australia based on the adjusted R^2 from a pooled regression of market-adjusted stock returns on each performance measure and its change, which also controls for industry and time effects. Interestingly, Worthington and West (2004) examine whether the trademarked variant of residual income known as economic value-added (EVA®) is more highly associated with stock returns than other common accounting metrics. The authors use relative information content tests, which reveal that returns are more closely associated with EVA® than residual income, earnings and net cash flow, respectively. Previously, Worthington (1998) investigated financial statement analysis using mathematical programming techniques with respect to 30 Australian gold producers. The results indicate that simple ratios are unlikely to provide efficiency rankings similar to those obtained from multiple-input, multiple-output methodologies based on Data Envelopment Analysis. In addition, Houghton and Woodliff (1987) analyse 48 companies (12 failure and 36 non-failure cases) using five variables: the quick ratio, income, dividend policy, cash flow and leverage. The research focuses on both the usefulness of the ratios and whether decision makers are able to interpret them in order to predict firms with relatively higher earnings per share (EPS). The authors emphasise that the quick ratio plays a key role with respect to the successful firms. However, not one test subject significantly outperformed a random model with respect to predicting relative EPS.

In a similar vein, Cotter (1996) examines the relative ability of the accrual and cash flow accounting models to capture events that are relevant to the value of stock returns. She concludes that the relationship between stock returns and earnings is stronger than that for total cash flows for return intervals of between one to 10 years. Furthermore, cash flows from operations and current accruals are able to recognise value-relevant events in a timely manner, while non-current and non-operating accruals only become consistently relevant when longer return intervals are considered. Furthermore, Loftus and Sin (1997) examine the role of accruals in the relationship between stock returns and earnings for intervals of one to four years. The results suggest that accruals strengthen the association between stock returns and earnings and that they are more important for shorter intervals. Hodgson and Stephenson-Clarke (2000) indicate that a non-linear relationship between stock returns and earnings (and stock returns and cashflows) exists. In addition, Chia et al. (1997) compare aggregated earnings and disaggregated earnings (cash from operations, accruals and non-current accruals) in terms of their association with stock returns. Disaggregated earnings are determined to have a stronger relationship with stock returns, even when using simple techniques such as linear regression.

Most recently, Clinch et al. (2012) investigate whether there is evidence of the accrual anomaly in Australia. The results generally support the existence of the anomaly, although returns to a hedged portfolio trading strategy are statistically significant only in the first year and the results are attributable to a limited number of firm-year observations in the extreme positive tail of returns. Taylor and Wong (2012) show that evidence of an accrual anomaly in Australia is sensitive to research design specifications such as the choice of total accruals measurement, the definition of abnormal returns, how outliers are treated and the use of value versus equal-weighting of returns. Related literature indicates that other accounting anomalies, such as the asset growth effect (Bettman et al., 2011; Dou et al., 2012), profitability (Dou et al., 2012), leverage and liquidity effects (Gharghori et al., 2009), are not prevalent in the Australian equity market. Dou et al. (2012) determine that the existence of the profitability (ROA), asset growth and accrual anomalies is primarily driven by micro-capitalisation stocks.

Overall, the accounting literature has focused on profitability and financial stability metrics, although these have been studied individually. However, both the profitability metrics (ROA, accruals and OCF) and the financial stability metrics (working capital/assets, leverage) are relevant to the Australian equity market. Accordingly, investigation into the relationship between stock returns and a composite measure is warranted. In addition, there is support for the use of a non-linear approach.

Coulton et al. (2005) investigate earnings quality by focusing on ‘benchmark beaters’, which are Australian firms that report small profits and/or small increases in earnings, which may be considered indicative of upward earnings management. The authors use unexpected accruals to capture this ‘benchmark beating’ earnings management and the results show that the unusual kink around zero in the distribution of earnings levels or earnings changes is not caused by earnings management. Accruals quality has also been investigated in relation to corporate governance (Kent et al., 2010), the cost of capital (Gray et al., 2009) and earnings persistence (Oei et al., 2008). However, quality as an investment style has not been researched in Australia to our knowledge.

To date, the equity mutual fund literature has not explored whether fund managers hold quality stocks and whether high-quality stocks are related to fund performance. Pinnuck (2004) finds strong evidence that fund managers prefer large, liquid and low-volatility stocks. Covrig et al. (2006) analyse the portfolio holdings characteristics of foreign and domestic fund managers in 11 developed markets, including Australia. The authors conclude that ‘both groups of managers prefer stocks with high return on equity, large turnover, and low return variability. Domestic managers also favor firms that pay large dividends, have low financial distress and high growth potential, whereas foreign managers prefer to invest in corporations that are globally well known’ (p.407).

Recent Australian equity fund research relates to manager trading and trade performance. Fong et al. (2011) aggregate manager trades over time into trade packages and find that packages which use multiple brokers are associated with fewer follower trades. Furthermore, they generate higher positive adjusted returns than single-broker packages over horizons up to one year. Similarly, Pinnuck (2003) examines the performance of the individual trades of Australian fund managers determining that the stocks they buy realise abnormal returns, whereas there is no evidence of abnormal returns for sell trades.

Furthermore, the extant equity fund literature focuses on performance persistence and evaluation. Humphrey and O’Brien (2010) find no evidence of performance persistence for Australian fund managers using the Carhart (1997) performance evaluation model. In addition, Fong et al. (2008) propose adjustments to the DGTW (1997) performance evaluation methodology. In particular, the characteristic benchmarks are updated monthly and neutrality to the Standard and Poor’s (S&P)/Australian Securities Exchange (ASX) 300 is ensured. The modified benchmarks are characterised by statistically different and lower tracking error. Interestingly, Heaney (2008) empirically tests Berk and Green’s (2004) model of a superannuation fund industry with a limited population of superior fund managers and a competitive investor market. Australian Morningstar Retail and Wholesale equity fund data from 1995–2005 is used and support for Berk and Green’s (2004) predictions is found. Finally, Gharghori et al. (2007) indicate that investors chase funds that have performed well in the past and that cash flows to funds are persistent.

There is also a body of multi-sector fund research that concentrates on performance evaluation (Gallagher, 2003; Holmes and Faff, 2004), performance persistence (Bilson et al., 2005; Dempsey, 2009), fund ratings (Faff et al., 2007; Gerrans, 2006), asset allocation (Benson et al., 2007), time-changing alpha (Heaney et al., 2007) and tournament behaviour (Hallahan et al., 2008).

3. Data

The accounting data used to compute the Q-Score are sourced from the Aspect Financial database via FinAnalysis for all firms with financial year end data from January 1989 to December 2008.

Table 1. Individual quality metrics.

Category	Signal	Measurement
Profitability	Return on Equity[a] (ROE)	NPAT before Abnormals$_t$ (NPAT) / (Shareholders' Equity$_{t-1}$ – Outside Equity Interests $_{t-1}$ (TE))
	Change in ROE[b] (ΔROE)	$NPAT_t - NPAT_{t-1}/((TE_{t-1} + TE_{t-2}) * 0.5)$
	Return on Assets[c] (ROA)	$NPAT_t$/Total Assets$_{t-1}$ (TA)
	Change in ROA[d] (ΔROA)	$NPAT_t - NPAT_{t-1}/((TA_{t-1} + TA_{t-2}) * 0.5)$
	Operating Cash Flow[e] (OCF)	Net Cash Flow from Operations$_t$ / $((TA_t + TA_{t-1}) * 0.5)$
	Accruals[f] (ACC)	ACC = Earnings – OCF Where Earnings = $NPAT_t/((TA_t + TA_{t-1}) * 0.5)$
Operating efficiency	Asset Turnover[g] (ATO)	Trading Revenue $(TR)_t/TA_{t-1}$
	Change in ATO[h] (ΔATO)	$TR_t - TR_{t-1}/((TA_{t-1} + TA_{t-2}) * 0.5)$
Financial health	Leverage[i] (LEV)	Non-Current $Debt_t/TE_t$
	Liquidity[j] (LIQ)	Working Capital/TA_t Where Working Capital = Current Assets$_t$ - Current Liabilities$_t$
	Change in Shares Outstanding[k] (ΔSH)	$SH_t - SH_{t-1}/SH_{t-1}$
	Change in TE[l] (ΔTE)	$TE_t - TE_{t-1}/TE_{t-1}$

Table 1 details the 12 accounting metrics across three categories – profitability, operating efficiency and financial health – which are considered for inclusion in the Q-Score. All individual metric values are scaled by the population median for the prior fiscal year.

[a]Bird and Casavecchia (2007); Chen and Zhang (2007); Zhang (2000)
[b]Bird and Casavecchia (2007)
[c]Dou et al. (2012)
[d]Bird and Casavecchia (2007); Fairfield and Whisenant (2000); Piotroski (2000)
[e]Chia et al. (1997)
[f]Chia et al. (1997); Clinch et al. (2012); Cotter (1996); Loftus and Sin (1997); Taylor and Wong (2012)
[g]Bird and Casavecchia (2007); Soliman (2008)
[h]Bird and Casavecchia (2007); Piotroski (2000); Soliman (2008)
[i]Houghton and Woodliff (1987)
[j]Houghton and Woodliff (1987)
[k]Donaldson (1961); Myers and Majluf (1984)
[l]Donaldson (1961); Myers and Majluf (1984).

Table 1 outlines how each signal is calculated.[4] The individual metric values are scaled by the population median for the prior fiscal year.[5] These scaled metric values are winsorised at the 1st and 99th percentiles.

Stock level data, such as returns (which account for capitalisation changes and dividends) and market capitalisation, are obtained from the Share Price and Price Relative (SPPR) database from Sirca Limited. Our primary excess return computation is based on the Daniel et al. (DGTW) (1997) characteristic benchmark approach.[6] DGTW benchmarks are calculated by first sorting stocks into five groups based on size (market capitalisation as at December of the year prior), then into four groups based on book-to-market (for the prior fiscal year) and then into three groups based on momentum (for prior one year skip one month as at December of the year prior). Adjusted returns are thus calculated by subtracting the return to a stock's DGTW benchmark from its raw return. The sample consists of all stocks listed on the ASX, which comprise the Aspect/SPPR/DGTW universe. Returns are computed from April 2000 to March 2010.

CAPM-adjusted returns using a 1-Factor model approach are also presented as a robustness test. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the S&P/ASX 300 return, both x and y are in excess of the 30-day Bank Accepted Bill (BAB) rate. Excess returns are then calculated by subtracting the product of each stock's beta and the market return from its raw return each month.

Financial firms are excluded given that certain metrics such as leverage and accruals are not consistent for firms in this sector (Taylor and Wong, 2012), that is, stocks with Global Industry Classification Standards (GICS) codes between 4000 and 4099 are excluded. If the GICS code is missing then the Center for Research in Finance (CRIF) industry class code is used, and stocks classified as 18–22 (i.e. financial firms) are excluded. Furthermore, only Ordinary/Common Shares are included.

The mutual fund analysis is undertaken using a sample of managers from the Russell Investments research database, which contains monthly stock holdings for long-only Australian active equity fund managers. The dataset was constructed by Bennett et al. (2012).[7] The authors state that there is no minimum survival requirement for a fund to be included in their database, thus it is unlikely to exhibit survivorship bias. The authors also indicate that selection bias is minute, establishing this by comparing the performance of new funds and pre-existing funds. Bennett et al. (2012) provide a detailed discussion of the dataset.

