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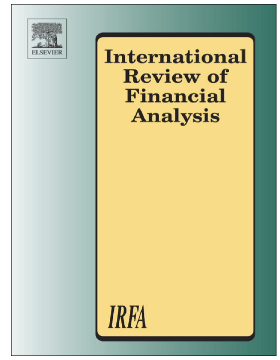

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The profitability of trading NOA and accruals: One effect or two?

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Abstract

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JEL classification: G12, G14
Keywords: anomaly; mispricing; market efficiency; net operating assets; accruals

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Abstract

This paper documents a negative relationship between future stock returns and each of accruals and net operating assets (NOA). While accruals and NOA convey unique information for future returns, NOA appears to have an important moderating influence on the accrual effect. A significant accrual effect is observed amongst stocks with high NOA. In contrast, no accrual effect exists for stocks with low NOA. This finding suggests that high levels of accruals per se are not bad news. An accrual effect only arises for firms that have a sustained track record of not converting accruals into cashflow.

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1. Introduction

The primary purpose of financial statements is to provide relevant and reliable information to a variety of end users, including shareholders, potential investors and equity analysts. In an efficient market, new information inherent in financial statements is impounded into prices quickly and in an unbiased manner. While pricing errors may occur in an efficient market, not only are they unlikely to be systematic, but competition between investors will ensure that any mispricing is short lived.

Increasingly, however, financial economists are questioning whether market participants have the requisite cognitive ability to facilitate market efficiency. Hirshleifer, Hou, Teoh and Zhang (HHTZ) (2004, p.298) note that “information is vast and attention limited”. They conjecture that investors focus on selected financial statement line items, thereby forming their judgements from a subset of all available information. In such instances, investors may make systematic errors in processing information which manifest in stock prices.

Sloan’s (1996) study of accruals is a prominent example of apparent investor mispricing of financial statement information. While the cashflow and accrual components of current-period earnings have different implications for future earnings, stock returns behave as if investors fixate on the aggregate earnings line item. This failure to adequately differentiate between the components of earnings suggests an obvious trading strategy based on companies’ relative levels of reported accruals. Indeed, the magnitude of profits documented by Sloan (1996) from trading the so-called accrual anomaly has had a profound impact on investment practice.

Under the accrual-based approach to accounting, accruals arise as revenue and expenses are assigned to the accounting period in which they occur, irrespective of when the associated cashflow transpires. Accruals are made with an expectation that they will convert into cashflow in a timely manner, at which point the previous accrual is reversed. In the event that accruals do not generate the anticipated cashflow, then earnings were misstated in the period during which the accrual was raised. While, in theory, rational investors will monitor the conversion of accruals into cashflow and make appropriate inferences about the likely persistence of earnings, Sloan's (1996) empirical findings suggest otherwise.

Of particular relevance to the current paper, HHTZ (2004) study the relationship between net operating assets (NOA) and the cross-section of stock returns. In doing so, they build on two key aspects of the above discussion. First, NOA are defined as the inter-temporal accumulation of periodic differences between operating earnings and free cash flow. In effect, NOA are the 'lifetime' discrepancy between accounting value added and cash value added. If the decomposition of single-year earnings into cashflow and accrual components provides a signal of mispricing, then a multi-period counterpart like NOA is also likely to convey mispricing. Second, given that accruals are intended to be a temporary accounting treatment to accommodate the timing difference between a transaction and its resulting cashflow, NOA measures the extent to which past accruals have persistently *not* translated into realised cashflow. Consistent with these arguments, HHTZ (2004) document a strongly negative relationship between NOA and future returns on US stocks.

The current paper makes a number of contributions to this literature. First, the paper extends HHTZ (2004) by studying the *unique* predictive ability of NOA and accruals. NOA and accruals are closely related, yet distinct, concepts. Since NOA are a cumulative (i.e., multi-period) measure of accruals, HHTZ (2004) conjecture that NOA are likely to be a superior predictor of future returns. Indeed, their cross-sectional regressions show that NOA are significantly negatively associated with future returns and this relationship remains when accruals are also included as an independent variable. However, accruals themselves are also significantly negatively related to future returns (even in the presence of NOA). This finding motivates our examination of the unique information content of NOA and accruals for future stock returns. After a preliminary statistical analysis using cross-sectional regressions, this paper focuses on the economic importance of each variable. Portfolios double-sorted on NOA and accruals are constructed to control for one variable while allowing the other to vary. In addition to quantifying the influence of each variable on future returns, the double-sorted portfolios also allow an examination of the extent to which the information content of NOA and accruals interact. Given that accruals are a widely-used stock selection filter, investment practice stands to benefit from understanding how the influence of accruals on future returns is mediated by NOA. This is the second contribution of the paper.

Several recent papers document that the profitability of trading many anomalies in the US (including accruals) has decayed with time. Chordia, Subrahmanyam and Tong (2014) report an attenuation of anomaly profits after decimalisation decreased tick sizes, thereby reducing the cost to arbitrage. Studying 97 different predictors, McLean and Pontiff (2016) estimate that the average long-short return shrinks by 58% post publication. Green, Hand and Soliman (2011) report that, subsequent to the publication of Sloan (1996), accruals profits are no longer reliably positive which they attribute to increased hedge fund activity. Similarly, Green, Hand and Zhang (2013) document diminished returns and Sharpe ratios to accruals trading. In contrast to the accruals effect, the more-recent NOA anomaly is relatively less known. Our study is the first to investigate the relationship between NOA and Australian stock returns, and one of the few to provide evidence of this effect outside the US.

In addition to providing an out-of-sample test of the generalisability of HHTZ's (2004) findings, the study benefits from a number of distinct idiosyncrasies of the Australian equity market that are potentially relevant to understanding the information content and (mis)pricing of accruals, cashflow and NOA. In particular, in comparison to the US, Australian firms: (i) are notably less profitable, with approximately half of all firms reporting losses, (ii) generate modest cashflow that on average is more than offset by negative accruals, and (iii) have a high representation of resource-sector stocks. Given that the relationship of stock returns with earnings, accruals and cashflow is known to differ for profit and loss firms, the close association of accruals and NOA suggests that NOA mispricing may also be a function of profitability. Similarly, prior work highlights that resource sector stocks use accruals to manage the impact of exploration risk on earnings variability (Pincus and Rajgopal, 2002). The prevalence of mining stocks in Australia, many with significant accruals in the early stages of their existence, makes it an interesting setting in which to study earnings/cashflow/accrual/NOA behaviour.

The final contribution relates to the implementation of rational pricing tests of accounting information. Following Sloan (1996), many capital market studies have employed the Mishkin (1981, 1983) test to examine whether the time series properties of variables of interest (e.g., earnings, accruals, cashflow) are rationally impounded into stock prices. However, Kraft, Leone and Wasley (KLW) (2007) highlight the vulnerability of the Mishkin procedure to omitted variable problems. Kraft et al. (2007) propose an OLS regression-based approach that is equivalent to the Mishkin test, yet is more conducive to accommodating potential omitted variables. Further, recent literature has also warned that cross-sectional and/or time-series dependence in panel data sets can generate spurious inferences in regression settings (Petersen, 2009; Gow, Ormazabal and Taylor, 2010). As a starting point, our study of the mispricing of cashflow, accruals and NOA adopts Kraft et al.'s (2007) approach to control for potential omitted variables. We then lever off this regression-based framework to investigate the extent to which key assumptions over error terms may influence inferences from common rationality tests.

The main findings of the paper are summarised as follows. Using data for ASX-listed firms spanning 1991 to 2016, accruals and NOA are each shown to exhibit a significantly negative relationship with future returns. This is apparent both in regressions of individual stock returns on characteristics of interest and using portfolio sorts. The effects are economically significant. On an annualised basis, value-weighted spread portfolios sorted by accruals and NOA generate returns in the vicinity 14% and 17% respectively. Adjusting for risk factors via a three-factor asset pricing model diminishes the spread returns, yet they remain statistically significant.

While NOA and accruals convey unique information for future returns, we show that NOA are the dominant effect. Portfolios formed by double sorting on the two characteristics reveal an interesting interaction. Controlling for accruals, a significant NOA effect is documented in each of the five accrual quintiles. In contrast, controlling for NOA, an accrual effect exists only in the highest NOA grouping. This finding challenges conventional beliefs that low accrual stocks consistently outperform high accrual stocks. Rather, it suggests that high levels of accruals per se are not 'bad'. Viewing accruals and NOA as single- and multi-period metrics respectively, the finding implies that a high level of accruals is only bad news when a firm has a sustained track record of accruals not translating into future cashflow (i.e., high NOA). For stocks with modest NOA, a one-off incident of high accruals does not signal lower future returns.

While Mishkin-style rationality tests are popular in the empirical literature, our findings demonstrate that statistical inferences relating to the mispricing of variables are highly sensitive to assumptions over the distribution of model error terms. Rationality tests that make 'vanilla' OLS assumptions can significantly understate standard errors and therefore exaggerate *p*-values. In all cases, the seemingly strong statistical evidence of accrual mispricing under vanilla assumptions vanishes when cross-sectional and inter-temporal patterns in error terms are accommodated. These findings suggest that it is imperative to utilise an econometric approach that accommodates more realistic assumptions over model error terms when conducting rationality tests of the pricing of accounting information.

The remainder of the paper is structured as follows. Section 2 presents a brief review of relevant literature relating to the mispricing of NOA and accruals, including prior Australian findings on the accrual anomaly. Data sources, construction of key variables and descriptive statistics are described in Section 3. Section 4 presents the main empirical analysis examining the unique information content of NOA and accruals. The rational pricing of these variables and the importance of statistical assumptions in rationality tests is explored in Section 5, while Section 6 conducts robustness analysis. Section 7 concludes the paper.

