The Piotroski F Score in the Australian Market: Performance and Fundamental Drivers

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1. Introduction

The Piotroski F score is an investment signal that employs accounting information to identify stocks with high financial strength. Such stocks were shown by Piotroski (2000) to generate strong excess returns in the US. Subsequent out-of-sample studies have largely reaffirmed the original findings – these are discussed in more detail below. The appeal of the F score as an investment signal is that it is simple to construct and thus easy to understand and explain. Moreover, it is intuitively appealing as most investors have a deep-seated belief that high quality stocks should outperform over the long run. These factors have led to the F score becoming well known amongst both institutional and retail investors.[1]

The F score builds on earlier work by Ou and Penman (1989) and Frankel and Lee (1998) who showed that historical accounting information could predict future stock returns. Lev and Thiagarajan (1993) refined and simplified this idea, providing an easy to implement approach that explained over 70% of future excess returns.

The purpose of this study is two-fold. First, we seek to understand whether the F score signal generates outperformance in Australia, a developed market that has as yet not been examined. Our second objective is to shed light on the underlying mechanisms driving the performance of the signal. The previous literature on the signal has had little to say about why high F score stocks generate higher returns than other stocks. Understanding the source of the outperformance would greatly increase the utility of the signal to practitioners as it would facilitate a more sophisticated implementation of the signal in an investment strategy. For example, if it were known that the speed with which new information is impounded into prices was the key driver of returns, this might suggest that timing and speed of implementation are critical and that it is a relatively 'fast burn' signal suited to short holding periods. It would also provide insights that allow investors to judiciously time their exposure to the signal, perhaps tilting towards it during and immediately after reporting seasons and away from it during other periods.

Piotroski (2000) showed that the F score was an effective signal for identifying winners amongst deep value stocks in the US over the period 1976 to 1996. Within the 20% of stocks with the highest

[1] There are dozens of online investor forums which explain and discuss the F score. Examples include the 'The Graham Investor' (http://www.grahaminvestor.com/articles/quantitative-tools/the-piotroski-score/) and the American Association of Individual Investors (http://www.aaii.com/stock-screens/screendata/Piotroski). It gets discussed in the financial press and company F scores are now incorporated into the product offerings of vendors of market data (http://www.bloomberg.com/money-gallery/2011-12-06/piotroski-s-best-and-worst-large-cap-stocks.html) and online trading forums (http://www.gurufocus.com). Institutional stock brokers have also taken notice, with JP Morgan for example regularly publishing the 'Fundamental Scorecard'. For an example of an institutional investor with an interest in the F score, see Hyde (2014).

book-to-price ratio, high F score stocks outperformed all stocks by 7.5% pa. The effect was most pronounced for small stocks with low share turnover and no analyst coverage. Moreover, firms with high F scores were observed to record strong positive market reactions to subsequent earnings announcements. These findings suggest that the underlying mechanism driving the effectiveness of the F score signal is that the market is slow to incorporate new financial information for some stocks. A number of studies have found the F score to be effective in identifying winners in growth stocks (Mohanram, 2004; Mohr, 2012), in Euro-zone stocks (Mohr, 2012) and in individual emerging market countries (Kang and Ding, 2005; Galdi and Lopes, 2010; Tantipanichkul, 2011) and in the global emerging markets universe as a whole (Hyde, 2014).

Piotroski motivates the F score as an overlay to a value strategy that seeks to screen out those deep value stocks which are cheap for a good reason – that is, they are financially distressed stocks that are unlikely to recover and hence are likely to deliver negative returns. Subsequent research has shown, however, that the predictive power of the F score extends beyond value stocks (Mohr, 2012; Hyde, 2014). For this reason we include all stocks within the chosen benchmark in this study. We use Australian market data from 1992-2013 and employ a 6-month holding period as this approximates the typical holding period of many institutional investors.

We find that a long/short strategy based solely upon the F score generates a substantial equal-weighted return of about 1.0% per month against stocks in the S&P/ASX 200. However, much of the return is generated by the short side of the strategy. Thus, the signal has little appeal for traditional long-only managers investing in the S&P/ASX 200, which most institutional investors consider to be the investable universe. It also suggests that hedge funds would need to be confident of the availability of stock borrow and to have a thorough understanding of the costs of shorting (e.g., interest on margin balance) due to the strong reliance of the strategy on the short leg.

The F score strategy performs substantially better on small companies. Stocks in the All Ordinaries Index but outside of the S&P/ASX 200 (i.e., cap tier 201-500) seem particularly well suited to the strategy. Stocks in cap tier 201-300 generate a long/short return of 2.1% pm, while stocks in cap tier 301-500 generate a long/short return of 1.4% pa. In both cases, the contributions from the long and short sides are similar in magnitude. The monthly hit rate of the strategy is 74% for both cap tiers, meaning there are relatively few months when the strategy generates a loss. The annualized information ratios are high, at 1.08 and 1.25 respectively.