Table 2 provides descriptive statistics for the sample, which contains stock holdings for 232 unique funds over 2000–2010. The average return presented for each year is the annualised mean monthly return. The funds' DGTW-adjusted performance is strongest in 2007, with an alpha of 3.65%; similarly, a CAPM-alpha of 3.98% is determined. However, once the global financial crisis (GFC) sets in the funds underperform with mean alphas of −3.54% and −3.52% using DGTW and CAPM, respectively. Furthermore, the DGTW-adjusted underperformance continues into 2009 with a return of −4.17%. The average DGTW size quintiles, book-to-market quartiles and momentum terciles are similar across the sample period years. The funds prefer large stocks as the average size quintile is about four in every year. They also prefer stocks towards the growth end of the value–growth spectrum and stocks with moderate momentum. The number of stocks held is similar across the years ranging from 49 to 58. The value of assets under management is relatively stable throughout the sample period.

4. Methodology

In order to calculate a Q-Score for each stock the weights to be applied to each accounting metric must first be determined. This is achieved by using ordinary least squares (OLS) regression. Recently, Zhu (2012) indicates that the use of ratios with common divisors in a multivariate regression setting can lead to spurious test statistics, as the true confidence levels differ from the standard conventions. In this study, a number of the accounting ratios have been scaled by divisors that are correlated with each other, and the divisor of returns (the dependent variable). Therefore, to ensure the results and inferences made are not spurious, a univariate regression approach is employed. Specifically, the weights to apply to each metric and its square are ascertained by running a series of expanding-window univariate regressions as per Equation (1) below:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon \tag{1}$$

Table 2. Descriptive statistics for mutual fund sample.

Year	Raw return (%)	DGTW-alpha (%)	CAPM-alpha (%)	Size quintile	B/M quartile	MOM tercile	No. stocks	Assets (A$m)
2000	8.19	2.08	4.50	3.95	1.04	1.12	53	1314
2001	13.53	0.67	4.21	3.97	1.12	1.30	54	1977
2002	−7.24	−2.53	2.55	3.97	1.22	1.21	56	3115
2003	15.74	−0.90	2.46	3.96	1.37	1.04	56	1283
2004	27.78	2.71	−0.27	3.96	1.27	0.74	54	1121
2005	22.10	1.61	−1.20	3.96	1.52	0.96	49	1725
2006	26.23	2.02	−3.59	3.97	1.65	1.26	50	2402
2007	21.64	3.65	3.98	3.96	1.27	1.20	52	2081
2008	−40.14	−3.54	−3.52	3.97	1.54	1.35	55	1441
2009	43.62	−4.17	3.47	3.98	1.35	1.42	58	1162
2010	3.08	1.22	−0.60	3.97	1.07	0.96	58	1494

Table 2 presents summary statistics for a sample of 232 Australian Active Equity Mutual Funds over 2000–2010. Raw return is the annualised average monthly raw fund return. The average raw return is first calculated for each fund whereby each stock's raw return is weighted by its holding value as at the end of the prior month. The average across all funds is then calculated per month and weighted by a fund's assets as at the end of the prior month. Daniel, Grinblatt, Titman and Wermers (DGTW)-alpha is the annualised average adjusted return for each fund, whereby the return to each stock held has been adjusted by the return to one of 60 benchmark portfolios with the same size, book-to-market and momentum characteristics. Stocks are first sorted into five groups based on size, then four groups based on book-to-market and finally three groups based on momentum. Capital asset pricing model (CAPM)-alpha is the annualised average adjusted monthly return for each fund, whereby the return to each stock held has been adjusted using the CAPM 1-Factor model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 return, both x and y are in excess of the 30-day Bank Accepted Bill (BAB) rate. Size Quintile is the asset-weighted (AW) average size quintile, B/M Quartile is the AW average book-to-market quartile and MOM tercile is the average AW momentum tercile to which the stocks held by a fund fall into. The mean for each fund is first calculated by weighting each stock's quintile, quartile and tercile value by its holding value as at the end of the prior month. No. stocks is the average number of stocks held each year. The AW mean no. stocks held is first calculated for each month and then the equal-weighted average of these monthly values is calculated each year. Assets is the AW average of assets as at the end of the prior month across each year.

where y represents DGTW-alpha – the dependent variable, β_0 represents the intercept, β_1 represents the parameter estimate for the metric in question – x, β_2 represents the coefficient estimate for the squared value of the metric in question and ε represents the error term.

The standard financial year end month for Australia is June. However, there are still a considerable number of firms using a December financial year end. Therefore, portfolios are formed in March of each year t. This allows a three-month gap prior to portfolio formation to ensure the accounting data are publicly available. DGTW-adjusted returns are thus computed from April of year t to March of year t+1. The annual DGTW-alpha values for each stock are regressed on the accounting metrics x and x^2 for the prior fiscal year.

Expanding regressions are run over 10 subsets commencing with a historical period of 1992–1998 and the parameter estimates obtained are then applied to the accounting metric values for 1999 as per Equation (2) below. The final regression uses a historical period of 1992–2007; the parameter estimates are applied to the metric values for 2008 to compute the Q-Score. The β_1 and β_2 parameter estimates for the 10 expanding regressions are not statistically significant for Accruals (ACC), Asset Turnover (ATO), Leverage (LEV) or Liquidity (LIQ); therefore, these four metrics are omitted when computing the Q-Score:[8]

Table 3. Quality signal parameter estimates.

Metric	β_1	β_2
Return on Equity (ROE)	12.35	1.38
ΔROE	6.50	−1.25
Return on Assets (ROA)	10.29	2.81
ΔROA	18.76	−3.52
Operating Cash Flow (OCF)	19.21	29.30
ΔAsset Turnover (ATO)	−11.22	4.42
ΔShares Outstanding (SH)	9.57	−3.55
ΔTotal Equity (TE)	−4.84	0.24

Table 3 presents mean values of the coefficient estimates for the eight quality signals included in the Q-Score. The annual Daniel, Grinblatt, Titman and Wermers (DGTW)-alpha for each stock in the Aspect/Share Price and Price Relative (SPPR)/DGTW universe is regressed on the metric value for the stock as well as the metric value squared in order to capture any non-linear relationships, as per the following model: $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$. Alpha is measured over April year t to March year $t+1$ and the metric values are for the fiscal year ending in year $t-1$.The regressions are run over 10 rolling time periods; the first of which is 1992–1998 and the last estimation period is 1992–2007. The average of the 10 coefficient estimates is provided – refer to the Appendix for a detailed summary of the estimates.

$$Q\text{-}Score^9 = \sum_{i=1}^{8} \beta_{1,i} Metric_i + \sum_{i=1}^{8} \beta_{2,i} Metric_i^2 \quad (2)$$

where $\beta_{1,i}$ is the parameter estimate for metric i and $\beta_{2,i}$ is the parameter estimate for the square of metric i.

Raw and DGTW-adjusted returns for Q-Score portfolios are then examined over 10 periods; the first portfolio formation occurs in March 2000, based on the Q-Score for 1999, and returns are then examined from April 2000 to March 2001. The final portfolio formation occurs in March 2009 based on the Q-Score for 2008 and then returns are generated from April 2009 to March 2010.

5. Results

5.1. Univariate results

Table 3 presents average coefficient estimates for each metric based on the 10 expanding univariate regressions. Refer to the Appendix for a detailed summary of the coefficient estimates for each regression. Table 3 shows that the profitability metrics OCF, ΔROA and to a lesser extent ROE and ROA have a strong positive relationship with DGTW-alpha. In general, the parameter estimate results are qualitatively similar to those for the US.

Interestingly, OCF is characterised by a non-linear relationship with stock returns, which follow a U-shape (indicated by the positive β_2 estimate of 29.30). This is consistent with the US results. The largest average negative β_1 estimate is −11.22 for ΔATO, which is characterised by a slight inverted U-shape, thus large increases/decreases in asset turnover are not favourable e.g. if a dramatic increase in asset turnover is fuelled by a substantial fall in product price. In contrast, the parameter estimates for ΔATO in the US ($\beta_1 = -0.30$, $\beta_2 = -3.11$) indicate that it does not have a strong relationship with alpha. ΔTE has a negative relationship with DGTW-alpha given its β_1 estimate of −4.84, which is consistent with Donaldson's (1961) Pecking Order Theory. In particular, if equity is considered a less preferred means to raise capital, by issuing new equity managers are signalling to investors that the firm is overvalued, thus an increase in TE leads to a decrease in stock returns.

5.2. Multivariate results for stock universe

Table 4 reports descriptive statistics for the universe of stocks sorted into quintiles based on their Q-Score in March of each year *t*.

The average Q-Score for the low-quality stocks is −25 compared to 12 for the high-quality stocks. On average, stocks in the lowest quality quintile perform particularly poorly, with a DGTW-adjusted return of −7.98%, which is significant at the 5% level.[10] Conversely, stocks in the highest quality quintile outperform generating an average DGTW-adjusted return of 6.37%, which is significant at the 5% level. Stocks in the lowest quality quintile are more sensitive to market movements with an average beta of 1.45.[11] The CAPM-adjusted returns show a similar pattern to the DGTW-adjusted returns, although they are statistically insignificant.[12] However, a paired sample *t*-test of the difference in means between Quintiles 1 and 5 reveals that the high-quality stocks' CAPM-adjusted returns are 10.17% higher on average than those for Quintile 1, and this difference is significant at the 5% level. In addition, the tracking error of the quality portfolios almost monotonically decreases moving from the low- to the high-quality end of the spectrum. Furthermore, there is a direct (inverse) relationship between size (volatility) and quality.

Figure 1 shows the performance of the Q-Score quintiles using the stock universe over portfolio formation years 2000–2009. Quintile 2 performs strongly in 2000 with an average DGTW-alpha of 19.84%. However, in the aftermath of the dot-com crash the lower quality quintiles perform very poorly with average returns of −25.21% and −10.23% for Quintiles 1 and 2, respectively. In contrast, the higher quality quintiles provide downside protection, generating positive DGTW-alphas in 2001. High-quality stocks perform very well in 2003, 2004 and 2005, generating average DGTW-alphas of 13.66%, 19.81% and 15.66%, respectively. In 2007 all quintiles outperform except for the lowest quality quintile, which underperforms by 9.93%. Amid the GFC in 2008 only Quintiles 4 and 5 avoid negative returns, with small positive DGTW-alphas of 0.79% and 0.95% determined. In 2009 Quintiles 1 and 2 recover strongly, achieving alphas of 9.18% and 24.27%, respectively, whilst Quintile 5 underperforms slightly with a −2.47% DGTW-alpha.

The analysis is also repeated on a subset of stocks that are held by at least one mutual fund in the Russell Investments universe in March of each year *t*.[13] Table 5 demonstrates that Australian mutual funds avoid the poorest quality stocks; the average Q-Score is −17 compared to −25 for the universe. Furthermore, the average excess return to Quintile 1 is an insignificant −2.00%. The mutual funds also hold larger stocks on average with the mean market capitalisation for each quintile falling above that for the universe.

Figure 2 shows the performance of the Q-Score quintiles using the subset of stocks that are held by at least one mutual fund as at March of year *t* over portfolio formation years 2000–2009. In general, the performance of this subset over time is similar to that for the universe.