2. Literature Review

2.1 Background on Accruals and NOA Anomalies

Starting with Sloan (1996), an extensive empirical literature has examined the relationship between the cross-section of stock returns and accruals. Company earnings are highly persistent from year to year. Similarly, the cashflow and accrual components of earnings are also persistent, but to differing degrees. The ability of investors to accurately infer the persistence of earnings, cashflow and accruals lies at the heart of the accrual anomaly.

Unlike the cash component of earnings which is highly objective, accruals are unavoidably subjective. While many accruals arise naturally during the course of business, these non-discretionary accruals are nonetheless premised on an anticipated translation into cash in the near future. Management also make discretionary accruals which are potentially vulnerable to earnings manipulation. The quality of such discretionary accruals adds a further element of subjectivity. For these reasons, cashflow is more persistent than accruals, and therefore has greater influence on future earnings.

While these are elementary concepts, Sloan (1996) demonstrates that stock prices behave as if investors fixate on the aggregate earnings line item, without differentiating between the persistence of the cashflow and accrual components. In doing so, investors overestimate the persistence of accruals and underestimate the persistence of cashflow. Sloan (1996) reports that a trading strategy that enters long (short) positions in low (high) accruals stocks generates statistically and economically significant future returns.

One explanation offered for the accrual and other accounting-based anomalies is that market participants do not have the requisite cognitive ability to accurately price financial statement components and thereby facilitate market efficiency. HHTZ (2004) suggest that information that is salient and easily processed is more likely to be accurately impounded into stock prices. Conversely, investors with limited attention are susceptible to firm attempts to manipulate their perceptions (through earnings management, for example) (Hirshleifer and Teoh, 2003). When accounting distortions exist, therefore, investors are less likely to accurately price earnings components (Xie, 2001; Dechow and Dichev, 2002; Richardson et al., 2005). If these distortions are due to unsustainable accounting practices that will have to be reversed in the future (e.g., earnings management via excessive accruals), investors will be disappointed at that time (Barton and Simko, 2002). Even if firms do not intentionally distort financials, investors with limited attention might still fail to fully utilise all available financial information, resulting in mispriced securities (HHTZ, 2004).

Many papers subsequent to Sloan (1996) have investigated extensions and variations of the accrual anomaly. Chan, Chan, Jegadeesh and Lakonishok (2006) examine the individual components of accruals. While changes in accounts receivable and accounts payable contribute to the anomaly, changes in inventory primarily drive the profitability of trading accruals. Similarly, Thomas and Zhang (2002) also find strong evidence attributing the accrual anomaly to inventory changes. Xie (2001) borrows from the earnings management literature by using the Jones (1991) model to partition total accruals into discretionary and normal accruals. Statistical tests suggest that the market overestimates the persistence of both normal and discretionary accruals (and underestimates the persistence of cashflow), but it is the mispricing of discretionary accruals that gives rise to profitable trading strategies. Rather than using the Jones (1991) model, Chan et al. (2006) estimate discretionary accruals by extrapolating past trends in sales growth and accruals. Nonetheless, they report similar findings to Xie (2001). Allen, Larson and Sloan (2013) decompose accruals into three components and show that the overall mispricing of accruals is attributable to accrual estimation error and 'good' accruals relating to firm growth, but is unrelated to 'good' accruals reflecting temporary fluctuations in working capital.

Lewellen and Resutek (2016) study whether firm investment can explain the accrual anomaly by partitioning total accruals into investment-related and non-transactional components. They show that the strong negative relation between accruals and future stock returns derives primarily from non-transactional accruals. Similarly, Momente, Reggiani and Richardson (2015) find no risk-based explanation via investment activity and attribute the accrual effect to firm-specific factors. Radhakrishnan and Wu (2014) show that accrual mispricing is smaller when analysts provide both earnings and cashflow forecasts, suggesting that the latter encourages investors to focus attention toward the accrual component of earnings. Mohanram (2014) also finds that the returns on trading accruals diminish with the incidence and accuracy of analyst cashflow forecasts. Miao, Teoh and Zhu (2016) report that accrual mispricing is diminished when companies provide a statement of cashflows in conjunction with earnings announcements.

While the majority of this literature retains Sloan's 'single-period' decomposition of earnings into cashflow and accruals, HHTZ (2004) take a different tack by introducing the concept of net operating assets (NOA). NOA are defined as the inter-temporal accumulation of annual differences between operating income and free cash flow over the life of a company:

$$\text{Net Operating Assets}_T = \sum_{t=0}^{T} \text{Operating Income}_t - \sum_{t=0}^{T} \text{Free Cash Flow}_t \quad (1)$$

Clearly, NOA and accruals are closely related concepts. Whereas accruals are simply the difference between accounting earnings and cashflow at a given point in time, NOA capture the lifetime discrepancy between accounting value added and cash value added. In essence, NOA are a measure of cumulative (net) accruals.

As noted above, accruals are raised with an anticipation that they will convert into cashflow (and be reversed) in a timely manner. If this indeed transpires, the magnitude of NOA will be small and earnings quality will be high. Conversely, a large discrepancy between accounting and cash value added (which HHTZ denote 'balance sheet bloat') suggests that past accruals have persistently not translated into cash, thereby raising concerns over the persistence of future earnings.

Using a similar argument to Sloan's (1996) suggestion that investors fail to differentiate the implications of accruals and cashflow for future earnings, HHTZ (2004) argue that, if investors have limited attention and fail to understand the implications of NOA, then firms with high NOA may be overvalued relative to those with low NOA. To the extent that such mispricing is subsequently corrected, high (low) NOA firms are expected to earn negative (positive) abnormal returns. Further, since NOA capture cumulative differences between earnings and cash flow, HHTZ (2004, p.300) conjecture that "NOA may be a more comprehensive predictor of future returns than a single-period slice like accruals".

Using both portfolio sorts and Fama and MacBeth (1973) cross-sectional regressions, HHTZ (2004) document a strongly negative relationship between NOA and future stock returns. Notably, the regression slope on NOA remains significant when accruals are also included as an independent variable. As such, the NOA effect does not appear to be a simple manifestation of the accrual anomaly. Curiously, while the regression slope on accruals is also significantly negative, HHTZ (2004) do not compare the economic significance of accruals and NOA using portfolio returns.

2.2 Prior Australian Findings

The accrual anomaly has been exhaustively researched and documented in the US (for example, Xie, 2001; Collins et al., 2003; Desai et al., 2004; Mashruwala et al., 2006; Lev and Nissim, 2006; Xu and Lacina, 2009; Allen et al., 2013; Mohanram, 2014; Momente et al., 2015; Radhakrishnan and Wu, 2014; Miao et al., 2016). Outside the US, Soares and Stark (2009) report evidence of profitable accrual-spread trading in the UK. Akbar, Shah and Stark (2011) document the value relevance of cashflows, current and non-current accruals for UK stocks. Further, Pincus et al. (2007) study the anomaly in 20 countries and suggest that it is a global phenomenon.

Only a handful of prior studies have examined the Australian accrual anomaly, with mixed findings to date. Pincus et al. (2007) report evidence that the market inefficiently prices accruals and that this generates economically significant abnormal returns on accrual-spread trading. Their study, however, is limited to approximately 200 Australian stocks per annum over 1994-2002. Anderson et al. (2009) examine the persistence and pricing of earnings, free cashflow and accruals over the period 1992-2004 with a modest sample of approximately 260 firms per year. They report an underestimation of the persistence of both accruals and cashflow.

Clinch et al. (2012) benefit from a broader cross-section of sample stocks over an extended time period (1991-2008). While they report evidence of an accrual anomaly, with the accrual-spread portfolio generating positive abnormal returns, their Australian results exhibit some idiosyncrasies. Contrary to Sloan (1996), investors appear to underestimate the persistence of aggregate earnings, but curiously, they make greater errors in assessing the impact of cashflow on the persistence of earnings than accruals.

Less concerned with the existence of the accrual anomaly per se, Taylor and Wong (2012) highlight the importance of methodological choices and research design issues to inferences drawn in anomaly studies. In particular, they demonstrate that the treatment of outliers (often arising on small stocks) can play a pivotal role in findings. Evidence supporting the existence of an accrual anomaly attenuates when extreme return observations are trimmed from the sample and/or stocks are value-weighted into accrual portfolios. Dou et al. (2013) corroborate these findings. Using both portfolio sorts and cross-sectional regressions, they provide strong evidence that the Australian accrual anomaly is driven by small/micro stocks.

Finally, it is worth highlighting that, while Australia is a well-developed capital market, the corporate landscape exhibits some notable differences from the US that are potentially relevant to the mispricing of accruals, cashflow and NOA. Sloan (1996, Table 1) and HHTZ (2004, Table 1) document that US firms, on average, generate healthy cashflow and earnings. In contrast, approximately half of all Australian firms report losses in any given year (Balkrishna et al., 2007). On average, cashflow is modest and is more than offset by negative accruals. This is attributable in no small way to the prevalence of resource-sector stocks, many of which are small companies in the early exploration stage of their life cycle. Pincus and Rajgopal (2002) suggest that managers of mining stocks use accruals to partially hedge the impact of exploration risk on earnings. These incentives are likely to manifest in higher accruals with flow-on effects for NOA.