Assessed against the S&P/ASX 300 universe, we show the F score strategy has generated a negative return in only two calendar years in the 21 years to 2013. The premium to high F score stocks is robust to controls for the size, value and momentum risk premia, indicating that it is rooted in some other risk premium or has a behavioural basis.

Piotroski hypothesized that the reason high F score stocks outperform other stocks is that they tend to be smaller and thus neglected by analysts. This means it takes longer for new financial information to be impounded into the stock price, providing an opportunity to generate positive returns by trading on the new financial information. Research by Choi and Sias (2012) on financial strength indicators also comes to the conclusion that the slow release of new information plays a key role. Our finding that the F score premium is much larger for small stocks is thus consistent with Piotroski's hypothesis about the underlying drivers of the premium to high F score stocks.

Closer inspection of the results, however, casts considerable doubt on the analyst neglect hypothesis. We examine four different implications of the hypothesis and find that the analysis provides support in only one of the four cases. First, we show that the number of analysts covering a stock – a proxy for the speed of transmission of new information into stock prices – shows no relationship, either positive or negative, to the size of the F score premium. This suggests that analyst neglect does not play an important role in determining the size of the F score premium.

Second, we show that the F score premium is not statistically significantly higher for portfolios formed at the end of reporting season compared to other times. If analyst neglect is the key driver, then the premium should be amplified during periods of intense information flow. Thus, the evidence does not support the analyst neglect hypothesis.

Third, we show that the premium does not decrease more rapidly over the holding period for high coverage stocks as would be expected if analyst neglect was underpinning the premium. For well covered stocks, the entire holding period premium should occur in the first month since it seems likely it will take no more than a month for the new information to be impounded into the price of these stocks. Because this process takes longer for neglected stocks, the premium should decline more gradually over the holding period. We find no evidence of such a pattern occurring, nor even for a trend decline in the premium over the holding period. Lastly, we find that the value to using perfect foresight to implement the F score strategy is larger for high coverage stocks than low coverage stocks. In contrast to the three preceding tests, this finding is consistent with the idea that low coverage stocks yield a higher F score premium because new information about these stocks is released slowly – having perfect foresight should be less valuable for such stocks.

To conclude, the results here suggest that the speed of availability of new information to investors is not the decisive factor in determining the magnitude of the F score premium

Data and Methodology

We use month-end data spanning January 1992 to December 2013 for the constituents of the S&P/ASX 300 index. Institutional investors in Australia rarely invest outside of this universe. We also use the constituents of the All Ordinaries index to analyse micro-cap stocks outside of the S&P/ASX 300 index, although for this index the month-end data spans April 2000 to December 2013. The market and financial data are from Datastream. Only stock-dates for which at least 7 of the 9 components of the F score have non-null values are included in the analysis – this amounts to 69% of all data points in the initial sample, leaving a total of 53,270 stocks-dates from the S&P/ASX 300 sample. The data was neither winsorized nor trimmed in any other way.

The F score is a composite of nine financial items/ratios and attempts to measure the financial strength of a company. A stock is assigned a score of one if the value for that item is favourable and a score of zero otherwise. The scores on the nine items are then summed to give the F score for the stock, which is an integer between zero and nine. The items together with their desired properties are: (i) positive profitability, (ii) increase in profitability, (iii) positive cash flow, (iv) negative accruals, (v) increase in profit margin, (vi) increase in asset turnover, (vii) decrease in leverage, (viii) increase in financial liquidity, and (ix) no issuance of new equity.

The details of the construction of the F score are discussed in Table A.1 in the Appendix. Data on both interim and full-year revenue and earnings are used, but all other financial statement data used here is annual. Thus, the three F score components containing revenue or earnings change semi-annually, the net equity issuance component changes monthly due to relying only on market capitalization data, and the remaining four components change annually. The equal-weighted average F score varies from a minimum of 3.62 in 1993 to 5.00 in 2004. It is slightly higher on average for large cap stocks than for small cap stocks: 4.68 vs. 4.32.

Unless otherwise stated, portfolios are formed monthly, equal-weighted and held for a 6-month period. Returns are calculated as the 6-month buy-and-hold return (stated on a monthly basis) for a portfolio formed in that month. In the event that a stock is removed from the index, the market return is substituted for that stock. Returns include dividends. Long/short portfolios are generated by taking long positions in stocks with scores of $F \geq 7$ and short positions in stocks with scores of $F \leq 2$. Of the subset of S&P/ASX 300 stocks used in this study, 8% of stock-dates satisfy $F \leq 2$ or lower while 10% satisfy $F \geq 7$.[2]

[2] Piotroski's long/short strategy was based on F score thresholds of 8 and 1 respectively. Due to the smaller number of stocks in the Australian market, these cut-offs result in too few stocks to reliably estimate returns.