Table 6 provides returns for the Q-Score sorted stock quintiles in up versus down market months over April 2000–March 2010. The DGTW-adjusted performance of the quintiles does not vary greatly during up market months. However, Quintile 1 (5) stocks perform the worst (best) using value-weighting (VW) or Equal Weighting (EW). In particular, the return to Quintile 1 (5) is 0.07% (5.98%) using VW and −1.07% (4.37%) using EW. On a CAPM-adjusted basis the Quintile 1 stocks perform poorly with an average return of −21.02% and −3.50% using VW and EW, respectively.

The downside protection offered by quality stocks is clear when examining the DGTW-adjusted returns across the down market months. On a VW basis, Quintile 1 stocks underperform

Table 4. Returns and characteristics of stocks by Q-Score-sorted quintile portfolios.

Quintile portfolios	No. of stocks	Size (A$m)	Q-Scorevalue	Raw return (%)	DGTW-alpha (%)	Raw return volatility (%)	DGTW-alpha volatility (%)	DGTW benchmark volatility (%)	CAPM-alpha (%)	Beta	Tracking error (%)	Idiosyncratic volatility (%)
P1 (Low)	158	55	−24.99	−3.80 (−0.36)	−7.98** (−2.45)	63.56	59.47	22.14	−3.01 (−0.36)	1.45	6.54	20.49
P2	159	243	−6.00	−5.14 (−0.47)	3.28 (0.72)	56.64	51.51	20.99	2.97 (0.50)	1.24	5.79	14.94
P3	159	704	0.84	5.85 (0.71)	0.82 (0.35)	38.16	32.72	18.00	6.39 (1.39)	1.21	3.65	10.89
P4	159	682	5.06	9.44 (1.40)	2.75 (1.66)	27.42	25.26	13.90	6.52 (1.21)	0.88	2.14	7.16
P5 (High)	159	1911	12.03	16.15** (2.34)	6.37** (2.44)	27.83	22.11	14.20	7.16 (1.21)	1.03	2.82	7.06

Table 4 reports the mean values of returns and stock characteristics over the sample period for the stocks comprised in quintile portfolios formed by sorting the universe of Aspect/Share Price and Price Relative (SPPR)/Daniel, Grinblatt, Titman and Wermers (DGTW) stocks into equally weighted portfolios in each year *t* based on their Q-Scores. Quintile 1 (5) contains stocks with the lowest (highest) values of the Q-Score. The Q-Score has been computed as the aggregate of eight accounting metrics: Return on Equity (ROE), ΔROE, Return on Assets (ROA), ΔROA, Operating Cash Flow (OCF), ΔAsset Turnover (ATO), ΔShares Outstanding (SH) and Δ Total Equity (TE). All of the individual metrics have been scaled by the median value for each metric's population, in the previous fiscal year. The DGTW-alpha for each stock in the Aspect/SPPR/DGTW universe is regressed on the metric value for each stock as well as the metric value squared in order to capture any non-linear relationships, as per the following model: $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$. The regressions are run over expanding time periods – the first regression is run using the estimation period 1992–1998; the parameter estimates obtained are then used to calculate each metric's contribution to the Q-Score using the metric values for 1999. The Q-Score for 1999 is then merged with the mutual fund holdings as at March of 2000, and alpha is examined from April 2000 to March 2001. The means are obtained by value-weighting the returns and characteristics for each stock in the quintile by its market capitalisation as at December of year $t-1$. No. of stocks is the average number of stocks contained in each quintile portfolio over the sample period. Size is the mean market capitalisation of each stock in the portfolio, as at December of year $t-1$. Q-Score value is the mean Q-Score per quintile portfolio over the sample period. Raw return is the average unadjusted buy-and-hold return from April of year *t* to March of year $t+1$ to the stocks in the portfolio. The annual returns are calculated by compounding the monthly SPPR returns for each stock. DGTW-alpha is the mean excess annual return to the stocks in each portfolio over the sample period whereby each stock's raw return is adjusted by the return on an appropriate DGTW benchmark portfolio. Raw return volatility is the mean annualised standard deviation of the unadjusted monthly returns from April of year *t* to March of year $t+1$ for each stock in the portfolio. DGTW-alpha volatility is the average annualised standard deviation of the DGTW-adjusted monthly returns from April of year *t* to March of year $t+1$ for each stock in the portfolio. DGTW benchmark volatility is the mean annualised volatility of the monthly returns from April of year *t* to March of year $t+1$ for each stock's DGTW benchmark portfolio. Capital asset pricing model (CAPM)-alpha is the average annual excess return calculated using a 1-Factor market model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where *y* is the raw stock return and *x* is the Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 return, both *x* and *y* are in excess of the 30-day Bank Accepted Bill (BAB) rate. Beta is the average beta in March of year *t* for each stock in the portfolio, where beta has been calculated using the aforementioned model. N.B. there are a number of missing beta values, so the mean No. of stocks in each quintile is only 92 for this variable. Tracking error is the average of the square root of the squared monthly deviations of the raw return minus the return on the S&P/ASX 300. Idiosyncratic volatility is the standard deviation of the error term over the prior 60 months based on the same regression used to calculate beta. The *t*-statistics are in parentheses below the average returns reported.
Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

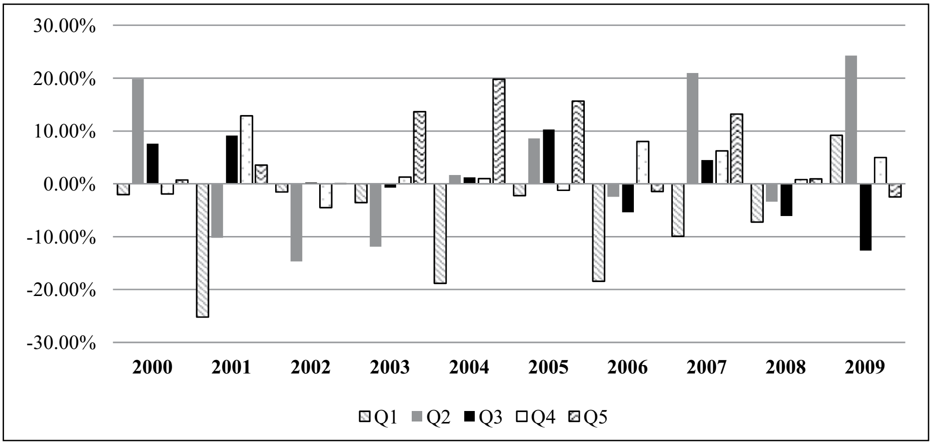

Figure 1. Average DGTW-adjusted return by Q-Score sorted quintiles for stock universe.
Figure 1 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted quintile over 2000–2009. The universe comprises stocks listed on the Australian Securities Exchange (ASX) for which Share Price and Price Relative (SPPR), Aspect and DGTW data is available. The quintiles are formed in March of each $year_t$ based on the Q-Score for the prior year, and buy-and-hold returns are computed from April of $year_t$ to March of $year_{t+1}$; for example, the return for 2000 is the return from April 2000 to March 2001. The weight applied to each stock's return is its market capitalisation as at December of $year_{t-1}$. Quintile 1 (5) contains low- (high-) quality stocks.

considerably with a mean return of −16.64% compared to Quintile 5 stocks, which are the only group to avoid negative returns, achieving a small positive return of 1.51%. On an EW basis, Quintile 1 stocks underperform with a return of −5.33%, compared to positive returns for the higher quality Quintiles 4 and 5 of 6.44% and 3.74%, respectively. The downside protection is not as clear using CAPM-adjusted returns; however, Quintile 5 outperforms Quintile 1 using either VW or EW.

5.3. Multivariate results for stock universe by size category

All stocks are sorted into one of three size categories: micro (<70%), small (70–90%) or large (>90%) based on their December year $t-1$ market capitalisation following Dou et al. (2012).[14] Table 7 provides average returns and characteristics for terciles of stocks within the three size group classifications.

There are a greater number of micro stocks on average, followed by small and finally large stocks. The difference in size between the three groups is very clear; for example, the average size for the high-quality micro stocks is A$3m compared to A$2012m for the high-quality large stocks. Furthermore, the low-quality micro stocks are very poor quality, with an average Q-Score of −27, compared to −8 for the small stocks and 0 for the large stocks.

The highest quality tercile of stocks within each size group generates statistically significant positive DGTW-adjusted returns. The top-quality micro stocks generate an average alpha of 5.04%, which is significant at the 5% level. The highest quality small stocks perform the strongest, with a statistically significant average DGTW-adjusted return of 14.02%. Finally, Tercile 3 within the large stock group generates an average DGTW-alpha of 5.72%, which is significant at the 10% level. Thus, the quality return premium identified at the stock level is pervasive across the size

Table 5. Returns and characteristics of Q-Score-sorted quintile portfolios for stocks held by mutual funds.

Quintile portfolios	No. of stocks	Size (A$m)	Q-Score value	Raw return (%)	DGTW-alpha (%)	Raw return volatility (%)	DGTW-alpha volatility (%)	DGTW benchmark volatility (%)	CAPM-alpha (%)	Beta	Tracking error (%)	Idiosyncratic volatility (%)
P1 (Low)	70	216	−17.07	−8.39 (−0.82)	−2.00 (−0.50)	60.37	54.70	21.22	−10.87* (−1.90)	1.50	6.40	17.49
P2	71	706	−0.55	2.57 (0.31)	−1.57 (−0.39)	38.38	33.27	18.09	−1.46 (−0.35)	1.19	4.77	11.31
P3	71	673	3.51	10.14 (1.47)	4.04 (1.54)	28.19	25.37	14.96	−0.74 (−0.29)	0.86	2.54	7.29
P4	71	961	6.55	12.32* (1.90)	5.39*** (3.80)	26.18	23.39	13.59	3.41 (1.35)	0.95	2.40	6.78
P5 (High)	71	2092	13.24	17.48** (2.40)	6.92* (2.09)	27.56	21.29	13.99	7.50** (2.60)	1.05	3.12	7.03