These stylised facts have influenced prior Australian research on the accrual anomaly, and are also potentially relevant to our study of NOA. For example, in the population of stocks, Clinch et al. (2012) report the usual overpricing of earnings persistence attributable to accruals, but an underpricing of persistence attributable to cashflow. These full sample findings are robust to the exclusion of mining stocks. However, when their sample is partitioned according to whether a firm makes a profit or loss, the underpricing of cashflow is confined to loss-making firms.

Anderson et al. (2009) also consider asymmetric effects in the persistence and pricing of accruals and cashflow depending on how the sample is partitioned. Their ‘base case’ firms (which comprise loss-making, microcap, non-dividend paying resource firms) are expected to exhibit transitory earnings, the persistence of which are more likely to be mispriced. Contrary to their priors, the accruals and cashflow of base case firms appear to be rationally priced, while both earnings components of industrial sector firms were mispriced. Their piecewise linear variation of the Mishkin approach detects no statistical difference between profit and loss partitions.

3. Data and Descriptive Statistics

3.1 Data Sources and Key Variables

Data for the study are drawn from two sources. Aspect Huntley provides annual financial statement data for ASX-listed firms from 1989 to 2015. Monthly stock market data (returns, market capitalisation, industry codes) are available from SIRCA's Share Price and Price Relative (SPPR) database spanning the period 1974-2016.

The key variable of interest in this study is net operating assets. Firm *i*'s NOA in year *t* is estimated as the difference between operating assets and operating liabilities, scaled by prior year's total assets:

$$NOA_{i,t} = \frac{\text{Operating Assets}_{i,t} - \text{Operating Liabilities}_{i,t}}{\text{Total Assets}_{i,t-1}}. \qquad (2)$$

Following Penman (2012), total assets can be partitioned into operating assets and financial assets. Accordingly, operating assets in (2) are estimated as total assets (Aspect Huntley data item #5090) less the sum of cash (#4990) and short-term investments (#5010). Similarly, operating liabilities are estimated as total liabilities (#6040) less the sum of short-term debt (#6000) and long-term debt (#6020).

Accruals are estimated using the direct approach, which is facilitated by the introduction of AASB 1026 Statement of Cashflows in 1992. Given that Aspect Huntley data commences in 1989, it is possible to commence the analysis in 1990 by using the indirect approach to estimating accruals. Hribar and Collins (1995), however, warn that this approach can induce substantial measurement error (see also Austin and Bradbury, 1995; Clinch, Sidhu and Sin, 2002; Clinch et al., 2012 for Australian evidence of this measurement error). Accordingly, the analysis trades off two extra years of data for the greater precision with which cashflow and accruals are estimated using the direct approach. Consistent with Clinch et al. (2012), firm *i*'s accruals in year *t* are estimated as earnings before tax, net interest, abnormal and significant items (#8012), less cashflow from operations (#9100) adjusted for interest

(#9065, #9070) and tax (#9075). As with net operating assets, accruals are scaled by prior year's total assets.

Several other variables are employed, either as controls in the regression analysis or in the formation of factor-mimicking portfolios. Firm size (Size) is the market capitalisation drawn from SIRCA SPPR. Book-to-market (BM) is book value (total shareholders' equity (#7010) less outside equity interests (#280), preference shares (#201, #202) and future tax benefits (#319, #366, #457, #1169) scaled by market capitalisation. To capture short- and long-term performance, Prior12 and Prior36 measure a stock's buy-and-hold return over the previous 12 and 36 months respectively. Firm age is the number of years that have elapsed since the firm was listed on the ASX.

It is relevant to note that 81% of our sample companies have June reporting dates and over 84% report in June or earlier. Accordingly, in a given year *t*, variables based on financial accounting data (e.g., NOA, accruals, cashflow, earnings, BM) utilise year *t* accounting information if the company's reporting date is June or earlier. For companies with reporting dates July through December, year *t* variables are estimated using year *t*-1 accounting data. This provides a conservative lag of at least six months between the reporting date and the time at which key variables are assumed to be in the public domain.

Given our use of the direct approach to estimating accruals, and the fact that key variables are scaled by lagged total assets, the initial sample comprises all firm-year observations from Aspect Huntley between 1991 and 2015 for which matching records are available in SIRCA SPPR. Stocks with non-ordinary share type and/or identified as investment funds or property trusts are excluded. Similarly, stocks in the banking, insurance and financial sectors are also excluded. Reasonableness checks are applied to the components of operating assets, operating liabilities and accruals.[1] The primary sample for the study comprises 21,299 firm-year observations on 3,054 unique firms. The cross-section ranges from 504 firms in 1992 to 1,397 in 2012, with an average of 887 firms per annum.

[1] For example, on the asset side, total assets must be positive, while short-term investments and operating assets must be non-negative. On the liability side, total liabilities, short-term debts, and operating liabilities must be non-negative. A handful of records showing non-positive total assets are removed, since total assets are used to scale key variables.

3.2 Descriptive Statistics

Table 1 presents descriptive statistics for key variables utilised in the study. NOA ranges from -0.1400 to 4.4081.[2] The mean (median) NOA of 0.7159 (0.6927), along with the interquartile range (0.4396 to 0.8892), indicate that the sample falls in an economically plausible range. For their US sample, HHTZ (2004, Table 1) only report summary statistics for decile portfolios. However, mean NOA for these decile portfolios ranges from 0.247 to 1.596, which is broadly consistent with the current summary statistics.

Table 1 also presents summary statistics on other stock characteristics that provide a useful depiction of the composition of the Australian equity market. First, the distribution of market capitalisation of Australian stocks is severely right skewed. While the mean market cap is \$356m, the median is only \$24m.[3] Second, BM ratios are also right skewed, with a median of 0.6515 indicating a tendency towards growth. Both of these characteristics have been well documented in prior work (Dou et al., 2013). The prior momentum variables show modest medians, but extremely high dispersion.

Summary statistics on earnings, accruals, cashflow and retained earnings also highlight important features of Australian stocks that differentiate them from their US counterparts. Over the sample period, the average Australian firm recorded an annual loss of 12.77% of lagged total assets. While this may seem incredulous, it is in fact highly consistent with prior findings. For example, Clinch et al. (2012) report average earnings-to-assets of -9.50% over the 1991-2008 period which they attribute to the high representation of resource stocks, many of which are in the early exploration stages of their life. Earnings are also severely left skewed, with a handful of firms reporting large losses. Arguably, the sample medians paint a more realistic portrait. The median earnings (-0.0527) is consistent with prior evidence that just over half of all Australian firms make losses. Similarly, the median firm is also cashflow negative (-0.0292).

[2] Given the definition of operating assets and operating liabilities, there is nothing to suggest that NOA must be strictly positive. Be that as it may, only 653 of the 21,299 firm-year observations (3.1% of the sample) have negative NOA.

[3] It is important to note that the study: (i) excludes banks, insurance and financial sector stocks, and (ii) winsorises variables (including market cap) at the 1st and 99th percentiles. As a result, the mean market cap (\$356m) is lower than often reported in studies that utilise the population of Australian stocks and/or do not winsorise.

Table 2 reports correlations between key variables, with Pearson (Spearman) correlations in the lower (upper) triangles. Several key points emerge. First, NOA and accruals exhibit positive correlation (+0.17 Spearman). This is consistent with the notion that NOA are a measure of cumulative accruals. It also further motivates our analysis of the unique influences of NOA and accruals on the cross-section of stock returns. The fact that the magnitude of this correlation is modest alleviates concerns over multicollinearity when both NOA and accruals are included in the regression analysis of Section 4.1. Second, consistent with intuition, earnings are highly correlated with cashflow (+0.83 Spearman), while cashflow and accruals are negatively related (-0.15 Spearman). Finally, and somewhat surprisingly, the correlation between NOA and firm age is negligible (+0.02 Spearman). Given that NOA are effectively the inter-temporal accumulation of annual differences between accounting and cash value added, it is reasonable to conjecture that firms with high NOA may simply be older (and conversely, younger firms may not have had time to accumulate significant NOA). Table 2, however, clearly shows that this is not the case.

4. Empirical Analysis and Results

4.1 Preliminary Regression Analysis

Fama and French (2008) advocate the regression approach for its ability to estimate the marginal influence of a variable of interest, while simultaneously controlling for other stock characteristics known to be associated with returns. Accordingly, the following regression is employed to provide a preliminary analysis of the potential joint roles that NOA and accruals play in the cross-section of stock returns:

$$\begin{aligned} R_{i,t+1} &= \alpha + \beta_1 \ln(\text{Size}_{i,t}) + \beta_2 \ln(\text{BM}_{i,t}) + \beta_3 \text{Prior12}_{i,t} + \beta_4 \text{Prior36}_{i,t} \\ &\quad + \beta_5 \text{Accruals}_{i,t} + \beta_6 \text{NOA}_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

The dependent variable is the 12-month buy-and-hold return on stock *i* from January to December of year *t*+1. The independent variables are constructed as described in Section 3.1; specifically, they are estimated as at December of each year *t*. The sample comprises

21,457 firm-year observations spanning 1992-2015. In light of the positive skewness documented in market capitalisation and BM in Section 3.2, natural logs of these variables are taken. Further, all variables are winsorised at the 1st and 99th percentiles to mitigate the potential influence of extreme values. Table 3 reports the regression results.

As a base case, Model 3a includes only the four control variables.[4] Consistent with the existence of size and value effects, the negative (positive) relationships between returns and size (BM) are statistically significant. Neither of the price momentum variables (Prior12 and Prior36) display explanatory power. These findings for the base case remain intact when the other key independent variables are added (i.e., NOA and accruals).