The factors employed in the four factor model have been constructed using data from the S&P/ASX 300 index, with the stocks returns being equal weighted. The break point for the size factor is the S&P/ASX 100 index – stocks in this index were designated Big and stocks in the S&P/ASX 300 ex100 were designated Small.[3] The breakpoints used for the value and momentum factors are the 30th and 70th percentiles, as used in Fama and French (2012). The Australian 90 day Bank Accepted Bill yield is used for the risk free rate. All factor returns are calculated in a manner consistent with the way portfolio returns are constructed (as described in the previous paragraph).

Data on the number of analysts covering each stock and analyst earnings revisions are obtained from the IBES database. The OLS regression analysis is conducted using version 8 of Eviews. All standard errors are corrected for heteroskedasticity and autocorrelation.

2. Results

2.1 Performance

We begin by providing a direct point of comparison with the Piotroski (2000) analysis. He showed that within the top quintile of value stocks, stocks with scores of F ≥ 8 outperformed all stocks by 7.5% pa. There are too few stock-dates satisfying F ≥ 8 in our sample to reliably estimate this particular performance differential.[4] Nonetheless, Table 1 shows that the performance differential is monotonically increasing as the F score threshold increases from 4 up to 7. Moreover, the extent of the outperformance by the F ≥ 7 portfolio (relative to all deep value stocks) is 31.6% pa, which is statistically significant at the p = 0.01 level and substantially larger than the outperformance observed by Piotroski. Since Piotroski used a 12-month holding period, we note that the equal-weighted outperformance of the F ≥ 7 portfolio over a 12-month holding period is 25.2% pa, still well in excess of 7.5% pa.

Table 1: Within Deep Value Stocks, the Return to High F Score Stocks Relative to All Stocks

	S&P/ASX 300; 6mo hold; Top quintile (Q1) of BP					
	F ≥ 4	F ≥ 5	F ≥ 6	F ≥ 7	F ≥ 8	F = 9
EW average return* (% pa)	2.25	5.49	18.71	31.60	-1.51	1.26
Standard error	1.17	1.27	1.41	3.31	5.51	2.87
No. stocks	6,288	3,966	1,853	571	76	3

* Relative to all stocks in Q1

We now turn to an analysis of the long/short strategy involving taking long positions in stocks with scores of F ≥ 7 and short positions in stocks with scores of F ≤ 2. In contrast to Piotroski (and Table 1

[3] The S&P/ASX 100 index accounts for about 90-95% of the market capitalization of the S&P/ASX 300 index, so this lines up well with the breakpoint used by Fama and French (2012).
[4] The fact that the performance differential is negative or small and positive for F ≥ 8 and F = 9 suggests that the signal may not be reliable in the extreme upper tail for the Australian market.

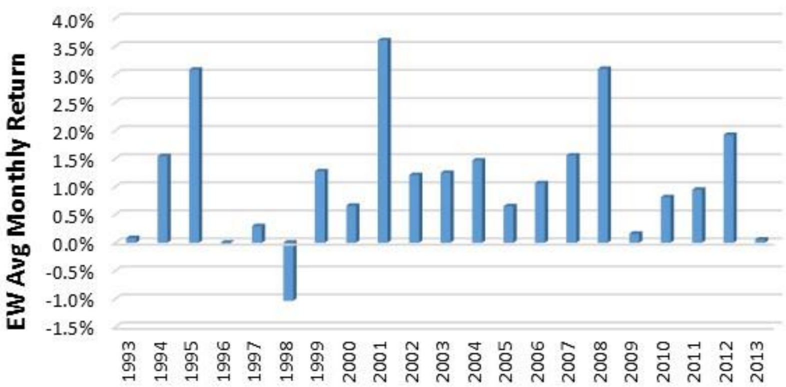
above), we apply this strategy over the entire S&P/ASX 300 universe (i.e., not just over deep value stocks). The performance of the strategy is summarized in Table 2 below. The monthly return is large and statistically significant (p=0.01) at both the 6- and 12-month holds. The hit rate measuring the proportion of months that the strategy generates a positive return is also very high at 73% for both holding periods. Of note is the fact that the long/short return is skewed to the short side in terms of the contribution to overall return, particularly for the 6-month holding period.