Table 5 reports the mean values of returns and stock characteristics over the sample period for quintile portfolios formed by sorting stocks in the Aspect/Share Price and Price Relative (SPPR)/Daniel, Grinblatt, Titman and Wermers (DGTW) universe, which are held by at least one mutual fund in March of year *t*, into equally weighted portfolios based on their Q-Scores. Quintile 1 (5) contains stocks with the lowest (highest) values of the Q-Score. The Q-Score has been computed as the aggregate of eight accounting metrics: Return on Equity (ROE), ΔROE, Return on Assets (ROA), ΔROA, Operating Cash Flow (OCF), ΔAsset Turnover (ATO), ΔShares Outstanding (SH) and ΔTotal Equity (TE). All of the individual metrics have been scaled by the median value for each metric's population, in the previous fiscal year. The DGTW-alpha for each stock in the Aspect/SPPR/DGTW universe is regressed on the metric value for each stock as well as the metric value squared in order to capture any non-linear relationships, as per the following model: $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$. The regressions are run over expanding time periods – the first regression is run using the estimation period 1992–1998, the parameter estimates obtained are then used to calculate each metric's contribution to the Q-Score using the metric values for 1999. The Q-Score for 1999 is then merged with the mutual fund holdings as at March of 2000, and alpha is examined from April 2000 to March 2001. The means are obtained by value-weighting the returns and characteristics for each stock in the quintile by its market capitalisation as at December of year $t-1$. No. of stocks is the average number of stocks contained in each quintile portfolio over the sample period. Size is the mean market capitalisation of each stock in the portfolio, as at December of year $t-1$. Raw return volatility is the mean annualised standard deviation of the unadjusted monthly returns from April of year *t* to March of year $t+1$ for each stock in the portfolio. Q-Score value is the mean Q-Score per quintile portfolio over the sample period. Raw return is the average unadjusted buy-and-hold return from April of year *t* to March of year $t+1$ to the stocks in the portfolio. The annual returns are calculated by compounding the monthly SPPR returns for each stock. DGTW-alpha is the mean excess annual return to the stocks in each portfolio over the sample period whereby each stock's raw return is adjusted by the return on an appropriate DGTW benchmark portfolio. DGTW-alpha volatility is the average annualised standard deviation of the DGTW-adjusted monthly returns from April of year *t* to March of year $t+1$ for each stock in the portfolio. DGTW benchmark volatility is the mean annualised volatility of the monthly returns from April of year *t* to March of year $t+1$ for each stock's DGTW benchmark portfolio. Capital asset pricing model (CAPM)-alpha is the average annual excess return calculated using a 1-Factor market model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where *y* is the raw stock return and *x* is the Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 return, both *x* and *y* are in excess of the 30-day Bank Accepted Bill (BAB) rate. Beta is the average beta in March of year *t* for each stock in the portfolio, where beta has been calculated using the aforementioned model. N.B. there are a number of missing beta values, so the mean No. of stocks in each quintile is only 53 for this variable. Tracking error is the average of the square root of the squared monthly deviations of the raw return minus the return on the S&P/ASX 300. Idiosyncratic volatility is the standard deviation of the error term over the prior 60 months based on the same regression used to calculate beta. The *t*-statistics are in parentheses below the average returns reported.

Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

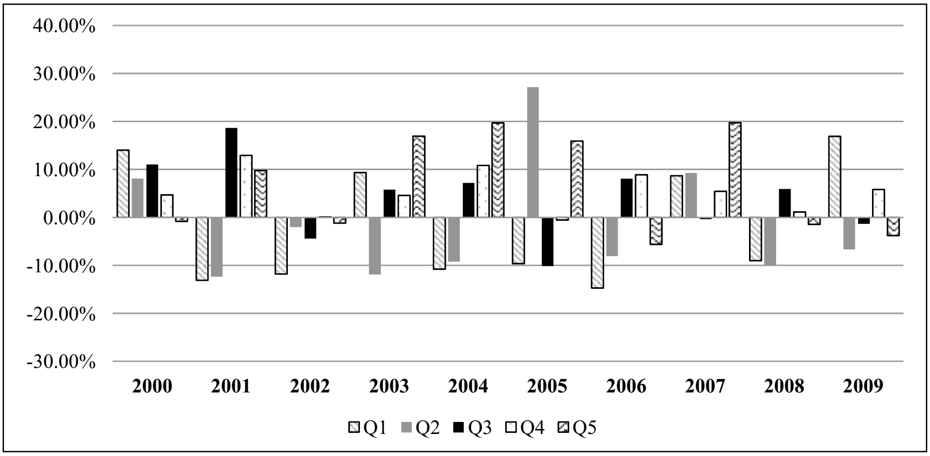

Figure 2. Average DGTW-adjusted return by Q-Score sorted quintiles for a subset of stocks held by at least one mutual fund as at March year *t*.

Figure 2 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted quintile over 2000–2009. The sample comprises stocks listed on the Australian Securities Exchange (ASX) for which Share Price and Price Relative (SPPR), Aspect and DGTW data is available and that are held by at least one mutual fund in March of $year_t$. The quintiles are formed in March of each $year_t$ based on the Q-Score for the prior year, and buy-and-hold returns are computed from April of $year_t$ to March of $year_{t+1}$; for example, the return for 2000 is the return from April 2000 to March 2001. The weight applied to each stock's return is its market capitalisation as at December of $year_{t-1}$. Quintile 1 (5) contains low- (high-) quality stocks.

Table 6. Performance of quality quintiles in up versus down markets.

Q-Score quintile	*Up market months*				*Down market months*			
	DGTW-adj. VW (%)	DGTW-adj. EW (%)	CAPM-adj. VW (%)	CAPM-adj. EW (%)	DGTW-adj. VW (%)	DGTW-adj. EW (%)	CAPM-adj. VW (%)	CAPM-adj. EW (%)
1	0.07	−1.07	−21.02	−3.50	−16.64	−5.33	7.77	3.46
2	5.22	2.96	−4.30	2.16	−2.11	1.58	12.32	13.17
3	2.12	2.69	−3.49	4.48	−0.64	1.98	9.14	15.02
4	1.79	1.71	3.21	4.09	−1.44	6.44	0.01	9.92
5	5.98	4.37	4.08	2.70	1.51	3.74	9.37	9.64

Table 6 presents annualised average monthly returns for Q-Score sorted quintiles of stocks in the Aspect/Share Price and Price Relative (SPPR)/Daniel, Grinblatt, Titman and Wermers (DGTW) universe over April 2000–March 2010. The Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 is used as the market index and the risk free rate is the 30-day Bank Accepted Bill (BAB) rate. Up (Down) market months are those when the S&P/ASX 300 return is greater (less) than the risk free rate. Returns value-weighted (VW) by a stock's market capitalisation as at the end of the month prior and equally weighted (EW) returns are provided. DGTW-adj. is the average monthly excess return whereby each stock's return has been adjusted by the return to one of 60 benchmark portfolios assigned based on a stock's size, book-to-market and momentum characteristics. Capital asset pricing model (CAPM)-adj. is the annualised average adjusted monthly return for each fund, whereby the return to each stock held has been adjusted using the CAPM 1-Factor model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the S&P/ASX 300 return, both x and y are in excess of the 30-day BAB rate.

groups. The volatility measures for the micro stocks show a similar pattern – as quality increases, volatility monotonically decreases. Furthermore, the volatilities across the quality terciles are

Table 7. Returns and characteristics of Q-Score sorted tercile portfolios within size groups.

Size group	Q-Score tercile	No. stocks	Size (A$m)	Q-Score value	Raw return (%)	DGTW-alpha (%)	Raw return volatility (%)	DGTW-alpha volatility (%)	DGTW benchmark volatility (%)	CAPM-alpha (%)	Beta	Tracking error (%)	Idiosyncratic volatility (%)
Micro	1	142	2	−26.74	8.20 (0.43)	2.45 (0.59)	72.37	67.58	28.77	−2.38 (−0.34)	1.35	7.13	24.16
Micro	2	246	3	−2.96	11.76 (1.03)	0.65 (0.15)	63.34	59.61	24.98	3.51 (0.73)	1.11	5.70	19.59
Micro	3	167	3	11.47	34.27* (2.09)	5.04** (2.27)	54.45	52.12	23.32	6.32 (1.09)	0.93	4.66	16.43
Small	1	54	24	−8.26	−4.69 (−0.58)	1.09 (0.34)	54.19	50.93	19.41	−2.90 (−0.87)	1.23	5.17	15.66
Small	2	62	28	4.12	9.62 (1.14)	4.94 (1.40)	38.32	37.14	16.12	5.46 (1.31)	0.93	3.51	10.59
Small	3	43	26	13.74	21.03* (2.09)	14.02** (2.36)	38.35	36.32	17.34	13.56** (2.80)	1.00	3.58	11.67
Large	1	24	819	−0.18	0.55 (0.06)	1.35 (0.45)	34.05	29.14	17.12	−2.28 (−0.65)	1.20	3.62	9.47
Large	2	36	834	4.55	11.41 (1.50)	3.54 (1.73)	27.99	24.62	14.62	4.99 (1.87)	0.89	2.06	7.11
Large	3	27	2012	11.24	14.64* (2.09)	5.72* (1.93)	26.23	20.26	14.18	7.76** (2.72)	1.05	2.71	6.68

Table 7 reports the mean values of returns and stock characteristics over the sample period for stocks in the Aspect/Share Price and Price Relative (SPPR)/Daniel, Grinblatt, Titman and Wermers (DGTW) universe, which are classified into one of three size groups: micro (<70%), small (70–90%) or large (>90%) based on their market capitalisation as at December of year *t−1*.Then within each size group tercile portfolios are formed by sorting stocks into equally weighted portfolios based on their Q-Scores as at March year *t*. Tercile 1 (3) contains stocks with the lowest (highest) values of the Q-Score. The means are obtained by value-weighting the returns and characteristics for each stock in the tercile by its market capitalisation as at December of year *t−1*. No. of stocks is the average number of stocks contained in each tercile portfolio over the sample period. Size is the mean market capitalisation of each stock in the portfolio, as at December of year *t−1*. Raw return volatility is the mean annualised standard deviation of the unadjusted monthly returns from April of year *t* to March of year *t+1* for each stock in the portfolio. Q-Score value is the mean Q-Score per tercile portfolio over the sample period. Raw return is the average unadjusted buy-and-hold return from April of year *t* to March of year *t+1* to the stocks in the portfolio. The annual returns are calculated by compounding the monthly SPPR returns for each stock. DGTW-alpha is the mean excess annual return to the stocks in each portfolio over the sample period whereby each stock's raw return is adjusted by the return on an appropriate DGTW benchmark portfolio. DGTW-alpha volatility is the average annualised standard deviation of the DGTW-adjusted monthly returns from April of year *t* to March of year *t+1* for each stock in the portfolio. DGTW benchmark volatility is the mean annualised volatility of the monthly returns from April of year *t* to March of year *t+1* for each stock's DGTW benchmark portfolio. Capital asset pricing model (CAPM)-alpha is the average annual excess return calculated using a 1-Factor market model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 return, both x and y are in excess of the 30-day Bank Accepted Bill (BAB) rate. Beta is the average beta in March of year *t* for each stock in the portfolio, where beta has been calculated using the aforementioned model. Tracking error is the average of the square root of the squared monthly deviations of the raw return minus the return on the S&P/ASX 300. Idiosyncratic volatility is the standard deviation of the error term over the prior 60 months based on the same regression used to calculate beta. The *t*-statistics are in parentheses below the average returns reported.

Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

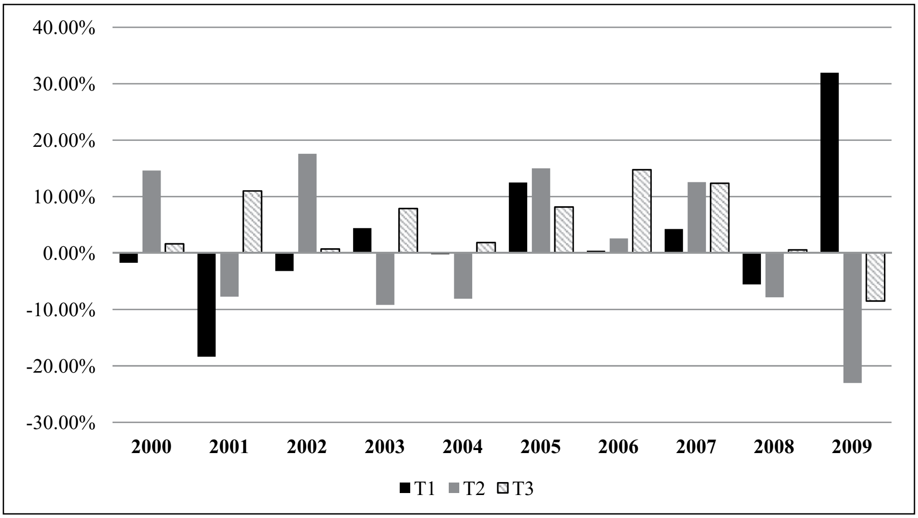

Figure 3. Average DGTW-adjusted returns to Q-Score sorted terciles formed using micro stocks over 2000–2009.