Model 3b shows a highly significantly negative association between NOA and future stock returns (β_6 = -0.1106, p < 0.001). As such, a 10% increase in year t NOA (expressed as a percentage of lagged total assets) results in a 1.106% decline in stock returns over year t+1. Similarly, Model 3c documents a significantly negative relationship between accruals and future stock returns (β_5 = -0.1309, p = 0.0068).

Section 3.2 reports a modestly positive correlation between NOA and accruals, consistent with the notion that NOA are a cumulative measure of accruals. Naturally, this raises the possibility that NOA and accruals may capture similar information. Model 3d, however, suggests that NOA and accruals have unique influences on future stock returns. The relationship between NOA and future stock returns is largely unaffected by the inclusion of accruals (β_6 = -0.1072, p < 0.001). The negative association between accruals and returns also remains, albeit with reduced statistical significance (β_5 = -0.1140, p = 0.0178).

These findings for Model 3 suggest that NOA and accruals have unique roles (at least statistically) in explaining the cross-section of stock returns. Whether or not NOA and accruals each have economically important predictive ability for future stock returns is explored next by documenting the returns on portfolios sorted on these variables.

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[4] All models were also estimated with firm age included as an additional control. The results were virtually unchanged from those reported in Table 3.

4.2 NOA Portfolio Sorts

Starting in December 1992, all sample stocks are ranked by NOA and sorted into decile portfolios. The portfolios are held without rebalancing for the next 12 months.[5] This procedure is repeated annually through to December 2015, resulting in a 288-month time series of returns on NOA-sorted decile portfolios spanning January 1993 through December 2016.

Table 4 Panel A reports summary statistics that characterise the stocks in the NOA-sorted portfolios. By construction, NOA increases from 0.0757 for portfolio #1 to 1.7113 for portfolio #10. This spread is remarkably similar to HHTZ (2004, Table 1), where NOA ranges from 0.247 to 1.596. Mean accruals generally increases across NOA deciles, consistent with the modestly positive correlation reported in Table 2. Portfolio #1 comprises the smallest sample stocks by market capitalisation ($63m), raising concerns about the potential influence of a small-firm effect. However, by Australian standards, $63m is by no means small.[6] Portfolio #1 also comprises stocks with the lowest BM (0.6639). With reference to the value premium, the fact that Portfolio #1 contains growth stocks mitigates concerns that BM may drive any NOA effect. There is little variation in BM across other NOA deciles. Of the two momentum variables, the most discernible pattern is an increase in Prior36 across NOA deciles.[7]

In Table 4 Panel B, the relationship between NOA and future stock returns is examined using both raw and risk-adjusted portfolio returns. While the relationship is not monotonic, the low and high NOA deciles generate the highest and lowest average raw return respectively. This is the case regardless of whether stocks are value or equal weighted into portfolios. A spread portfolio that enters long (short) positions in the low (high) NOA stocks generates statistically significant average monthly returns of 1.3291% when stocks are value-weighted

[5] To be specific, the portfolios are genuine buy-and-hold investments. Portfolio returns are estimated following the approach of Liu and Strong (2008) and Gray (2014) to avoid potential rebalancing bias.

[6] To illustrate, as at December 1992 (December 2015), a market capitalization of $64m would place a stock in the top 22^{nd} (32^{nd}) percentile.

[7] Note, however, that the results are unlikely to be unduly influenced by long-term reversals effects. Prior work shows no evidence of reversals (Dou et al., 2013). Similarly, Table 3 finds no relationship between Prior36 and future returns.

and 2.2134% when stocks are equally-weighted.[8] The magnitude of this NOA effect is economically significant. On an annualised basis, the average returns on low and high value-weighted NOA portfolios are 18.18% and 0.87% respectively, with the spread portfolio averaging around 17%.

In order to estimate risk-adjusted returns, we construct the requisite factor-mimicking portfolios to employ the Fama and French (1993) three-factor asset pricing model. Prior asset-pricing research argues that the composition of the Australian equity market warrants two minor departures from the strict Fama and French (1993) approach to constructing factors (see, Brailsford, Gaunt and O'Brien, 2012; Zhong, Limkriangkrai and Gray, 2014; Chiah, Chai, Zhong and Li, 2016; Huynh, 2017).

First, since the distribution of Australian market capitalisation is severely right skewed, the median market capitalisation does not adequately differentiate between 'small' and 'big' stocks.[9] As such, we follow prior Australian asset-pricing work by denoting the largest 200 stocks at each portfolio-formation point as 'big' and the remainder as 'small'. Second, rather than determining the book-to-market (BM) cutoffs using the population of stocks, we use the 30th and 70th percentiles from the Top 200 stocks by market capitalisation at each portfolio formation point. This reflects the observation of Fama and French (2008) that small and micro stocks are not only numerous, but exhibit much greater dispersion of characteristics like BM. Accordingly, if cutoffs are based on the population, very few big stocks will be assigned to extreme BM portfolios. Although these procedures for determining the size and BM cutoffs differ from Fama and French (1993), Brailsford et al. (2012) show that they generate size/BM sorted portfolios that capture genuine differences in size and BM of Australian firms.

[8] Since equally-weighted portfolios are more susceptible to extreme returns that can occur on small stocks (Taylor and Wong, 2012), we emphasise the findings for the value-weighted portfolios throughout this paper.

[9] To illustrate, as at December 2015, the mean and median market capitalisations are $571m and $21m respectively. Clearly, if the median market cap is the cutoff point for classifying stocks as big and small (as per Fama and French), stocks as small as $21m will be regarded as 'big'. The resulting SMB size factor may not capture the true extent of the size premium.

Given the size and BM cutoffs at a particular portfolio formation point, the usual Fama-French procedure is followed. In brief, each December, stocks are sorted into six portfolios (two size groups, three BM groups) using independent cutoffs based on the procedure described above. The six portfolios are held without rebalancing for 12 months and value-weighted returns on each portfolio are estimated. This procedure is repeated each year through to December 2015. Following Fama and French (1993), returns on the six portfolios are averaged such that the size-mimicking factor (*SMB*) is BM-neutral and the BM-mimicking factor (*HML*) is size-neutral. Finally, the market risk premium is the difference between the SPPR value-weighted market index and the risk free rate.

Panel B reports risk-adjusted returns on the spread portfolio in the form of intercepts from the Fama-French three-factor model. Monthly alphas on VW and EW portfolios are 0.9344 and 1.9491 respectively, each significant at the 1% level. Accordingly, the profitability of the NOA spread portfolio remains highly significant after controlling for common risk factors.

Overall, Table 4 presents strong evidence to support the existence of an economically significant NOA effect in average stock returns in Australia. The magnitude of Australian findings (average monthly returns of 1.33% and 2.21% to the value and equal weighted NOA spread portfolio respectively) is larger than US findings reported by HHTZ (0.76% and 1.48%). With reference to Green et al. (2011) and McLean and Pontiff (2016), this may reflect the absence of any prior research exposing the NOA anomaly in Australian equities. Nevertheless, the NOA effect of HHTZ (2004) appears to be generalisable to an equity market that is dissimilar to the US in many respects.

4.3 Accruals Portfolio Sorts

Decile portfolios sorted by accruals are constructed in an identical manner to the NOA portfolios in Section 4.2, with the first and last portfolio formation dates in December 1992 and 2015 respectively. Table 5 Panel A reports that accruals range from -0.3582 for portfolio #1 to 0.1401 for portfolio #10. Again, the modestly positive correlation between NOA and accruals is evident. With the exception of a positive relation between Prior36 and accruals, there are no obvious patterns between accruals and other characteristics that might be proxying for risk factors.

Table 5 Panel B exhibits the familiar accrual anomaly. When stocks are value-weighted into portfolios, there is a discernible difference between the average return on stocks with extreme accruals. Portfolio #1 (low accruals stocks) generates an average return of 0.8975% per month, while Portfolio #10 (high accruals stocks) averages -0.2259% per month. The spread portfolio that enters long (short) positions in portfolio #1 (portfolio #10) generates 1.1234% per month, which is significant at the 1% level. On an annualised basis, the average returns on low and high value-weighted accruals portfolios are 11.32% and -2.68% respectively, with the spread portfolio averaging around 14%. Adjusting for common risk factors, the Fama-French three-factor alpha is 0.7188% and significant at the 10% level.[10]

At face value, a comparison of Table 4 and Table 5 suggests that the NOA and accrual anomalies are each economically significant. For value-weighted portfolios, the raw and risk-adjusted returns on NOA spread portfolios are marginally higher than for accruals. Further, both strategies perform consistently over the 24-year sample period. Figure 1 presents the annualised buy-and-hold return to NOA and accrual-spread trading on a year-by-year basis. NOA (accrual) spread trading generates positive annual returns in all but three (six) of the 24 years. As such, the findings strongly suggest that NOA and accruals exhibit a negative relationship with future returns.

4.4 NOA/Accruals Double-Sorted Portfolios

The empirical findings to this point can be summarised as follows. The regression analysis of Section 4.1 suggests that NOA and accruals have unique influences on average returns, at least from a statistical perspective. Portfolio sorts in Section 4.2 and Section 4.3 document a negative relationship between average returns and NOA and accruals respectively. Economically, both effects are significant and consistent across time.

[10] Methodological differences make direct comparisons with the prior findings of Clinch et al. (2012) difficult. Rather than using an asset-pricing model to adjust for risk, Clinch et al. (2012) report market-adjusted abnormal returns with reference to the equal-weighted market portfolio. Their accruals spread trading strategy generates an abnormal return of 6.9% pa. Despite studying different time horizons, this is broadly consistent with the annualised alpha of 8.97% from Table 5.