Table 2: The Return to the Long/Short F Score Strategy

S&P/ASX 300	Avg. No. Stocks	Excess Return (%, monthly EW Avg)		Hit Rate (% of +ve months)	
		6mo hold	12mo hold	6mo hold	12mo hold
Long (F ≥ 7)	21.6	0.36	0.42		
Short (F ≤ 2)	14.8	-0.92	-0.71		
L/S portfolio	36.4	1.28	1.13	72.5%	73.5%
Std. error		0.15	0.11		

Given the relative similarity of the results for the 6- and 12-month holding periods, from here on we focus on the 6-month holding period. On a calendar year basis, the average premium to high F score stocks has been negative only twice over the sample period of 21 years (1996 and 1998), being substantially negative only in 1998 – see Figure 1 below.

Figure 1: Premium to High F Score Stocks by Calendar Year

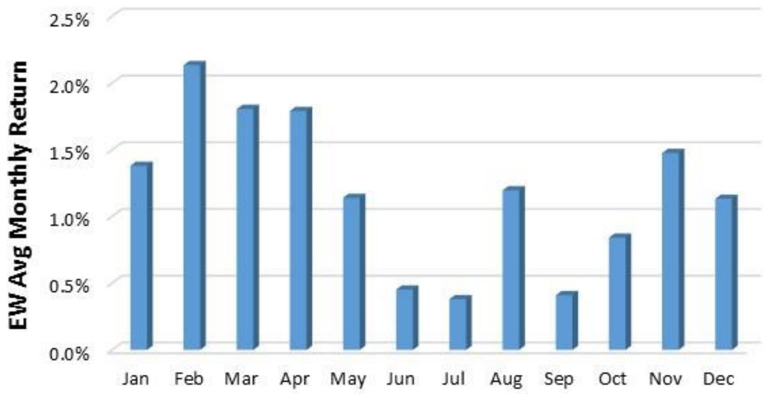


Given that the F score signal is based on reported company financial data and there is a seasonal structure to the reporting of this data, we now look at the calendar month average returns to the strategy. Figure 2 below shows that the returns to portfolios constructed at the end of the interim (February) and full-year (August) reporting months are noticeably higher than for those constructed in the preceding or following month.[5] Moreover, the returns to portfolios constructed in the last two

[5] Companies reporting in February and August make up 75% of the entire data sample.

months before financial year-end reporting (June and July), when the financial data being used in the signal is at its stalest, generate the lowest returns.

Figure 2: Premium to High F Score Stocks by Calendar Month



As Piotroski found that the F score is a more effective signal in relation to small stocks, it is natural to question whether the premium to high F score stocks is being driven by the size effect or indeed any of the other well-known anomalies. We now estimate the Carhart four-factor model which controls for the market, size, value and price momentum premia. Table 3 shows that the estimated alpha is 0.71% per month which is statistically significant at the p = 0.01 level. While slightly lower than the return reported in Table 2, this nonetheless indicates that the excess return generated by the long/short F score strategy is largely independent of well documented risk premia.

Table 3: Four Factor Model Coefficients for Long/Short F Score Strategy

	S&P/ASX 300; 6mo hold; EW Returns (% pm)			
	Coefficient	**Std Error**	**t-Statistic**	**Prob.**
α	0.708	0.191	3.71	0.000
Market	-0.332	0.096	-3.47	0.001
Size	-0.493	0.137	-3.60	0.000
Value	0.046	0.129	0.36	0.723
Momentum	-0.059	0.034	-1.72	0.087

$\text{Adj.}\, R^2 = 0.18$

As the S&P/ASX 300 spans a wide range of stock sizes, we now take a more detailed look at how the premium to high F scores stocks varies across cap tiers. Table 4 shows that the long/short returns reported in Tables 2 and 3 are very much driven by the smallest stocks. The strategy generates returns of 0.9-1.0% pm over the largest 100 stocks and stocks 101-200, while returning a much higher 2.1% pm over stocks 201-300 and 1.4% pm over stocks 301-500.[6] The long and short sides

[6] These cap tiers correspond to the S&P/ASX 100, S&P/ASX 200 ex100, S&P/ASX 300 ex200 and All Ordinaries ex S&P/ASX 300 respectively.

both contribute over 1% to the long/short return for the 201-300 cap tier, indicating a more equal contribution from the two sides for small cap stocks than for large caps.[7] Similarly, the long side makes a larger contribution to long/short returns than the short side for the 301-500 cap tier. Despite the higher volatility of small cap returns, the Sharpe ratio of the strategy is higher for stocks in the smallest two cap tiers, as is the hit rate of 74%.