Figure 3 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted tercile over 2000–2009. The sample is micro stocks listed on the Australian Securities Exchange (ASX) for which Share Price and Price Relative (SPPR), Aspect and DGTW data is available. Stocks are classified as micro if their market capitalisation for December $year_{t-1}$ is less than the 70th percentile. The terciles are formed in March of each $year_t$ based on the Q-Score for the prior year, and buy-and-hold returns are computed from April of $year_t$ to March of $year_{t+1}$; for example, the return for 2000 is the return from April 2000 to March 2001. The weight applied to each stock's return is its market capitalisation as at December of $Year_{t-1}$. Tercile 1 (3) contains low- (high-) quality stocks.

higher for micro stocks, followed by small and then large stocks. Within the small and large size groups, the low-quality stocks have higher volatilities than the high-quality stocks.

The CAPM-adjusted returns across the size groups monotonically increase moving from the low- to high-quality terciles. A strong quality premium is evident for small and large stocks, with an average CAPM alpha of 13.56% and 7.76%, significant at the 5% level, respectively. In relation to beta, the low-quality micro stocks are the most sensitive to market movements, with an average beta of 1.35. Across the size categories the tracking error is higher for the micro stocks, followed by small and then large stocks. The low-quality micro stocks have the highest tracking error at 7.13%, whereas the tracking error is relatively similar across the quality terciles within the small and large size groups.

Figure 3 shows the performance of the quality terciles within the micro size group subset over 2000–2009. In 2000 stocks of moderate quality, that is, those in Tercile 2, outperform substantially with an average DGTW-alpha of 14.62%. In 2001 the low–moderate-quality micro stocks perform very poorly, with Terciles 1 and 2 incurring average returns of −18.37% and −7.74%, respectively, compared to the highest quality stocks, which generate an average return of 11.01%. All stock terciles achieve positive returns in 2007, although the low-quality stocks performance is muted compared to Terciles 2 and 3. The lowest quality micro stocks underperform in 2008 by −5.55%; however, they recover very strongly in 2009 with an average DGTW-alpha of 31.95%, whereas the highest quality micro stocks avoid underperforming amid the GFC in 2008, but in 2009 they underperform by −8.50%.

Figure 4 shows the performance of the quality terciles within the small size group subset over 2000–2009. Small stocks of moderate quality (Tercile 2) underperform in 2000 by −6.95%; Tercile 3 performs the strongest with an average DGTW-alpha of 17.06%. Small stocks in Tercile

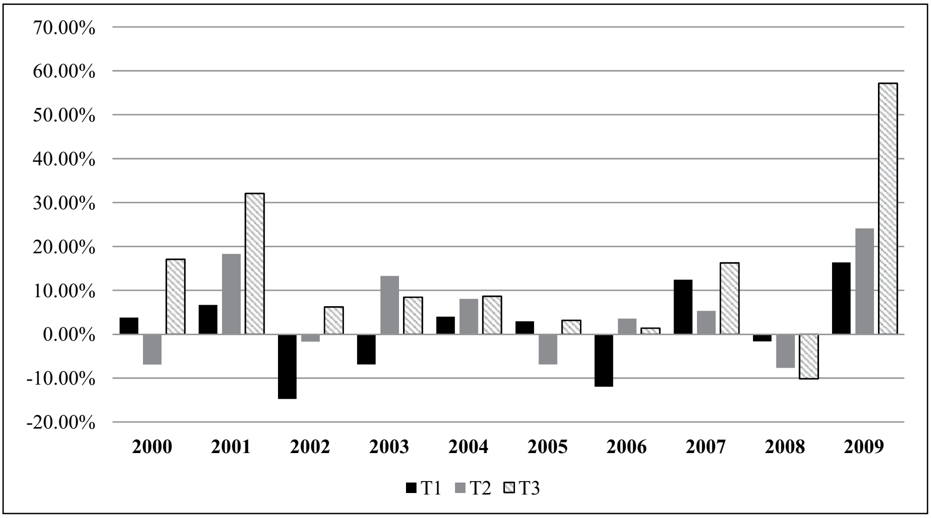

Figure 4. Average DGTW-adjusted returns to Q-Score sorted terciles formed using small stocks over 2000–2009.

Figure 4 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted tercile over 2000–2009. The sample is small stocks listed on the Australian Securities Exchange (ASX) for which Share Price and Price Relative (SPPR), Aspect and DGTW data is available. Stocks are classified as small if their market capitalisation for December $year_{t-1}$ is between the 70th and 90th percentiles. The terciles are formed in March of each $year_t$ based on the Q-Score for the prior year, and buy-and-hold returns are computed from April of $year_t$ to March of $year_{t+1}$; for example, the return for 2000 is the return from April 2000 to March 2001. The weight applied to each stock's return is its market capitalisation as at December of $year_{t-1}$. Tercile 1 (3) contains low- (high-) quality stocks.

3 perform particularly strongly in 2001, with a mean DGTW-alpha of 32.07%. All small stocks generate positive DGTW-alpha in 2007; in 2008 it is the high-quality small stocks that perform the worst, with an average alpha of −10.15%. However, it is the top-quality tercile that posts the strongest recovery in 2009, with an average DGTW-alpha of 57.18%.

Figure 5 shows the performance of the quality terciles within the large size group subset over 2000–2009. The highest quality large stocks underperform slightly in 2000. However, in 2001 it is the lowest quality large stocks that underperform slightly, whilst Tercile 2 stocks outperform significantly with an average DGTW-alpha of 12.23%. The highest quality large stocks outperform significantly in 2003, 2004 and 2005, whilst low-quality stocks underperform in 2003 and 2004. In 2007, the high-quality large stocks generate the highest average DGTW-alpha at 13.04%.[15] Low- and high-quality stocks avoid underperforming in 2008. However, Tercile 1 underperforms significantly in 2009, with an average alpha of −12.94%, whilst stocks in Tercile 3 perform relatively better, incurring an average alpha of −5.80%.

In summary, the average and time-series performance of stocks segregated based on quality and on size, and then quality indicates two key trends. Firstly, there is a quality return premium to stocks that are of high quality as measured by the Q-Score. Secondly, quality stocks have historically provided downside protection during crises such as the dot-com crash and to a lesser extent the GFC.

5.4. Multivariate results for the mutual fund sample

The Russell Investments research database is used to test the performance of long-only Australian Active Equity fund managers segregated on the basis of portfolio quality. Table 8 provides return

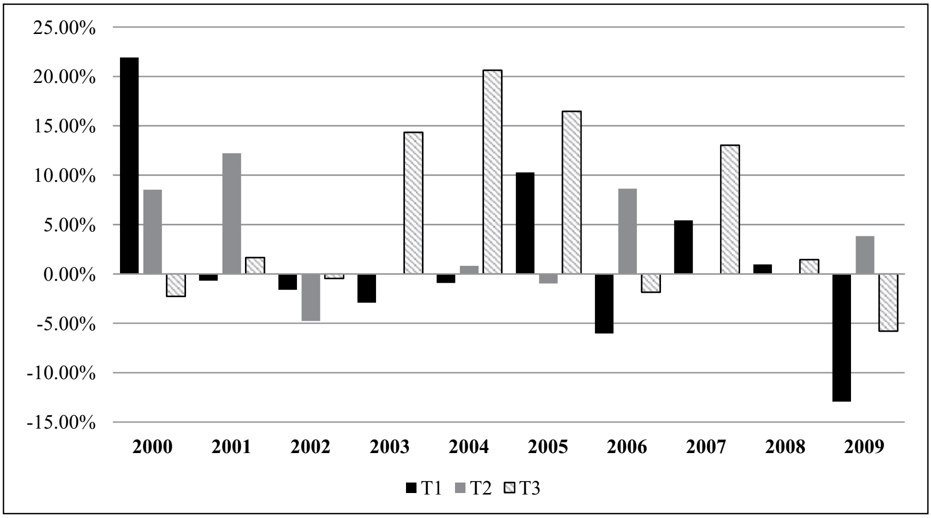

Figure 5. Average DGTW-adjusted returns to Q-Score sorted terciles formed using large stocks over 2000–2009.

Figure 5 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted tercile over 2000–2009. The sample is large stocks listed on the Australian Securities Exchange (ASX) for which Share Price and Price Relative (SPPR), Aspect and DGTW data is available. Stocks are classified as large if their market capitalisation for December year$_{t-1}$ is greater than the 90th percentile. The terciles are formed in March of each year$_t$ based on the Q-Score for the prior year, and buy-and-hold returns are computed from April of year$_t$ to March of year$_{t+1}$; for example, the return for 2000 is the return from April 2000 to March 2001. The weight applied to each stock's return is its market capitalisation as at December of year$_{t-1.}$ Tercile 1 (3) contains low- (high-) quality stocks.

and portfolio characteristics of terciles that have been formed by sorting funds based on the weighted-average Q-Score for their portfolios in March of year *t*. The weight applied to each stock is its holding value as at March of year *t*. Returns are then examined for each tercile from April of year *t* to March year *t*+1. The average return to each tercile is computed each month using all funds that existed in that month. The annual return is then computed as the simple compound of these 12 monthly averages. Thus, the results are free from survivorship bias. Asset-weighted returns are calculated by weighting the return to each fund by its assets as at the end of the prior month.

There are 204 unique funds for which Q-Scores can be computed over 2000–2009, whilst on average there are 33–36 funds in each tercile every month. The average Q-Scores do not differ substantially across the terciles – the mean Q-Score for Tercile 1 is 4.60 compared to 8.29 for Tercile 3. Furthermore, the average size of each fund is similar with average assets of A$1248m, A$1612m and A$1463m for Terciles 1, 2 and 3, respectively. Given that the Q-Scores and size for the terciles are similar, it is perhaps not surprising that the performance of the funds does not differ substantially across the terciles. On an equal-weighted basis, the top tercile of funds generates an average annual DGTW-alpha of 2.09%, which is significant at the 10% level over April 2000–March 2010. Similarly, the bottom tercile of funds generates an average DGTW-alpha of 2.17%, which is significant at the 10% level. Furthermore, on an EW CAPM-adjusted basis, Terciles 1, 2 and 3 achieve statistically significant returns of 4.49%, 3.22% and 3.86%, respectively. However, upon VW by assets no statistically significant returns are identified across the terciles. Furthermore, the DGTW size quintile, book-to-market quartile and momentum terciles means for each tercile are

Table 8. Returns and characteristics for Q-Score sorted tercile portfolios of mutual funds.