To further explore the unique roles of NOA and accruals for the cross-section of stock returns, an independent double-sorting procedure is employed to control for one characteristic while allowing the other to vary. Starting December 1992, quintile breakpoints are independently identified for both NOA and accruals. Sample stocks are sorted into 25 NOA/accrual portfolios. Monthly returns on value-weighted buy-and-hold portfolios are estimated over the following 12 months. This double sorting procedure is repeated annually through to December 2015. This generates a 288-month time series of returns on the 25 NOA/accruals portfolios.

Table 6 shows that the double sorting procedure does an excellent job at controlling for one characteristic while allowing the other to vary. Reading across each row of Panel A, there is little variation in NOA values across accrual quintiles. Reading down each column of Panel B, the accrual values are near identical for each NOA quintile. Finally, Table 6 Panel C documents a sufficient distribution of sample stocks across the 5×5 grid to mitigate the potential for outliers to unduly influence the return to a given portfolio. While the use of independent sorts often results in a lumpy distribution of stocks across portfolios and scarce representation in corners of the grid, this is not the case in Panel C.

Table 6 Panel D reports the average monthly returns on the double-sorted portfolios. Controlling for accruals (i.e., reading down each column), there is a clear NOA effect. For each level of accruals, the low NOA portfolio outperforms the high NOA portfolio, with a statistically significant NOA spread. In contrast, a stand-alone accruals effect is less apparent. Controlling for NOA (i.e., reading across each row), the average return on the low accruals portfolio exceeds the average return to the high accruals portfolio in all cases. However, the accruals spread is statistically significant only for the highest NOA grouping.

This striking finding potentially casts the accrual anomaly in a new light. Since Sloan (1996), it has been well documented that, on average, stocks reporting a high level of accruals in the most-recent period will subsequently underperform stocks with low accruals. In essence, high accruals are bad news for future returns. Table 6, however, suggests that this is not necessarily the case. Rather, the signal provided by current-period accruals depends on the stock's track record in converting accruals into cashflow. Viewing NOA as an inter-temporal measure of 'balance sheet bloat', a high level of accruals is only bad news if the company has a sustained track record of recording accruals that do not subsequently convert into cash (i.e., if the company has considerable balance sheet bloat). In contrast, in the absence of balance sheet bloat, the implications of high current-period accruals for future returns are negligible. For stocks with low-to-medium levels of NOA, future returns are similar regardless of the current level of accruals.

Finally, the interaction between accruals and NOA documented in Table 6 suggests an obvious trading strategy. A spread portfolio that enters long positions in stocks with low levels of both current accruals and NOA (1.7944%) and short positions in stocks with both high accruals and NOA (-0.2816%) generates a return of 2.08% per month on average over the following 12 months. Returns of this magnitude far exceed the returns on spread trading either accruals or NOA alone. Further, Figure 1 Panel C demonstrates the persistent profitability of this strategy. The annualised return is positive in all but three of the 24 years in the sample. As such, NOA may be a useful mediating variable to accrual filters that are commonly employed in investment practice.

5. Are NOA and Accruals Rationally Priced?

Although the primary purpose of this paper is to investigate the relationship between NOA, accruals and stock returns, it is common in capital markets studies to test whether stock prices rationally impound information about future earnings contained in observables like cashflow, accruals and, in our case, NOA. Accordingly, this section considers the rational pricing of these variables using an approach proposed by Kraft et al. (2007). In doing so, we lever upon the fact that the KLW test is an OLS-based procedure to also consider the extent to which key assumptions about error terms in the panel regression may influence inferences from the rationality tests.

Historically, rationality tests have been conducted by estimating a system of equations using non-linear least squares and testing a cross-equation restriction (Mishkin, 1981; 1983). Kraft et al. (2007) raise a number of important issues concerning the Mishkin test. First, they note that the Mishkin test is asymptotically equivalent to a simple and intuitive (single equation) OLS regression procedure. Kraft et al. (2007) demonstrate that the OLS and Mishkin approaches produce virtually identical coefficient estimates and inferences, and therefore see little advantage in utilising the more-complicated Mishkin test.

Second, Kraft et al. (2007) highlight that the Mishkin approach is vulnerable to the common omitted variable problem.[11] Specifically, even if the Mishkin test rejects market efficiency, it is difficult to infer that a specific variable (like accruals or NOA) is the cause of the mispricing rather than a correlated omitted variable. While the omitted variable problem is well-understood in classic OLS scenarios, Kraft et al. (2007) suggest that researchers may not fully understand its implications under the Mishkin approach. For these reasons, as well as those described shortly relating to standard errors, this paper adopts Kraft et al.'s (2007) OLS regression-based approach to conduct market efficiency tests and includes size, book-to-market and momentum as potential omitted variables.

In the current context, Kraft et al.'s (2007) OLS equivalent of the Mishkin approach is:

$$\begin{aligned} R_{i,t+1} &= \phi_0 + \phi_1 ACC_{i,t} + \phi_2 CFO_{i,t} + \phi_3 NOA_{i,t} \\ &+ \sum_{j=1}^{4}\gamma_j D_{i,t}^{SIZE} + \sum_{j=1}^{4}\lambda_j D_{i,t}^{BM} + \sum_{j=1}^{4}\eta_j D_{i,t}^{MOM} + \varepsilon_{i,t+1} \end{aligned} \tag{4}$$

The key test variables are firm *i*'s time-*t* accruals, cashflow and net operating assets ($ACC_{i,t}$, $CFO_{i,t}$ and $NOA_{i,t}$). $R_{i,t+1}$ is stock *i*'s buy-and-hold return from January to December of year *t*+1. Following Kraft et al. (2007), we include variables to capture firm size, book-to-market and prior 12-month momentum. For these variables, a dummy variable indicates firm *i*'s membership in the respective quintile grouping (with quintiles formed by ranking sample stocks as at each December).

[11] An omitted variable problem arises when a variable that is omitted from a model is correlated with both the dependent variable and one of the included independent variables. In such a case, even if the estimated slope on the included variable is significant, this may be spurious since the omitted variable has an association with the dependent variable.

Kraft et al. (2007) demonstrate that the rational pricing of an accounting variable (e.g., accruals, cashflow, NOA) requires that the variable is uncorrelated with future returns. Hence, Kraft et al.'s (2007) OLS-equivalent of the Mishkin test simply requires a *t*-test that the relevant slope (ϕ) equals zero. In contrast, a significantly positive (negative) estimate of a slope implies that the variable in question is underpriced (overpriced).[12]

As is the case when using the Mishkin approach, model (4) is estimated by pooling the sample across years and stocks. Increasingly, however, financial economists have become concerned with potential violation of the 'vanilla' OLS assumptions that model error terms are independently and identically distributed. In an attempt to address these issues, researchers employing the Mishkin approach have followed a Fama-MacBeth-style approach, whereby models are estimated on a year-by-year basis, after which annual coefficient estimates are averaged.[13] Kraft et al. (2007, footnote 13) are clearly aware of these econometric issues, noting that pooling data induces cross-sectional and inter-temporal correlations that potentially affect standard errors. Indeed, they go as far as estimating the Mishkin equations on an annual basis, presumably in response to these concerns. However, they do not address the issues within their OLS-based approach.

By recognising model (4) as an unbalanced panel regression, a major advantage of Kraft et al.'s (2007) regression-based approach is that the particular econometric concerns discussed above are easily accommodated using recently-developed techniques for clustering standard errors in panel regressions. Petersen (2009) conducts simulation experiments to demonstrate the perils of assuming vanilla OLS assumptions with panel data, thereby providing strong motivation to use clustered standard errors. Thompson (2011) further extends the idea by showing how to cluster standard errors on two (or more) dimensions, making it an ideal approach for panel regressions.

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[12] Kraft et al. (2007) demonstrate the equivalence of this OLS test to the better-known Mishkin procedure, both analytically and empirically.

[13] For example, HHTZ (2004, Table 8) and Kraft et al. (2007, Tables 3 and 4) estimate the Mishkin model annually. Annual estimation is intended to accommodate period-specific effects, and also alleviates numerical convergence difficulties with large pooled panels.

Our analysis of whether stock prices rationally impound information inherent in NOA, accruals and cashflow proceeds as follows. First, model (4) is estimated as per Kraft et al. (2007) with data pooled across years and stocks, using vanilla OLS assumptions over error terms for statistical inference. Second, model (4) is re-estimated as a panel regression with standard errors clustered by both year and firm. While the slope estimates (ϕ) are unaffected by the assumption over error terms, the standard errors and resulting *t*-statistics change to the extent that the vanilla assumptions are violated in the panel data. As such, in addition to the usual rational pricing analysis, our analysis examines the vulnerability of the KLW test (and indirectly by association, the Mishkin test) to distributional assumptions that are inconsistent with the panel data.

Table 7 reports the results of the rational pricing analysis. For each variation of model (4) estimated, Table 7 reports the estimated OLS slopes, the *p*-value under vanilla assumptions (in round parentheses) and the *p*-value using double clustered standard errors <in angle brackets>.

Model 4a is the KLW equivalent of the Mishkin test of the rational pricing of accruals and cashflow (used by Sloan, 1996; Clinch et al., 2012 and many others). Using vanilla standard errors, the significantly negative coefficient on accruals (-0.0970, p = 0.0026) indicates that accruals are overpriced. Conversely, the significantly positive coefficient on cashflow (0.1551, p < 0.001) indicates underpricing. These findings are highly consistent with the prior Australian work of Clinch et al. (2012, Table 3). Of course, this inference is based on vanilla standard errors. Table 7 shows a dramatic difference in *p*-values when standard errors are clustered by year and firm. Specifically, the double clustered standard errors provide no support for the notion that accruals <p=0.3211> or cashflow <p=0.1541> are mispriced.