Table 4: Long/Short F Score Strategy Returns by Cap Tier

	EW Avg Returns (% pm); 6mo hold			
Market Cap. Tier	**L/S Return**	**Std. Error**	**Sharpe Ratio***	**Monthly Hit Rate**
1-100	1.05	0.18	0.81	66%
101-200	0.92	0.26	0.44	66%
201-300	2.13	0.37	1.08	74%
301-500	1.42	0.22	1.25	74%

* Sharpe ratio is based on annualized returns

The estimated alphas from the four-factor model suggest even more strongly that the premium to high F score stocks exists primarily only on stocks outside of the largest 200 stocks in the Australian market. Table 5 shows that the estimated alpha on the largest 200 stocks is only 0.08% pm and not statistically significant, while it is a much larger 0.98% pm on stocks in the All Ordinaries ex S&P/ASX 200 and statistically significant at the p = 0.05 level.

Table 5: Estimated Alpha by Cap Tier

Cap Tier	**Alpha (% pm)**	**Std. Error**	**Adj. R^2**
1-200	0.08	0.29	0.41
201-500	0.98	0.44	0.06

Transaction costs are an important consideration in determining whether a strategy is likely to be profitable when implemented. So far we have only reported gross (or pre-cost) returns. It is particularly important to consider transaction costs when analysing strategies that target small cap stocks since transaction costs are typically high for these stocks. We now consider three key components of total transaction costs: turnover, bid-ask spread and commission. We ignore market impact as the magnitude of this cost is critically dependent on the size of the portfolio being traded.

The turnover of the strategy is naturally low due to the infrequent changes in the financial data being used to construct the F score. The average (one-way) turnover of the strategy for stocks in cap tier 201-500 is half as big again as that of cap tier 1-200 (30% vs. 20% pa) – see Table 6. The average

[7] For the 1-100 cap tier, the long side contributes only 9bp to the long/short return. For the 101-200 cap tier it is only 6bp.

bid-ask spread for the 1-200 cap tier as at December 2013 is 33bp while for the 201-500 tier we estimate it to be 193bp.[8]

Table 6: Components of Transaction Costs by Cap Tier

	Turnover* (pa)		Bid-Ask Spread (bp)	
	1-200	**201-500**	**1-200**	**201-500**
Average	20%	30%	33	193
% Months Zero	6%	9%		

* One-way annualized

Allowing 20bp (one-way) for broker commission associated with trading, we calculate average equal-weighted transaction costs to be 14bp pa for cap tier 1-200 and 69bp pa for cap tier 201-500.[9] On a monthly basis, the transaction costs are 1.2bp and 5.7bp respectively for the two cap tiers. We summarise the net returns and alpha for the two cap tiers in Table 7 below. The net return to the long/short strategy is strongly positive for both cap tiers, while the net risk-adjusted return (i.e., alpha) is strongly positive for cap tier 201-500 but only slightly positive for cap tier 1-200.

Table 7: Net Returns to the Long/Short F Score Strategy

	Net* (% pm)	
	L/S Return	**Alpha**
1-200	0.98	0.07
201-500	1.91	0.93

* After commission and bid-ask spread

We now examine the stand-alone performance of the individual components of the F score to obtain a sense of which items of fundamental accounting data contribute most to the observed premium for high F score stocks. We construct long/short returns to an F score component by forming portfolios that are long stocks assigned a score of 1 in relation to that component and short stocks assigned a score of 0. This analysis is not intended to give an attribution of the returns in Table 1 to the individual components of the F score, but rather just provide an indicative view as to the relative strength of the components. Table 8 below shows that operating cash flow component is by far the strongest of the individual components of the F score. Only the change in asset turnover generates a meaningfully negative long/short return on a stand-alone basis.

[8] The latter figure is based on the Comerton-Forde and Putnins (2012), who observed the average bid-ask spread for the All Ordinaries over the period February 2008 to October 2011 was 129bp.

[9] Transaction cost = Two-way turnover x ([Bid-ask spread]/2 + Commission). The assumption of 20bp for commission is conservative. Even retail traders can access fees as low as 20bp from execution-only internet-based platforms. Institutional traders often pay less than 10bp of commission.

Table 8: Long/Short Returns to Individual Components of the F Score

S&P/ASX 300	F Score Component								
	ROA	∆ROA	OCF	Accruals	∆Gr. Mgn	∆Ass. T/O	∆Lev	∆Liq	Eq. Iss.
L/S EW Return (% pm)	0.44	-0.01	1.73	0.47	0.15	-0.50	0.32	0.56	0.84

2.2 Fundamental Drivers

We now turn to an analysis of the underlying causes of the premium to high F score stocks. We identify four distinct implications of the analyst neglect hypothesis proposed by Piotroski and in each case ask whether the data is consistent with the pattern that would be expected under the hypothesis. To recap, the analyst neglect hypothesis is premised on the idea that it takes longer for new information to be impounded into the price of neglected stocks than well-covered stocks, resulting in a higher return to the former because there is more time to invest in a neglected high F score stock before the price reacts to the new (positive) information.