Tercile	No. funds	Q-Score value	Assets (A$m)	Raw return AW (%)	Raw return EW (%)	DGTW-adj. return AW (%)	DGTW-adj. return EW (%)	CAPM-adj. return AW (%)	CAPM-adj. return EW (%)	Size quintile	B/M quartile	MOM tercile
1	33	4.60	1248	11.13 (1.36)	14.74 (1.74)	−0.33 (−0.27)	2.17* (1.90)	0.91 (0.61)	4.49** (2.54)	3.89	1.35	1.15
2	36	7.04	1612	13.67* (1.94)	10.84* (2.00)	1.11 (1.19)	1.61 (1.75)	2.24 (1.39)	3.22* (2.03)	3.98	1.35	1.13
3	35	8.29	1463	12.78 (1.71)	14.80* (1.93)	0.06 (0.06)	2.09* (2.11)	2.05 (1.25)	3.86** (2.39)	3.97	1.32	1.19

Table 8 presents average returns and characteristics for tercile portfolios formed by sorting a sample of Australian Active Equity Mutual Funds based on the weighted-average Q-Score for their portfolios in March of each year t over 2000–2009. The Q-Score for each stock held by a fund is weighted by the stock's holding value as at March year t. Funds are then sorted into terciles and returns are measured over April year t to March year t+1. Monthly returns for each fund are calculated as the average of the return to the stocks contained in the portfolio, weighted by a stock's holding value as at the end of the month prior. Average tercile returns are calculated for each month and then the annual return presented is the time-series mean of these 12 monthly returns, thus the results are free from survivorship bias. Asset-weighted (AW) and Equal-weighted (EW) results are provided. No. funds is the time-series mean of the average number of funds in each tercile portfolio over the 12 months of each return accumulation period. Q-Score value is the time-series AW mean of the average Q-Score in March year t for funds in each tercile. Assets is the time-series AW average assets of funds in each tercile portfolio over the 12 months of each return accumulation period. Raw return is the average annual raw fund return. Daniel, Grinblatt, Titman and Wermers (DGTW)-adj. return is the average adjusted fund return whereby the return to each stock held has been adjusted by the return to one of 60 benchmark portfolios with the same size, book-to-market and momentum characteristics. Stocks are first sorted into five groups based on size, then four groups based on book-to-market and finally three groups based on momentum. Capital asset pricing model (CAPM) adj. return is the average annual excess return calculated using a 1-Factor market model approach. Specifically, each month the following model is run over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the Standard & Poor's (S&P)/Australian Securities Exchange (ASX) 300 return, both x and y are in excess of the 30-day Bank Accepted Bill (BAB) rate. Size quintile is the time-series AW mean of the average size quintile, B/M quartile is the time-series AW mean of the average book-to-market quartile and MOM tercile is the time-series AW mean of the average momentum tercile for funds in each tercile portfolio, computed over the 12 months of each return accumulation period. The means for each fund each month are first calculated by weighting each stock's quintile, quartile and tercile value by its holding value as at the end of the prior month. t-statistics are provided in parentheses below the mean returns.
Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

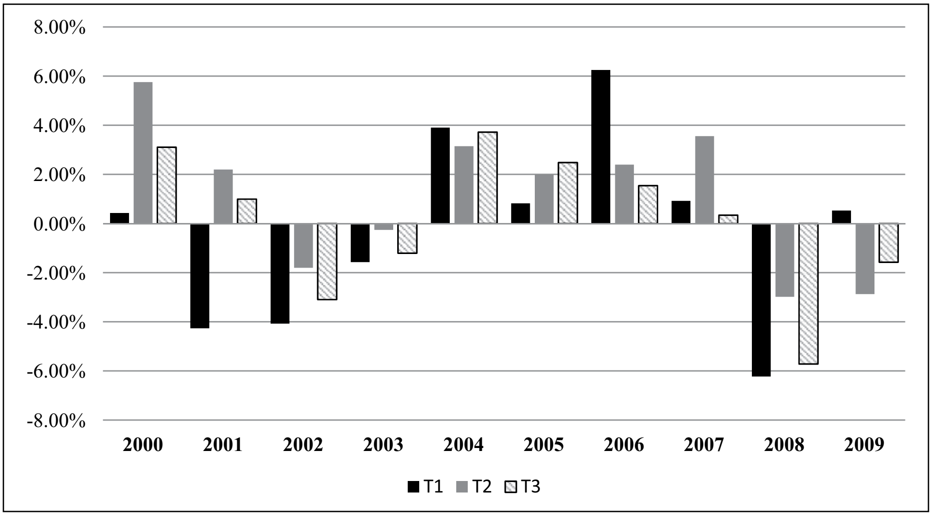

Figure 6. Average DGTW-adjusted returns to mutual funds sorted into terciles based on the average Q-Score for their portfolios over 2000–2009.

Figure 6 demonstrates the Daniel, Grinblatt, Titman and Wermers (DGTW)-adjusted return to each Q-Score sorted fund tercile over 2000–2009. The sample is long-only active Australian equity funds. Firstly, in March of each year$_t$ the weighted-average Q-Score is computed for each fund based on the holding value of each stock as at March of year$_t$. The funds are then ranked into terciles based on their average Q-Score. The mean returns are calculated from April of year$_t$ to March of year$_{t+1}$. All funds with holdings data available in a given quarter are included in the calculation of the mean annual return for that year. Therefore, the results are free from survivorship bias as the mean return is calculated on a quarterly basis and then the annual mean is the compound of these four mean returns. Tercile 1 (3) contains low- (high-) quality funds.

very similar. It seems that Australian funds are quite homogeneous with respect to the quality of the stocks in which they invest.

Figure 6 shows the performance of the Q-Score sorted mutual fund terciles for portfolios formed in March of year t over 2000–2009. The returns presented are asset-weighted DGTW-alphas from April of year t to March of year t+1. In 2001 the top-quality tercile provides some downside protection given the downturn following the dot-com crash with an average DGTW-alpha of 0.99% compared to −4.27% for the low-quality funds. In 2007 all terciles generate positive returns – the return to Tercile 1 is 0.92%, compared to 3.55% and 0.34% for Terciles 2 and 3, respectively. Amid the GFC all terciles of funds underperform; the average DGTW-alpha is −6.23%, −2.98% and −5.72% for Terciles 1, 2 and 3, respectively. The underperformance continues into 2009 for Terciles 2 and 3; however, the low-quality funds recover slightly, with an average DGTW-alpha of 0.53%.

Thus, there is weak evidence of the quality effect at the fund level on an asset-weighted basis. The level of quality of the funds across the terciles is similar and thus similar performance is not surprising. In light of this, the fund analysis demonstrates that high-quality mutual funds in Australia generate positive outperformance on an adjusted basis.

6. Conclusion

This paper provides an examination of Quality as an investment style in the Australian market over April 2000–March 2010. A symmetric relationship between DGTW-alpha and quality stocks is determined with stocks in the highest (lowest) quintile achieving (incurring) an average return of 6.37% (−7.98%), which is significant at the 5% level over the sample period. Thus, a quality return premium exists in the Australian market. Furthermore, this result is pervasive throughout the market with high-quality micro, small and large stocks all exhibiting a similar effect. Analysis of the performance of quality stocks in up versus down markets reveals the downside protection offered by quality stocks. In addition, quality stocks have historically provided security during financial market crises, such as the tech crash and to a lesser extent the GFC.

This research has a number of implications for the wealth management industry within Australia. Firstly, the research emphasises that financial statement analysis (still) plays an important role within the Australian market in terms of stock picking and investment strategy development. Moreover, the Quality return premium identified confirms that the fundamental variables included in the Q-Score are important measures to consider when analysing ASX listed stocks. This is a key takeaway for Self-Managed Super Fund investors, as it provides a structured approach to analysis of stocks with the objective of generating returns and withstanding crisis environments. In relation to the development of suitable post-retirement products, (high) Quality appears to be an exploitable return generation avenue, which is characterised by a sound accounting foundation and a low level of risk (particularly relative to low-quality stocks).

Furthermore, given the strong stock return results both on average and over time, including during crises, quality as an investment style appears relevant to retirees given the return/risk relationship apparent. Thus, this research provides a strong foundation for a Quality-focused approach to post-retirement portfolio construction. Further research investigating how investment vehicles at the stock level could be used within a portfolio developed with post-retirement objectives is warranted.

The quality analysis is also extended to a sample of stock holdings for long-only Australian Active Equity Mutual Funds. The level of quality of the funds in the sample is similar and therefore the performance across Q-Score sorted-fund terciles does not differ substantially. However, a key insight from the investigation is that high-quality funds generate statistically significant DGTW-alpha (CAPM-adjusted returns) of about 2% (3–5%) on an equally weighted basis over the sample period. However, no statistically significant DGTW- or CAPM-adjusted returns are identified when asset-weighting is used. Thus, weak evidence that the return premium also exists at the fund level is determined.

In terms of the role that quality funds could play with regards to post-retirement investments, the evidence on the performance of the funds during financial crises is mixed. In 2001 the lowest quality tercile underperforms whilst the top two outperform; however, in 2008 during the GFC all funds underperform. Given that funds in all terciles underperform in 2008 it appears that high-quality funds are not a panacea to possible future market crises. Although the Quality return premium identified is weaker at the fund level, it is worthwhile considering active equity funds along the dimensions highlighted as important indicators of Quality.

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Notes

1. DGTW refers to the performance evaluation method developed by Daniel et al. (1997) that involves assigning all stocks to one of 125 benchmark portfolios based on their size, book-to-market and momentum characteristics. Adjusted returns are calculated as the excess of each stock's raw return, over the value-weighted raw return to its characteristic-matched benchmark portfolio.
2. In the US, an asymmetric relationship is detected as only low-quality stocks significantly underperform on average.
3. In the US the DGTW portfolios are formed based on a five × five × five sort of stocks given their size, book-to-market and momentum characteristics, that is, 125 benchmark portfolios. Given the fact that there are fewer stocks listed on the ASX, the DGTW portfolios are formed based on a five × four × three sort, resulting in 60 benchmark portfolios, following Pinnuck (2003).
4. The variability metrics Sales Growth and ROA Variability have not been included in the Australian analysis as they require a four-year history of data that results in the overall Q-Score results only being able to be calculated robustly from 2002 onwards, as the first year in which the variability metrics have data is 1995 and then seven years of data are required to compute the parameter estimates (i.e. 1995–2001). These parameter estimates are used to compute the Q-Score in March 2002, hence the first period of return analysis is from April 2002 to March 2003 (whereas upon exclusion the return series commences in April 2000). Furthermore, the average β_1 and β_2 estimates for Sales Growth variability are 0 and thus this metric does not contribute to the Q-Score. Similarly, the ROA variability parameter estimates are very small and therefore they do not have a strong impact on the Q-Score either.
5. The results are similar when the individual metric values are scaled by the industry median for the prior fiscal year using the CRIF industry assignments instead of the population median.
6. The authors are grateful to Adrian Lee for providing valuable programming assistance to calculate the DGTW (1997) benchmarks for Australia.
7. The number of funds used in Bennett et al. (2012) and this study differs as the authors make various exclusions relevant to their analysis that are not made in this paper; for example, the removal of small-capitalisation funds.
8. We are aware that ROA has insignificant parameter estimates for subsets 1–3 and 5 and ΔTE for subset 9; however these variations are included in the computation of the Q-Score in all periods in the interests of consistency. If the inclusion of each metric is considered on a rolling basis then ROA and ΔTE would be excluded from the Q-Score in the aforementioned periods – these results are consistent with those presented.
9. As a robustness test, an alternative approach to aggregating the metrics included in the Q-Score is undertaken. In a similar vein to Piotroski (2000), a binary scoring system is used; if a stock's ROE, ΔROE, ROA, ΔROA and OCF are positive then indicator variables 1–5 equal one, zero otherwise and if a stock's ΔATO, ΔSH and ΔTE are negative then indicator variables 6–8 equal one, zero otherwise. The Q-Score is the sum of the eight indicator variables; therefore, the Q-Score values range from 0 to 8. The average return results generated using this method are consistent with the results presented in this paper.
10. The quintile results are similar when the Aspect/SPPR/DGTW universe is limited to the top 500 stocks based on market capitalisation as at December year *t–1*. Furthermore, when the top 10 stocks based on market capitalisation are removed the results are similar and more pronounced; for example, average DGTW-alpha for Quintile 1 (5) is –8.31% (14.45%), significant at the 5% (1%) level. The results are also consistent when only stocks with a June financial year end are used and returns are computed from October year *t* to September year *t*+1.
11. Beta is calculated based on the following regression model estimated over the prior 60 months: $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the raw stock return and x is the S&P/ASX 300 return, both x and y are in excess of the 30-day BAB rate.
12. Furthermore, the pattern of excess returns computed using a four-factor Carhart (1997) model are also consistent with the results presented in the paper.