In model 4b, the pricing of NOA are also considered in addition to accruals and cashflow. Again using vanilla standard errors, significantly negative coefficients on accruals (-0.0589, p = 0.0683) and NOA (-0.1381, p < 0.001) indicate overpricing, while the significant slope on cashflow (0.1502, p < 0.001) suggests underpricing. Importantly, the direction of these inferences on the mispricing of accruals, cashflow and NOA are identical to the Mishkin results reported by HHTZ (2004, Table 8). However, when cross-sectional and inter-temporal relationships in the data are accommodated in estimating standard errors, the apparent overpricing of accruals <p=0.5280> and underpricing of cashflow <p=0.1572> vanishes. The only remaining evidence of mispricing relates to the overpricing of NOA <p=0.0001>.

In considering the implications of Table 7, it is imperative to note that if the vanilla regression assumptions are a reasonable approximation for the dataset, the clustered standard errors will mimic the vanilla standard errors. The fact that inferences regarding the mispricing of key variables change so dramatically highlights the importance of using the more-sophisticated approach to estimating standard errors that better accommodate cross-sectional and time-series patterns in panel data.

6. Robustness Analysis

Section 2 highlights a number of idiosyncrasies of the Australian equity market that have the potential to influence a study involving earnings, accruals, cashflow and NOA. This section rounds off the paper by briefly considering the robustness of the main findings in several relevant partitions of the sample.

The persistence of earnings attributable to accruals and cashflow is known to differ for profit and loss firms. Further, Clinch et al. (2012) show that their cashflow anomaly (i.e., an underestimation of the persistence of earnings attributable to cashflow) only manifests amongst loss-making firms. Table 1 reports that the median earnings of Australian companies over the sample period marginally negative.[14] As such, the sample is divided approximately evenly between loss-making and profit-making firms. This provides a convenient setting to explore whether firm profitability is relevant to the mispricing of NOA, cashflow and accruals.

[14] Sloan (1996, Table 1) reports positive mean and median earnings for each accruals decile. Similarly, HHTZ (2004, Table 1) report positive mean earnings in all but one NOA decile. Clearly, US companies are more profitable than Australian companies.

Table 8 Panel A reports summary statistics for partitions of the full sample according to profitability. While there is little discernible difference in NOA or BM, loss-making firms tend to be younger, have significantly smaller market caps and are recent losers (perhaps better assessed via medians than means). The magnitude of retained earnings (i.e., retained *losses*) suggests that losses are quite persistent within the loss-making partition.

Table 9 Panel A reports the KLW-style rational pricing analysis for each partition. As was the case with the full sample, clustered standard errors provide no evidence that accruals or cashflow are mispriced, and strong evidence that NOA are overpriced. These findings are consistent within both the profit- and loss-making partitions. Had inferences been made using vanilla standard errors, the mispricing of accruals would have (erroneously) appeared stronger amongst profit-making firms. At face value, Table 9 Panel A shows no sign of the cashflow mispricing amongst loss-making firms reported by Clinch et al. (2012). To explore this further, we mimic the rationality testing of Clinch et al. (2012) by excluding NOA, leaving accruals, cashflow and the control variables. When vanilla standard errors are utilised (as per Clinch et al.), untabulated analysis does indeed suggest that cashflow persistence is underestimated amongst loss-making firms. However, this inference is not robust when the more-sophisticated clustered standard errors are employed.

In light of the prevalence of mining stocks in the Australian equity market, Table 8 Panel B partitions the full sample into resource and non-resource stocks. While it is often conjectured that Australian resource stocks tend to be small, unprofitable firms in early stages of their life, Table 8 does not entirely confirm this. Resource stocks have smaller market caps, although the difference is not as large as might have been expected. Surprisingly, there is little discernible difference in the age of firms in each partition. What is clear is that resource stocks are less profitable, have worse cashflow positions and more negative retained earnings.

Table 9 Panel B again finds that the overpricing of NOA is pervasive across both partitions. Using clustered standard errors, there is no evidence that the accruals or cashflow of resource stocks are mispriced. However, had inferences been made using vanilla standard errors, Panel B would have suggested the accruals (cashflow) of non-resource stocks are over (under) priced. This is precisely the finding of Clinch et al. (2012) in their robustness analysis. When clustered standard errors are employed, the mispricing of accruals vanishes, yet the underpricing of cashflow for non-resource stocks remains (ϕ_2 = 0.2430, $p < 0.001$). As such, our findings support the existence of the 'cashflow anomaly' recently reported by Clinch et al. (2012), at least for non-resource stocks.[15]

Finally, we explore mispricing when the sample is partitioned by firm size.[16] Table 8 Panel C reports summary statistics for Big and Small stock partitions, where the top 200 stocks by market capitalisation each December are classified Big. Big stocks clearly tend towards growth, have stronger momentum, and higher earnings and cashflows. Table 9 Panel C shows that the overpricing of NOA is pervasive across both Big and Small partitions. The underpricing of cashflows is restricted to Big firms. Given that non-resource firms tend to be have larger market caps, this finding is consistent with the underpricing of non-resource firms documented in Table 9 Panel B and in Clinch et al. (2012).

7. Conclusion

There is a vast amount of international literature that examines the relationship between stock returns and various financial statement items. While the so-called accrual anomaly of Sloan (1996) has attracted much attention, this paper studies a variation of accruals recently proposed by HHTZ (2004). Whereas accruals are simply the difference between earnings and cashflow at a single point in time, net operating assets capture the lifetime discrepancy between accounting value added and cash value added. In essence, NOA measures the extent to which past accruals have not translated into future cashflow ('balance sheet bloat').

Prior research documents a negative relationship between US stock returns and each of accruals and NOA. This paper contributes to the literature by showing that, while accruals

[15] While Clinch et al. (2012) examine the robustness of their full-sample results to the exclusion of mining stocks, they do not analyse mispricing for resource-sector stocks.

[16] We are grateful to an anonymous referee for suggesting this robustness analysis.

and NOA are closely related, they provide unique signals for future returns. That is, accruals and NOA both display a statistically and economically significantly negative relationship with future stock returns. In fact, value-weighted spread portfolios sorted by accruals and NOA generate significant abnormal returns.

NOA, however, has an important moderating influence on the accrual effect. Whereas low accrual stocks are commonly believed to consistently outperform high accrual stocks, we show that this is only the case for stocks with high levels of NOA. Viewing accruals and NOA as single- and multi-period metrics respectively, the finding implies that a high level of accruals is only 'bad' news when a firm has a sustained track record of accruals not translating into future cashflow (i.e., high NOA). For stocks with low NOA, a one-off incidence of high accruals does not adversely impact future returns.

The paper also makes an important contribution to the literature concerned with assessing the extent to which market prices rationally impound financial statement information. Kraft et al. (2007) advocate a regression-based equivalent of the popular Mishkin rationality test, on the grounds that it is more conducive to accommodating potential omitted variable problems. We also argue that the regression-based approach can (and should) be augmented with recently-developed procedures for estimating clustered standard errors in panel regressions. Our empirical results demonstrate that inferences drawn from Mishkin/KLW-style rationality tests are highly sensitive to distributional assumptions made over model error terms. Making vanilla assumptions over error terms can lead to erroneous conclusions that accruals (cashflow) are over (under) priced. When the panel regression accommodates standard errors clustered on both firm and time, neither accruals nor cashflow are mispriced in the full sample. In contrast, the mispricing of NOA is robust to the utilisation of more-sophisticated econometric assumptions. At the very least, the dramatic difference in inferences documented in this paper serves as a warning to researchers seeking to test the rational pricing of accounting information.

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Table 1: Descriptive Statistics

This table reports summary statistics for the pooled sample of 21,299 firm-year observations spanning 1992-2015. **NOA are** the difference between operating assets and operating liabilities, scaled by lagged total assets. **Market capitalisation** is number of ordinary shares multiplied by the closing share price each December. **Book-to-market** is the book value scaled by market capitalisation. **Prior12** and **Prior36** are the stock's buy-and-hold return over the prior 12 and 36 months respectively. **Earnings** are the reported earnings before interest, tax, abnormal and significant items, scaled by lagged total assets. **Cashflow** is the cashflow from operations, scaled by lagged total assets. **Accruals** is the difference between earnings and accruals, scaled by lagged total assets. **Retained Earnings** is the dollar value of retained earnings scaled by total assets. **Firm age** is the number of years that has elapsed since the firm was listed on the ASX. All variables are winsorised at the 1st and 99th percentiles.

	Mean	Std Dev	Min	25th	Median	75th	Max
Net operating assets	0.7159	0.4990	-0.1400	0.4396	0.6927	0.8892	4.4081
Market cap ($m)	356.3179	1,229.0002	0.8456	7.5770	24.0000	114.4168	8,984.9290
Book-to-market	1.0350	1.2172	0.0331	0.3272	0.6515	1.2455	7.7420
Prior 12-month	0.1422	0.8955	-0.8877	-0.3975	-0.0559	0.3622	4.6560
Prior 36-month	0.3761	1.7222	-0.9667	-0.6343	-0.1453	0.6591	9.6875
Earnings	-0.1277	0.3409	-1.5840	-0.2482	-0.0527	0.0884	0.4958
Cashflow	-0.0557	0.2812	-1.2252	-0.1570	-0.0292	0.1162	0.5546
Accruals	-0.0726	0.1924	-0.8885	-0.1169	-0.0397	0.0050	0.4874
Retained earnings	-1.7937	4.0225	-26.3466	-1.7073	-0.3878	0.0493	0.5348
Firm age	15.3026	12.8145	2.0000	6.0000	10.0000	19.0000	81.0000

Table 2: Correlation Matrix

This table reports correlations between key variables defined in Table 1. Pearson (Spearman) correlations are reported in the lower (upper) triangles. The correlation between each pair is estimated on a year-by-year basis over the period 1992-2015, with the time series average of yearly correlations reported. For the purpose of estimating correlations, Market capitalisation, BM and Firm Age are logged (since they enter our regressions in log form).