Based on the results from the analysis is section 3.1, we analyse cap tiers 1-200 and 201-500 separately given that the F score signal appears to behave differently on these two segments of the market.

2.2.1 Implication 1: High Analyst Coverage Means a Lower F Score Premium

If, as hypothesized by Piotroski, analyst neglect is the root cause of the observed premium to high F score stocks, then the premium should be lower for stocks which are more intensively researched since news for these stocks will be rapidly communicated to the wider market. Indeed, Piotroski found the premium to be higher for US stocks with no analyst following than for those with analyst following. We use different thresholds than Piotroski to define low vs. high coverage due to sample size constraints – for the same reason we use different thresholds for the two cap tiers.[10]

Table 9 shows that for cap tier 1-200, high analyst coverage is associated with a higher premium to high F score stocks. For cap tier 201-500 the opposite is true, consistent with the analyst neglect hypothesis. However, for neither cap tier is the observed premium differential statistically significant at the p = 0.01 or p = 0.05 level.

[10] Our sample size is not large enough to be able to generate reliable estimates of returns to stocks with no analyst coverage, particularly for large cap stocks.

Table 9: The Impact of Analyst Coverage on the Premium to High F Score Stocks

Cap Tier	Analyst Coverage*	EW L/S Return (% pm)	Std. Error
1-200	Low	-0.29	0.41
	High	0.40	0.21
201-500	Low	0.79	0.42
	High	0.42	0.43

* For 1-200: Low is ≤ 5 analysts; High is > 5 analysts.
For 201-500, Low is ≤ 2 analysts; High is > 2 analysts.

The alpha estimates obtained from the four-factor model paint a qualitatively similar picture in Table 10, and again the alpha differentials are not statistically significantly different from zero for either cap tier. Thus, on balance the data here does not support the analyst neglect hypothesis. The speed of transmission of new information appears not to be the source of the premium to high F score stocks.

Table 10: The Impact of Analyst Coverage on the Risk-Adjusted Premium to High F Score Stocks

Cap Tier	Analyst Coverage	Alpha (% pm)	Std. Error	$\text{Adj.}\,R^2$
1-200	Low	-0.91	0.66	0.02
	High	0.03	0.35	0.44
201-500	Low	0.01	0.57	0.23
	High	-0.32	0.66	0.00

2.2.2 Implication 2: The F Score Premium is Higher During Reporting Seasons

The analyst neglect hypothesis implies that the F score premium should be larger during periods when the flow of new fundamental financial information is at its peak – that is, during reporting seasons. After all, in periods when no new information is released, analysts have little news to convey to the market and so it matters little whether a stock is neglected or not. Hence, we restrict attention here to stocks that have June financial year ends and report their full year results in August in order to focus the analysis on the interim (February) and full year (August) reporting seasons. These stocks account for 52% of the observations in both the 1-200 and 201-500 cap tiers in our sample.

Specifically, we compare the F score premium for portfolios formed at the end of February and August to the premium in portfolios formed in the remaining 10 months of the year. Table 11 shows that the premium to high F score stocks is indeed higher in portfolios formed at the end of reporting months than for portfolios formed in other months – for both cap tiers. However, in neither case is the differential statistically significant at the p = 0.01 or p = 0.05 levels.

Table 11: The Impact of Reporting Season on the Premium to High F Score Stocks

Cap Tier	Time of Portfolio Formation*	EW L/S Return (% pm)	Std. Error
1-200	Reporting Season	1.04	0.87
	Non-Reporting Season	0.75	0.75
201-500	Reporting Season	0.88	0.47
	Non-Reporting Season	0.21	0.38

* Reporting season refers to portfolios formed at the end of February & August.

The results obtained from estimating the four-factor model with a dummy variable for each of the two reporting seasons are very similar to those reported above. Table 12 shows that the premium to high F score stocks is higher in portfolios formed at the end of reporting seasons for both cap tiers. However, once again, the differentials are not statistically significant.