13. The active-weighting approach used in the US Quality paper has not been applied to the subset of stocks held by at least one mutual fund, as it is problematic given the Australian market is concentrated and dominated by a number of large stocks.
14. The average number of stocks in each tercile is similar to the average number in each quartile for Dou et al. (2012). Furthermore, the results are qualitatively similar when stocks are sorted into quartiles within each size group. The results are also qualitatively similar when the subset of stocks held by at least one mutual fund is used for the size breakdown analysis.
15. In 2007 and 2008 no stocks are classified into Tercile 2, therefore return data for these two years is missing for Tercile 2.

References

Barton J, Hansen T and Pownall G (2010) Which performance measures do investors around the world value the most—And why? *Accounting Review* 85: 753–789.

Berk J and Green R (2004) Mutual fund flows and performance in rational markets. *The Journal of Political Economy* 112: 1269–1295.

Bennett S, Gallagher D, Harman G, et al. et al. (2012) Alpha generation in portfolio management: Long-run Australian equity fund evidence. Working paper. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2138149 (accessed 15 March 2013).

Benson K, Gallagher D and Teodorowski P (2007) Momentum investing and the asset allocation decision. *Accounting and Finance* 47: 571–598.

Bettman J, Kosev M and Sault S (2011) Exploring the asset growth effect in the Australian equity market. *Australian Journal of Management* 36: 200–216.

Bilson C, Frino A and Heaney R (2005) Australian retail fund performance persistence. *Accounting and Finance* 45: 25–42.

Bird R and Casavecchia L (2007) Sentiment and financial health indicators for value and growth stocks: The European experience. *The European Journal of Finance* 13: 769–793.

Carhart M (1997) On persistence in mutual fund performance. *The Journal of Finance* 52: 57–82.

Chia Y, Czernkowski R and Loftus J (1997) The association of aggregated and disaggregated earnings with annual stock returns. *Accounting and Finance* 37: 111–128.

Chen P and Zhang G (2007) How do accounting variables explain stock price movements? Theory and evidence. *Journal of Accounting and Economics* 43: 219–244.

Clinch G, Fuller D, Govendir B, et al. (2012) The accrual anomaly: Australian evidence. *Accounting and Finance* 52: 377–394.

Cotter J (1996) Accrual and cash flow accounting models: A comparison of the value relevance and timeliness of their components. *Accounting and Finance* 36: 127–150.

Coulton J, Taylor S and Taylor S (2005) Is 'benchmark beating' by Australian firms evidence of earnings management? *Accounting and Finance* 45: 553–576.

Covrig V, Lau ST and Ng L (2006) Do domestic and foreign fund managers have similar preferences for stock characteristics? A cross country analysis. *Journal of International Business Studies* 37: 407–429.

Daniel K, Grinblatt M, Titman S, et al. (1997) Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52: 1035–1058.

Dempsey M (2009) Rankings for Australian managed funds: Contrariness and performance index failure. *Journal of Asset Management* 10: 138–157.

Donaldson G (1961) *Corporate Debt Capacity*. Cambridge, MA: Harvard University Press.

Doran B, Drew M and Walk A (2012) The retirement risk zone: A baseline study. Discussion paper, July, Griffith Business School, Griffith University, Australia.

Dou P, Gallagher D and Schneider D (2012) Dissecting anomalies in the Australian stock market. *Australian Journal of Management* 37: 461–479.

Faff RW, Parwada JT and Poh HL (2007) The information content of Australian managed fund ratings. *Journal of Business Finance & Accounting* 34(9–10): 1528–1547.

Fairfield P and Whisenant S (2000) Using fundamental analysis to assess earnings quality: Evidence from the Center for Financial Research and Analysis. *Journal of Accounting, Auditing and Finance* 16: 273–295.

Fong K, Gallagher D and Lee A (2008) Benchmarking benchmarks: Measuring characteristic selectivity using portfolio holdings data. *Accounting and Finance* 48: 761–781.

Fong K, Gallagher D, Gardner P, et al. (2011) Follow the leader: Fund managers trading in signal-strength sequence. *Accounting and Finance* 51: 684–710.

Gallagher D (2003) Investment manager characteristics, strategy, top management changes and fund performance. *Accounting and Finance* 43: 283–309.

Gallagher D, Gardner P, Schmidt C, et al. (2013) Portfolio quality and mutual fund performance. Working paper. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2151658 (accessed 20 April 2013).

Gerrans P (2006) Morningstar ratings and future performance. *Accounting and Finance* 46: 605–628.

Gharghori P, Lee R and Veeraraghavan M (2009) Anomalies and stock returns: Australian evidence. *Accounting and Finance* 49: 555–576.

Gharghori P, Mudumba S and Veeraraghavan M (2007) How smart is money? An investigation into investor behaviour in the Australian managed fund industry. *Pacific-Basin Finance Journal* 15: 494–513.

Gray P, Koh P and Tong Y (2009) Accruals quality, information risk and cost of capital: Evidence from Australia. *Journal of Business Finance & Accounting* 36: 51–72.

Habib A (2010) Value relevance of alternative accounting performance measures: Australian evidence. *Accounting Research Journal* 23: 190–212.

Hallahan TA, Faff RW and Benson K (2008) Fortune favours the bold? Exploring tournament behavior among Australian superannuation funds. *Journal of Financial Services Research* 33: 205–220.

Heaney R (2008) Australian equity mutual fund size effects. *Accounting and Finance* 48: 807–827.

Heaney R, Hallahan T, Josev T, et al. (2007) Time-changing alpha? The case of Australian international mutual funds. *Australian Journal of Management* 32: 95–112.

Hodgson A and Stephenson-Clarke P (2000) Earnings, cashflows and returns: Functional relations and the impact of firm size. *Accounting and Finance* 40: 51–73.

Holmes K and Faff R (2004) Stability, asymmetry and seasonality of fund performance: An analysis of Australian multisector managed funds. *Journal of Business Finance & Accounting* 31: 539–578.

Houghton K and Woodliff D (1987) Financial ratios: The prediction of corporate success and failure. *Journal of Business Finance & Accounting* 4: 537–554.

Humphrey J and O'Brien M (2010) Persistence and the four-factor model in the Australian funds market: A note. *Accounting and Finance* 50: 103–119.

Kent P, Routledge J and Stewart J (2010) Innate and discretionary accruals quality and corporate governance. *Accounting and Finance* 50: 171–195.

Loftus J and Sin S (1997) The role of current and non-current accruals in the relation between stock returns and earnings. *Accounting and Finance* 37: 147–161.

Money Management (2013) Why equity income strategies are here to stay. Available at: http://www.moneymanagement.com.au/analysis/financial-services/2012/why-equity-income-strategies-are-here-to-stay (accessed 6 February 2013).

Myers S and Majluf N (1984) Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13: 187–221.

Oei R, Ramsay A and Mather P (2008) Earnings persistence, accruals and managerial share ownership. *Accounting and Finance* 48: 475–502.

Pinnuck M (2003) An examination of the performance of the trades and stock holdings of fund managers: Further evidence. *Journal of Financial and Quantitative Analysis* 38: 811–828.

Pinnuck M (2004) Stock preferences and derivative activities of Australian fund managers. *Accounting and Finance* 44: 97–120.

Soliman M (2008) The use of DuPont analysis by market participants. *The Accounting Review* 83: 823–853.

Taylor S and Wong L (2012) Robust anomalies? A close look at accrual-based trading strategy returns. *Accounting and Finance* 52: 573–603.

Worthington A (1998) The application of mathematical programming techniques to financial statement analysis: Australian gold production and exploration. *Australian Journal of Management* 23: 97–113.
Worthington A and West T (2004) Australian evidence concerning the information content of economic value-added. *Australian Journal of Management* 29: 201–223.
Zhang G (2000) Accounting information, capital investment decisions, and equity valuation: Theory and empirical implications. *Journal of Accounting Research* 38: 271–295.
Zhu Y (2012) Capital structure: The case of firms issuing debt. *Australian Journal of Management* 37: 283–295.

Appendix. Univariate regression results.

Subset	β_1	Standard error	*t*-statistic	*p*-value	β_2	Standard error	*t*-statistic	*p*-value	Year β_1 & β_2 applied to metric value
Return on Equity (ROE)									
1	15.49***	4.44	3.49	0.00	2.00	1.34	1.50	0.14	1999
2	14.99***	3.88	3.86	0.00	1.70	1.18	1.44	0.15	2000
3	13.22***	3.37	3.93	<.0001	1.32	1.04	1.28	0.20	2001
4	12.55***	3.03	4.14	<.0001	1.44	0.93	1.55	0.12	2002
5	12.61***	2.98	4.22	<.0001	1.29	0.92	1.40	0.16	2003
6	13.03***	2.70	4.82	<.0001	1.21	0.84	1.45	0.15	2004
7	11.55***	2.52	4.59	<.0001	1.23	0.77	1.59	0.11	2005
8	10.80***	2.35	4.60	<.0001	1.17*	0.71	1.65	0.10	2006
9	10.48***	2.17	4.83	<.0001	1.36*	0.65	2.11	0.04	2007
10	8.76***	1.97	4.45	<.0001	1.09*	0.59	1.86	0.06	2008
Change in ROE									
1	8.86**	4.35	2.04	0.04	−0.51	2.04	−0.25	0.80	1999
2	8.39**	3.86	2.18	0.03	−0.73	1.81	−0.40	0.69	2000
3	6.93**	3.39	2.05	0.04	−0.85	1.58	−0.54	0.59	2001
4	6.24**	3.02	2.07	0.04	−0.86	1.43	−0.60	0.55	2002
5	7.17**	2.93	2.44	0.01	−1.19	1.39	−0.86	0.39	2003
6	6.57**	2.66	2.47	0.01	−1.74	1.26	−1.38	0.17	2004
7	5.93**	2.52	2.35	0.02	−1.49	1.19	−1.24	0.21	2005
8	5.73**	2.35	2.44	0.01	−1.79	1.11	−1.61	0.11	2006
9	5.01**	2.15	2.34	0.02	−1.74*	1.02	−1.71	0.09	2007
10	4.20**	1.92	2.19	0.03	−1.64*	0.91	−1.80	0.07	2008
Return on Assets (ROA)									
1	−0.42	11.16	−0.04	0.97	−1.08	5.11	−0.21	0.83	1999
2	5.92	9.67	0.61	0.54	0.59	4.41	0.13	0.89	2000
3	13.13	8.52	1.54	0.12	3.86	3.83	1.01	0.31	2001
4	14.20*	7.49	1.90	0.06	4.26	3.42	1.25	0.21	2002
5	10.91	7.27	1.50	0.13	2.16	3.35	0.64	0.52	2003
6	11.83*	6.56	1.80	0.07	2.77	3.01	0.92	0.36	2004
7	11.71*	6.11	1.92	0.06	3.68	2.76	1.34	0.18	2005
8	12.25**	5.64	2.17	0.03	3.93	2.54	1.55	0.12	2006
9	12.47**	5.09	2.45	0.01	4.22*	2.28	1.85	0.06	2007
10	10.86**	4.56	2.39	0.02	3.74*	2.07	1.81	0.07	2008
Change in ROA									
1	29.39***	8.59	3.42	0.00	−0.74	8.45	−0.09	0.93	1999
2	28.04***	7.68	3.65	0.00	−2.52	7.65	−0.33	0.74	2000
3	24.59***	6.78	3.63	0.00	0.22	6.69	0.03	0.97	2001
4	22.26***	5.98	3.72	0.00	−0.98	5.99	−0.16	0.87	2002
5	19.50***	5.71	3.41	0.00	−4.03	5.80	−0.69	0.49	2003
6	16.91***	5.18	3.26	0.00	−5.39	5.29	−1.02	0.31	2004
7	13.66***	4.85	2.82	0.00	−5.99	4.95	−1.21	0.23	2005