	NOA	Mktcap	BM	Prior12	Prior36	Earnings	Cashflow	Accruals	Ret Earnings	Age
NOA	1	0.20	0.14	0.02	0.17	0.20	0.10	0.17	0.24	0.02
Mktcap	0.15	1	-034	0.34	0.50	0.52	0.50	0.07	0.60	0.19
BM	0.11	-0.31	1	-0.43	-0.48	0.05	0.06	0.06	0.14	0.02
Prior12	0.01	0.21	-0.43	1	0.57	0.25	0.21	0.06	0.18	0.05
Prior36	0.15	0.32	-0.43	0.49	1	0.36	0.29	0.11	0.34	0.09
Earnings	0.10	0.40	0.17	0.11	0.16	1	0.83	0.31	0.73	0.14
Cashflow	0.03	0.39	0.14	0.10	0.13	0.79	1	-0.15	0.68	0.16
Accruals	0.12	0.09	0.08	0.04	0.08	0.46	-0.14	1	0.15	0.01
Ret Earnings	0.25	0.35	0.26	0.02	0.13	0.45	0.40	0.16	1	0.03
Firm age	0.00	0.22	0.03	0.01	0.04	0.13	0.14	0.01	-0.06	1

Table 3: Preliminary Regression Estimates

This table reports regression estimates from model (3). The dependent variable is the 12-month buy-and-hold return on each stock from January-December of year *t*+1. The independent variables are estimated as at December of each year *t*. **ln(Size)** is the natural logarithm of the firm's market capitalisation as at December. **ln(BM)** is the natural logarithm of the firm's book-to-market ratio. **Prior12** and **Prior36** are the stock's buy-and-hold return over the prior 12 and 36 months respectively. **NOA are** the difference between the stocks' operating assets and operating liabilities, scaled by lagged total assets. **Accruals** is the difference between the stock's earnings and cashflow, scaled by lagged total assets. All variables are winsorised at the 1st and 99th percentiles. The sample comprises 21,457 firm-year observations over the period 1992-2015.

Model		ln(Size)	ln(BM)	Prior12	Prior36	NOA	Accruals	Adj R^2
3a	Coefficient	-0.0317	0.0521	0.0469	0.0028			3.64%
	p-value	0.0114	0.0003	0.1892	0.7093			
3b	Coefficient	-0.0269	0.0662	0.0445	0.0102	-0.1106		4.14%
	p-value	0.0272	0.0001	0.2066	0.2141	0.0001		
3c	Coefficient	-0.0307	0.0561	0.0479	0.0045		-0.1309	3.76%
	p-value	0.0126	0.0002	0.1690	0.5519		0.0068	
3d	Coefficient	-0.0263	0.0694	0.0455	0.0115	-0.1072	-0.1140	4.25%
	p-value	0.0291	0.0001	0.1860	0.1661	0.0001	0.0178	

Table 4: Summary Statistics and Monthly Returns by NOA Decile

This table reports summary statistics and returns for portfolios of stocks sorted by NOA. Each December from 1992 to 2015, sample stocks are sorted into decile portfolios by NOA. Buy-and-hold portfolios are held for 12 months without rebalancing. Panel A reports summary statistics that characterise stocks in each portfolio. All variables are winsorised at the 1st and 99th percentiles. Panel B reports average monthly returns on NOA-sorted decile portfolios (both value and equal weighted portfolios are shown). The spread portfolio enters long (short) positions in portfolio 1 (portfolio 10). The risk-adjusted spread return is estimated by the intercept from a Fama-French (1993) three-factor asset pricing model. Newey-West standard errors are used to correct for autocorrelation and heteroscedasticity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary Statistics by NOA Decile

	Low	2	3	4	5	6	7	8	9	High
NOA	0.0757	0.2935	0.4502	0.5623	0.6533	0.7299	0.8053	0.8901	1.0187	1.7113
Accruals	-0.0541	-0.0710	-0.0628	-0.0565	-0.0437	-0.0385	-0.0288	-0.0227	-0.0163	-0.0289
Cashflow	-0.1857	-0.0607	-0.0111	0.0184	0.0398	0.0631	0.0518	0.0120	-0.0232	-0.0776
Earnings	-0.2751	-0.1708	-0.0738	-0.0270	0.0049	0.0360	0.0316	0.0058	-0.0243	-0.0846
Size ($m)	63.3997	150.3137	291.4503	397.5829	555.4716	554.7696	491.1332	425.1801	301.2562	277.1224
BM	0.6639	0.8351	0.9258	0.9976	1.0534	1.0704	1.0848	1.1724	1.1461	0.9484
Prior12	-0.0302	-0.0459	-0.0222	-0.0096	0.0124	0.0211	0.0139	-0.0168	-0.0128	-0.0065
Prior36	-0.2830	-0.2065	-0.1801	-0.0454	0.0103	0.0410	0.0481	0.0308	0.1365	0.3775
Firm age	8.8542	9.1250	10.0000	10.6875	12.3542	11.6667	11.5833	10.8333	10.2917	9.2708

Panel B: Monthly Returns by NOA Decile

	Low	2	3	4	5	6	7	8	9	High	Spread	FF3f alpha
VW	1.4020***	1.0624***	0.8709**	1.0867***	0.8808***	0.9821***	0.8540***	0.5159*	0.6522**	0.0729	1.3291***	0.9344***
EW	2.4976***	2.2158***	1.7536***	1.5281***	1.4656***	1.1960***	1.2389***	1.2079***	0.9200**	0.2842	2.2134***	1.9491***

Table 5: Summary Statistics and Monthly Returns by Accruals Decile

This table reports summary statistics and returns for portfolios of stocks sorted by accruals. Each December from 1992 to 2015, sample stocks are sorted into decile portfolios by accruals. Buy-and-hold portfolios are held for 12 months without rebalancing. Panel A reports summary statistics that characterise stocks in each portfolio. All variables are winsorised at the 1st and 99th percentiles. Panel B reports average monthly returns on accruals-sorted decile portfolios (both value and equal weighted portfolios are shown). The spread portfolio enters long (short) positions in portfolio 1 (portfolio 10). The risk-adjusted spread return is estimated by the intercept from a Fama-French (1993) three-factor asset pricing model. Newey-West standard errors are used to correct for autocorrelation and heteroscedasticity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary Statistics by Accruals Decile

	Low	2	3	4	5	6	7	8	9	High
Accruals	-0.3582	-0.1783	-0.1093	-0.0723	-0.0487	-0.0293	-0.0125	0.0052	0.0376	0.1401
NOA	0.6519	0.6687	0.7002	0.6995	0.7193	0.7358	0.7545	0.7182	0.7441	0.8229
Cashflow	-0.0598	0.0061	0.0270	0.0546	0.0571	0.0502	0.0120	-0.0065	-0.0279	-0.1635
Earnings	-0.4547	-0.1825	-0.0830	-0.0179	0.0088	0.0207	-0.0001	0.0004	0.0110	-0.0074
Size ($m)	56.6468	188.0414	373.6383	525.9926	594.9773	573.9748	600.2691	365.8577	220.5547	94.3431
BM	0.8428	0.9432	1.0067	0.9850	0.9972	1.0367	1.1429	1.1290	1.0188	0.8869
Prior12	-0.1059	-0.0624	-0.0218	0.0166	0.0337	0.0088	0.0062	0.0075	0.0291	-0.0070
Prior36	-0.2554	-0.1778	-0.0928	0.0401	0.0566	0.0949	0.0462	0.0406	0.0290	0.1222
Firm age	9.2083	9.9583	10.1458	10.6875	11.5833	10.8125	10.8750	10.9375	10.5417	9.6458

Panel B: Monthly Returns by Accruals Decile

	Low	2	3	4	5	6	7	8	9	High	Spread	FF3f alpha
VW	0.8975*	1.1088***	0.9950***	0.9479***	0.8799***	0.5638*	0.8103***	0.5913*	0.3446	-0.2259	1.1234***	0.7188*
EW	1.8081***	1.6308***	1.7699***	1.3398***	1.5233***	1.2543***	1.3528***	1.3142***	1.2648***	1.3409***	0.4672	0.0949

Table 6: Returns on Double-Sorted Portfolios

Each December from 1992 to 2015, quintile breakpoints are identified for both NOA and accruals. Sample stocks are sorted independently into 25 portfolios. Buy-and-hold value-weighted portfolios are estimated over the following 12 months, at which point the portfolio sorting procedure is repeated. Panel A and Panel B report average NOA and accruals statistics respectively for the double-sorted portfolios. Panel C reports the average number of stocks in each portfolio. Panel D reports monthly returns on the double-sorted portfolios. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Average NOA by portfolio

		Accruals				
		Low	2	3	4	High
NOA	Low	0.19	0.20	0.20	0.18	0.19
	2	0.50	0.51	0.52	0.51	0.51
	3	0.69	0.69	0.69	0.70	0.69
	4	0.84	0.84	0.85	0.85	0.85
	High	1.60	1.36	1.26	1.23	1.35