Table 12: The Impact of Reporting Season on the Risk-Adjusted Premium to High F Score Stocks

Cap Tier	Time of Portfolio Formation	Alpha (% pm)	Std. Error	Adj. R^2
1-200	Reporting Season	0.79	0.53	0.28
	Non-Reporting Season	0.35	0.34	
201-500	Reporting Season	0.44	0.85	-0.02
	Non-Reporting Season	0.03	0.54	

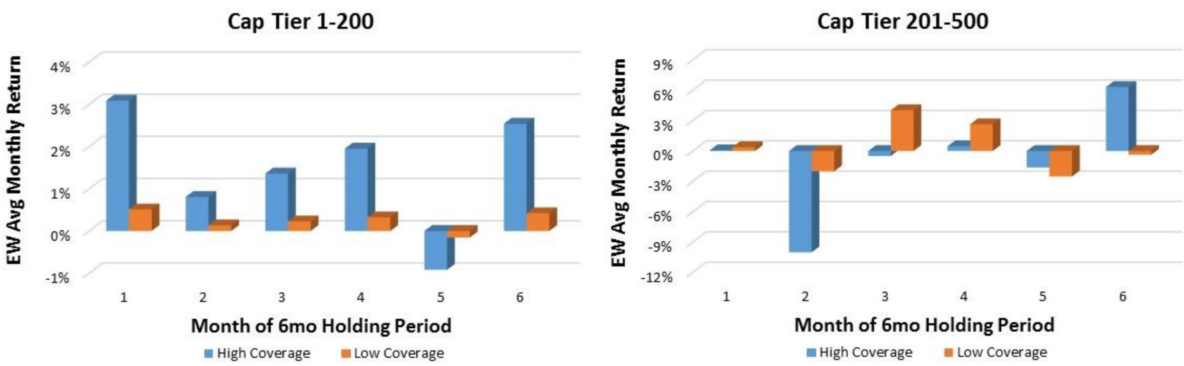
Thus, the results again do not support the hypothesis that analyst neglect is the key driver of the premium to high F score stocks.

2.2.3 Implication 3: The F Score Premium Should Decline Over the Holding Period Faster for High Coverage Stocks

Another implication of the analyst neglect hypothesis is that the pattern of returns over the course of the holding period will differ for high and low coverage stocks. To the extent that it is possible to generate a positive return from high F score stocks with high coverage, the opportunity should be fleeting. That is, there should be a sharp fall in returns from month to month across the holding period for high coverage stocks as the new information gets rapidly impounded into the stock prices and drives returns to zero. In contrast, the trajectory should be flatter, although still downward, for low coverage stocks. It is this pattern which we seek to detect here. We restrict attention to stocks with June financial year-ends that report in August and February in order to filter out the noise that would be introduced into portfolio returns by including stocks with other reporting dates.

Figure 3 below shows the month-by-month long/short returns over the 6 month holding period for both high and low coverage stocks. In neither cap tier is there any evidence that the premium to high F score stocks declines across the holding period, let alone that it declines more rapidly for high coverage stocks. Hence, we conclude once again that the evidence here does not support the analyst neglect hypothesis.

Figure 3: The Impact of Reporting Season on the Risk-Adjusted Premium to High F Score Stocks



2.2.4 Implication 4: Perfect Foresight Should be More Valuable for High Coverage Stocks

Perfect foresight, were it possible, would have value because it allows an investor to react to new information before the rest of the market and thus before the market price reacts to the new information. If new information is impounded slowly into stock prices, the value to having perfect foresight diminishes because an investor who is able to quickly acquire newly reported financials can still establish their investment position before prices have adjusted materially to the new information.

This logic suggests the following test of the analyst neglect hypothesis. Taking the portfolio formed at the end of reporting season and calculating the hypothetical return of this portfolio over the month prior to portfolio formation gives the return due to having perfect foresight. The difference between this return and the return during the first month of the holding period of the same portfolio is a measure of the relative benefit of having perfect foresight. This benefit should be higher for high coverage stocks than for low coverage stocks.

The results in Table 13 show that having perfect foresight is indeed much more valuable in relation to high coverage stocks than low coverage stocks, for both cap tiers.

Table 13: The Benefit to Having Perfect Foresight Prior to Reporting Season

	Prior Month - Month 1 Return of Reporting Season Portfolios (% pm)	
Analyst	Cap Tier	
Coverage	1-200	201-500
Low	0.23	0.24
High	1.44	2.43

To conclude, of the four different implications of the analyst neglect hypothesis we examine here, the data supports the hypothesis only in relation to Implication 4. On balance, the evidence in support of the analyst neglect hypothesis is very weak.

3. Discussion

The results in Table 2 suggest two things. First, a stand-alone strategy of selecting high F score stocks is unlikely to be attractive to Australian institutional investors who are typically unable to invest outside of the S&P/ASX 200 universe. First, for traditional long-only investors the returns on the long side of the long/short strategy we examine are modest, even on a pre-cost basis. A return of 40bp per month will generally be below that of a broad equity benchmark. Second, even a hedge fund that can contemplate shorting low F score stocks would need to make a careful assessment of shorting costs and the availability of stock borrow because the contribution of the short side is so critical to the overall profitability of the strategy.