Appendix. (Continued)

Subset	β_1	Standard error	t-statistic	p-value	β_2	Standard error	t-statistic	p-value	Year β_1 & β_2 applied to metric value
8	12.80***	4.50	2.85	0.00	−6.10	4.57	−1.34	0.18	2006
9	11.30***	4.08	2.77	0.01	−5.24	4.11	−1.28	0.20	2007
10	9.19**	3.61	2.55	0.01	−4.38	3.62	−1.21	0.23	2008
Operating Cash Flow									
1	11.64	13.54	0.86	0.39	37.28**	16.63	2.24	0.03	1999
2	15.85	11.85	1.34	0.18	35.16**	14.50	2.42	0.02	2000
3	24.89**	10.57	2.36	0.02	36.87***	12.83	2.87	0.00	2001
4	26.91***	9.42	2.86	0.00	35.87***	11.47	3.13	0.00	2002
5	20.36**	9.17	2.22	0.03	30.61***	11.06	2.77	0.01	2003
6	20.14**	8.31	2.42	0.02	25.15**	9.86	2.55	0.01	2004
7	16.11**	7.83	2.06	0.04	21.31**	9.15	2.33	0.02	2005
8	17.54**	7.34	2.39	0.02	23.24***	8.44	2.75	0.01	2006
9	19.55***	6.67	2.93	0.00	24.08***	7.70	3.13	0.00	2007
10	19.08***	6.14	3.11	0.00	23.47***	7.00	3.36	0.00	2008
Accruals									
1	−1.21	14.52	−0.08	0.93	−10.37	21.02	−0.49	0.62	1999
2	0.23	12.79	0.02	0.99	−11.29	18.10	−0.62	0.53	2000
3	−3.41	11.58	−0.29	0.77	−12.84	16.44	−0.78	0.44	2001
4	−2.95	10.41	−0.28	0.78	−12.64	14.38	−0.88	0.38	2002
5	3.17	10.23	0.31	0.76	−3.36	14.00	−0.24	0.81	2003
6	3.95	9.37	0.42	0.67	1.27	12.56	0.10	0.92	2004
7	7.99	8.85	0.90	0.37	8.91	11.91	0.75	0.45	2005
8	7.99	8.31	0.96	0.34	5.17	11.21	0.46	0.64	2006
9	4.40	7.65	0.58	0.57	1.06	10.17	0.10	0.92	2007
10	4.47	6.96	0.64	0.52	1.51	9.18	0.16	0.87	2008
Asset Turnover (ATO)									
1	−5.48	3.64	−1.50	0.13	1.06	1.03	1.03	0.31	1999
2	−3.68	3.21	−1.15	0.25	0.82	0.91	0.89	0.37	2000
3	−2.30	2.89	−0.80	0.43	0.84	0.81	1.04	0.30	2001
4	−0.63	2.59	−0.24	0.81	0.52	0.72	0.72	0.47	2002
5	−2.36	2.57	−0.92	0.36	0.84	0.72	1.17	0.24	2003
6	−2.10	2.37	−0.88	0.38	0.77	0.66	1.17	0.24	2004
7	−2.71	2.29	−1.18	0.24	0.78	0.63	1.24	0.21	2005
8	−2.57	2.18	−1.18	0.24	0.84	0.60	1.39	0.17	2006
9	−2.02	2.05	−0.98	0.33	0.65	0.57	1.14	0.26	2007
10	−1.81	1.93	−0.94	0.35	0.59	0.54	1.09	0.28	2008
Change in ATO									
1	−16.76**	7.31	−2.29	0.02	5.44	3.58	1.52	0.13	1999
2	−13.46**	6.39	−2.11	0.04	4.91	3.12	1.57	0.12	2000
3	−13.76**	5.67	−2.43	0.02	6.11	2.72	2.24	0.02	2001
4	−12.31**	4.98	−2.47	0.01	5.69	2.41	2.36	0.02	2002

(Continued)

Appendix. (Continued)

Subset	β_1	Standard error	*t*-statistic	*p*-value	β_2	Standard error	*t*-statistic	*p*-value	Year β_1 & β_2 applied to metric value
5	−11.37**	4.89	−2.32	0.02	4.59	2.38	1.93	0.05	2003
6	−10.27**	4.50	−2.28	0.02	4.06	2.20	1.85	0.06	2004
7	−10.93**	4.27	−2.56	0.01	3.93	2.09	1.88	0.06	2005
8	−8.89**	4.03	−2.20	0.03	3.47	1.97	1.76	0.08	2006
9	−7.07**	3.73	−1.90	0.06	3.03	1.85	1.64	0.10	2007
10	−7.36**	3.47	−2.12	0.03	3.00	1.72	1.74	0.08	2008
Leverage									
1	−5.60	7.57	−0.74	0.46	4.16	3.26	1.27	0.20	1999
2	−3.52	6.56	−0.54	0.59	3.06	2.86	1.07	0.29	2000
3	−0.31	5.93	−0.05	0.96	1.56	2.59	0.60	0.55	2001
4	0.30	5.35	0.06	0.96	1.37	2.34	0.59	0.56	2002
5	−5.16	5.24	−0.98	0.33	3.27	2.29	1.43	0.15	2003
6	−3.21	4.79	−0.67	0.50	2.56	2.09	1.23	0.22	2004
7	−4.67	4.60	−1.02	0.31	2.51	2.01	1.25	0.21	2005
8	−3.00	4.39	−0.68	0.50	2.14	1.93	1.11	0.27	2006
9	−2.25	4.12	−0.55	0.59	1.66	1.80	0.92	0.36	2007
10	−2.36	3.86	−0.61	0.54	1.65	1.69	0.98	0.33	2008
Liquidity									
1	0.37	6.87	0.05	0.96	−8.23	6.35	−1.30	0.20	1999
2	1.38	6.05	0.23	0.82	−7.54	5.61	−1.34	0.18	2000
3	3.47	5.42	0.64	0.52	−6.36	5.05	−1.26	0.21	2001
4	3.24	4.84	0.67	0.50	−5.52	4.54	−1.22	0.22	2002
5	1.60	4.71	0.34	0.73	−3.56	4.40	−0.81	0.42	2003
6	3.22	4.33	0.74	0.46	−3.00	4.03	−0.74	0.46	2004
7	3.19	4.11	0.78	0.44	−2.28	3.82	−0.60	0.55	2005
8	1.65	3.87	0.43	0.67	−3.50	3.61	−0.97	0.33	2006
9	1.17	3.57	0.33	0.74	−2.75	3.37	−0.82	0.41	2007
10	1.44	3.30	0.44	0.66	−2.46	3.16	−0.78	0.44	2008
Change in shares									
1	21.06***	7.28	2.89	0.00	−6.43***	2.12	−3.03	0.00	1999
2	15.49**	6.17	2.51	0.01	−5.12***	1.80	−2.85	0.00	2000
3	10.90**	5.45	2.00	0.05	−3.90**	1.58	−2.47	0.01	2001
4	8.77*	4.93	1.78	0.08	−3.17**	1.43	−2.22	0.03	2002
5	7.89	4.86	1.62	0.10	−3.30**	1.42	−2.32	0.02	2003
6	6.29	4.51	1.40	0.16	−2.91**	1.32	−2.21	0.03	2004
7	8.22*	4.28	1.92	0.06	−3.26***	1.26	−2.58	0.01	2005
8	6.27	4.07	1.54	0.12	−2.76**	1.20	−2.30	0.02	2006
9	5.45	3.77	1.45	0.15	−2.36**	1.12	−2.11	0.04	2007
10	5.31	3.48	1.53	0.13	−2.24**	1.04	−2.15	0.03	2008
Change in total equity									
1	−8.94***	2.42	−3.70	0.00	0.55**	0.24	2.32	0.02	1999
2	−7.39***	2.15	−3.43	0.00	0.40*	0.21	1.91	0.06	2000

(Continued)

Appendix. (Continued)

Subset	β_1	Standard error	*t*-statistic	*p*-value	β_2	Standard error	*t*-statistic	*p*-value	Year β_1 & β_2 applied to metric value
3	−5.67***	1.88	−3.02	0.00	0.29	0.18	1.58	0.11	2001
4	−5.03***	1.72	−2.93	0.00	0.25	0.17	1.50	0.14	2002
5	−5.14***	1.69	−3.04	0.00	0.25	0.17	1.47	0.14	2003
6	−4.28***	1.56	−2.75	0.01	0.17	0.16	1.10	0.27	2004
7	−3.61**	1.47	−2.46	0.01	0.13	0.15	0.91	0.36	2005
8	−3.13**	1.37	−2.28	0.02	0.12	0.14	0.86	0.39	2006
9	−2.91	2.52	−1.15	0.25	0.08	0.25	0.32	0.75	2007
10	−2.28**	1.16	−1.96	0.05	0.11	0.12	0.94	0.35	2008

This table summarises the results from univariate regressions of DGTW-alpha on each metric value and its square. The regressions are run over expanding time periods – the first regression is run using the estimation period 1992–1998 (subset 1); the parameter estimates obtained are then used to calculate each metric's contribution to the Q-Score using the metric values for 1999. Returns are then examined from April 2000 to March 2001. Essentially, this allows the predictive capability of the Q-Score constructed to be examined without the impact of any hindsight biases. The second regression is run using data from 1992–1999, the third from 1992–2000 and so on up to an estimation period of 1992–2007 (subset 10). Thus, the parameter estimates for each of the 10 regressions are used on the associated metric values for the following year. Overall, the Q-Score is calculated for 10 years ranging from 1999 to 2008 and the associated DGTW-alpha is examined over 10 periods from April 2000 to March 2010. The regression model is as follows: $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$.

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.