Our analysis strongly indicates that the F score signal has greatest application amongst small and micro cap stocks. Even allowing for realistic levels of transaction costs in trading these stocks, it seems likely that the F score strategy will yield strong positive returns over the long term. Importantly, we show that the returns to the F score strategy are not driven by the size or any other well known risk premium.

An important contribution of this paper has been to improve our understanding of the likely drivers of the F score premium. In particular, we show that there is little evidence that the power of the F score signal is due to analyst neglect of small stocks. On the other hand, the results presented here provide little insight into alternative plausible explanations for the premium. Divining the deep driver of the F score premium clearly requires further careful research.

4. References

Choi, N.Y., Sias R.W., 2012. 'Why does financial strength forecast stock returns? Evidence from subsequent demand from institutional investors'. *Review of Financial Studies*. 25, 1550-1587.

Comerton-Forde, C., and T. Putnins, 2013. 'Dark trading and price discovery', Available at http://ssrn.com/abstract=2183392.

Fama, E. and K. French, 2012. 'Size, value, and momentum in international stock returns', *Journal of Financial Economics* 105, 457-472.

Frankel, R. and C. Lee, 1998. 'Accounting valuation, market expectation, and cross-sectional stock returns', *Journal of Accounting and Economics* 25, 283-319.

Galdi, F.C., and B. Lopes, 2010. Limits to arbitrage and value investing: Evidence from Brazil. Available at http://ssrn.com/abstract=1099524.

Hyde, C. E., 2014. 'An emerging markets analysis of the Piotroski F score', JASSA,

Kang, J., Ding, D., 2005. Value and growth investing in Asian stock markets 1991-2002, in: Chen, A.H. (Eds.), Research in Finance. JAI Press, Greenwich, vol. 22, pp. 113-139.

Lev, B., and R. Thiagarajan, 1993. 'Fundamental information analysis', Journal of Accounting Research 31 (Autumn): 190-214.

Mohanram, P., 2005. 'Separating winners from losers among low book-to-market stocks using financial statement analysis', Review of Accounting Studies. 10, 133-70.

Mohr, J-H.M., 2012. 'Utility of Piotroski F-score for predicting growth stock returns', Working paper, MFIE Capital.

Ou, J., and S. Penman, 1989. 'Accounting measures, price-earnings ratio, and the information content of security prices.' Journal of Accounting Research 27 (Supplement): 111-143.

Piotroski, J., 2000, 'Value investing: The use of historical financial statement analysis to separate winners from losers.' Journal of Accounting Research 38: 1-41.

Tantipanichkul, P., 2011. Separating winners from losers in Thai stock markets using financial statement analysis. Paper presented at the 2011 Barcelona European Academic Conference.

5. Appendix

The nine component items contained in the F score are detailed below in Table A.1. The F score is defined as $F = \sum_{i=1}^{9} F_i$, implying that it is integer-valued with a range of 0-9.

Table A.1: Components of the F Score

	Name	Definition	Formula
F_1	Profitability	Net Profit After Tax (Incl. Extraordinary Items) / Total Assets at start of period.	F_1 = 1 if Profitability > 0, otherwise F_1 = 0.
F_2	ΔProfitability	Profitability in current period – Profitability in one-year prior period.	F_2 = 1 if ΔProfitability > 0, otherwise F_2 = 0.
F_3	Cash Flow	Operating Cash Flow / Total Assets.	F_3 = 1 if Cash Flow > 0, otherwise F_3 = 0.
F_4	Accruals	Profitability – Cash Flow.	F_4 = 1 if Accruals < 0, otherwise F_4 = 0.
F_5	ΔProfit Margin	Gross Margin in current period – Gross Margin one-year prior.	F_5 = 1 if ΔProfit Margin > 0, otherwise F_5 = 0.
F_6	ΔAsset Turnover	Revenue / Total Assets in current period – Revenue / Total Assets one-year prior.	F_6 = 1 if ΔAsset Turnover > 0, otherwise F_6 = 0.
F_7	ΔLeverage	(Total Long Term Debt / Total Assets in current period) – (Total Long Term Debt / Total Assets one-year prior).	F_7 = 1 if ΔLeverage < 0, otherwise F_7 = 0.
F_8	ΔLiquidity	(Current Assets / Current Liabilities in current period) – (Current Assets / Current Liabilities in one-year prior period).	F_8 = 1 if ΔLiquidity > 0, otherwise F_8 = 0.
F_9	ΔNet Capital	Change in market cap over the prior 6 months – change in market cap due to the change in share price.	F_9 = 1 if ΔNet Capital < 0, otherwise F_9 = 0.