Panel B: Average accruals by portfolio

		Accruals				
		Low	2	3	4	High
NOA	Low	-0.29	-0.09	-0.04	0.00	0.07
	2	-0.25	-0.09	-0.04	0.00	0.08
	3	-0.21	-0.09	-0.04	-0.01	0.06
	4	-0.20	-0.09	-0.04	0.00	0.07
	High	-0.25	-0.09	-0.04	0.00	0.10

Panel C: Average number of stocks per portfolio

		Accruals				
		Low	2	3	4	High
NOA	Low	59	34	28	30	35
	2	48	42	34	31	31
	3	29	43	43	39	31
	4	19	36	47	46	38
	High	30	30	34	41	50

Panel D: Monthly returns by portfolio

		Accruals					
		Low	2	3	4	High	Spread
NOA	Low	1.7944	1.4091	1.4114	1.3708	1.2850	0.5094
	2	0.9522	0.8268	1.2082	0.7518	0.8738	0.0784
	3	0.4166	1.0458	0.8565	0.9176	0.3606	0.0560
	4	0.9417	0.8615	0.6498	1.0988	0.2099	0.7318
	High	0.9027	0.4410	0.2165	0.3215	-0.2816	1.1843**
	Spread	0.8918*	0.9980**	1.1949***	1.0493**	1.5666***	

Table 7: Mispricing Tests

This table reports results of the Kraft et al. (2007) OLS-equivalent of the Mishkin test as shown in model (4). The dependent variable is firm *i*'s buy-and-hold return over the subsequent 12 months. The key test variables are accruals, cashflow and net operating assets. A positive (negative) slope on a test variable indicates under (over) pricing. Each model also controls for firm size, book-to-market and prior 12-month momentum using (for each of these three variables) dummy variables representing the firm's membership in a quintile portfolio as at December each year. Model (4) is estimated after pooling firm-year observations across the period 1992-2015 (n = 21,753 firm-year observations). Standard errors of regression slopes and their corresponding p-values are estimated in two ways. First, "vanilla" OLS assumptions assuming that standard errors are distributed iid are estimated and p-values are reported in (round) parentheses. Second, a panel regression with standard errors double clustered by year and firm are estimated as per Petersen (2009) and Thompson (2011), with and p-values reported in <angle> brackets.

Independent Variable		Model 4a	Model 4b
ACC	slope	-0.0970	-0.0589
	vanilla	(0.0026)	(0.0683)
	clustered	<0.3211>	<0.5280>
CFO	slope	0.1551	0.1502
	vanilla	(0.0001)	(0.0001)
	clustered	<0.1541>	<0.1572>
NOA	slope		-0.1381
	vanilla		(0.0001)
	clustered		<0.0001>
Controls	Firm size	Yes	Yes
	Book-to-market	Yes	Yes
	Prior 12-mth momentum	Yes	Yes

Table 8: Descriptive Statistics: Robustness Analysis

This table reports summary statistics for the robustness analysis. In Panel A, the full sample is partitioned into profit and loss-making firms, according to year *t* earnings. In Panel B, the full sample is partitioned into resource and non-resource stocks. **NOA are** the difference between operating assets and operating liabilities, scaled by lagged total assets. **Market capitalisation** is number of ordinary shares multiplied by the closing share price each December. **Book-to-market** is the book value scaled by market capitalisation. **Prior12** and **Prior36** are the buy-and-hold return over the previous 12 and 36 months respectively. **Earnings** are the reported earnings before interest, tax, abnormal and significant items, scaled by lagged total assets. **Cashflow** is the cashflow from operations, scaled by lagged total assets. **Accruals** is the difference between earnings and accruals, scaled by lagged total assets. **Retained Earnings** is the dollar value of retained earnings scaled by total assets. **Firm age** is the number of years that has elapsed since the firm was listed on the ASX. Within each partition, all variables are winsorised at the 1st and 99th percentiles.

Panel A	Loss-making firms (*n* = 12,501)							Profit-making firms (*n* = 9,252)						
	Mean	Std Dev	Min	25th	Median	75th	Max	Mean	Std Dev	Min	25th	Median	75th	Max
Net operating assets	0.68	0.55	-0.14	0.33	0.63	0.89	4.41	0.77	0.41	-0.14	0.58	0.74	0.88	4.34
Market cap ($m)	46.79	113.76	0.81	4.98	12.04	33.13	814.35	891.95	2,434.50	1.95	23.92	100.44	479.32	16.6bn
Book-to-market	1.14	1.44	0.03	0.30	0.66	1.37	8.82	0.89	0.84	0.07	0.36	0.64	1.10	5.11
Prior 12-month	0.10	1.04	-0.91	-0.51	-0.21	0.28	5.29	0.21	0.65	-0.80	-0.18	0.09	0.42	3.20
Prior 36-month	0.11	1.69	-0.98	-0.76	-0.45	0.20	10.03	0.75	1.70	-0.90	-0.24	0.27	1.09	9.30
Earnings	-0.32	0.35	-1.88	-0.42	-0.20	-0.09	0.00	0.14	0.12	0.00	0.06	0.11	0.17	0.69
Cashflow	-0.20	0.28	-1.46	-0.27	-0.12	-0.05	0.19	0.15	0.15	-0.26	0.07	0.13	0.21	0.73
Accruals	-0.12	0.23	-1.03	-0.18	-0.06	0.00	0.45	-0.01	0.12	-0.31	-0.07	-0.03	0.02	0.58
Retained earnings	-3.07	5.53	-36.12	-3.13	-1.16	-0.41	0.25	-0.13	0.79	-4.86	-0.09	0.07	0.18	0.62
Firm age	12.71	10.88	2.00	5.00	9.00	17.00	61.00	18.93	18.56	2.00	7.00	12.00	24.00	92.00

Panel B	Non-resource firms (*n* = 10,663)							Resource firms (*n* = 11,090)						
	Mean	Std Dev	Min	25th	Median	75th	Max	Mean	Std Dev	Min	25th	Median	75th	Max
Net operating assets	0.67	0.45	-0.14	0.43	0.66	0.84	4.41	0.76	0.54	-0.13	0.45	0.73	0.94	4.41
Market cap ($m)	449.83	1,354.10	1.09	10.55	37.78	192.18	9,243.30	268.29	1,099.20	0.91	5.98	16.52	64.41	8,834.30
Book-to-market	0.90	0.96	0.03	0.31	0.61	1.12	5.95	1.16	1.38	0.04	0.34	0.70	1.39	8.13
Prior 12-month	0.14	0.73	-0.87	-0.31	0.00	0.36	3.62	0.15	1.02	-0.90	-0.48	-0.13	0.36	5.18
Prior 36-month	0.44	1.54	-0.96	-0.51	0.02	0.77	8.38	0.32	1.92	-0.97	-0.71	-0.32	0.48	11.13
Earnings	-0.04	0.31	-1.41	-0.11	0.06	0.13	0.50	-0.21	0.35	-1.71	-0.33	-0.13	-0.03	0.49
Cashflow	0.00	0.28	-1.16	-0.08	0.07	0.15	0.55	-0.11	0.27	-1.29	-0.19	-0.08	-0.01	0.56
Accruals	-0.04	0.14	-0.63	-0.09	-0.03	0.01	0.42	-0.10	0.23	-1.02	-0.16	-0.05	0.00	0.53
Retained earnings	-1.35	3.61	-23.30	-1.04	-0.04	0.11	0.58	-2.20	4.31	-27.86	-2.22	-0.74	-0.18	0.49
Firm age	16.00	16.05	2.00	6.00	11.00	19.00	87.00	14.66	13.65	2.00	6.00	10.00	19.00	76.00

Table 8: Descriptive Statistics: Robustness Analysis (con't)

Panel C	Big firms (*n* = 4,800)							Small firms (*n* = 16,953)						
	Mean	Std Dev	Min	25th	Median	75th	Max	Mean	Std Dev	Min	25th	Median	75th	Max
Net operating assets	0.81	0.45	-0.13	0.61	0.75	0.90	4.34	0.69	0.51	-0.14	0.39	0.67	0.89	4.4081
Market cap ($m)	1.99bn	4.3bn	44.90	241.86	556.86	1.6bn	3.07bn	34.15	48.75	0.89	5.83	14.56	39.13	254.41
Book-to-market	0.57	0.44	0.03	0.26	0.46	0.76	2.38	1.16	1.34	0.04	0.36	0.74	1.40	8.21
Prior 12-month	0.31	0.78	-0.71	-0.10	0.15	0.47	4.55	0.10	0.92	-0.90	-0.46	-0.13	0.32	4.69
Prior 36-month	1.32	2.76	-0.79	-0.01	0.54	1.47	17.96	0.14	1.45	-0.97	-0.71	-0.33	0.37	7.75
Earnings	0.10	0.16	-0.58	0.06	0.10	0.16	0.60	-0.19	0.35	-1.69	-0.31	-0.11	0.03	0.45
Cashflow	0.13	0.18	-0.56	0.07	0.13	0.21	0.71	-0.11	0.28	-1.32	-0.20	-0.06	0.06	0.49
Accruals	-0.04	0.08	-0.34	-0.07	-0.03	0.00	0.26	-0.08	0.21	-0.93	-0.14	-0.04	0.01	0.52
Retained earnings	0.01	0.40	-2.15	-0.01	-0.09	0.19	0.61	-2.32	4.71	-30.90	-2.32	-0.71	-0.12	0.51
Firm age	21.38	20.48	2.00	8.00	13.00	28.00	95.00	13.63	12.24	2.00	5.00	10.00	18.00	69.00

Table 9: Mispricing Tests: Robustness Analysis

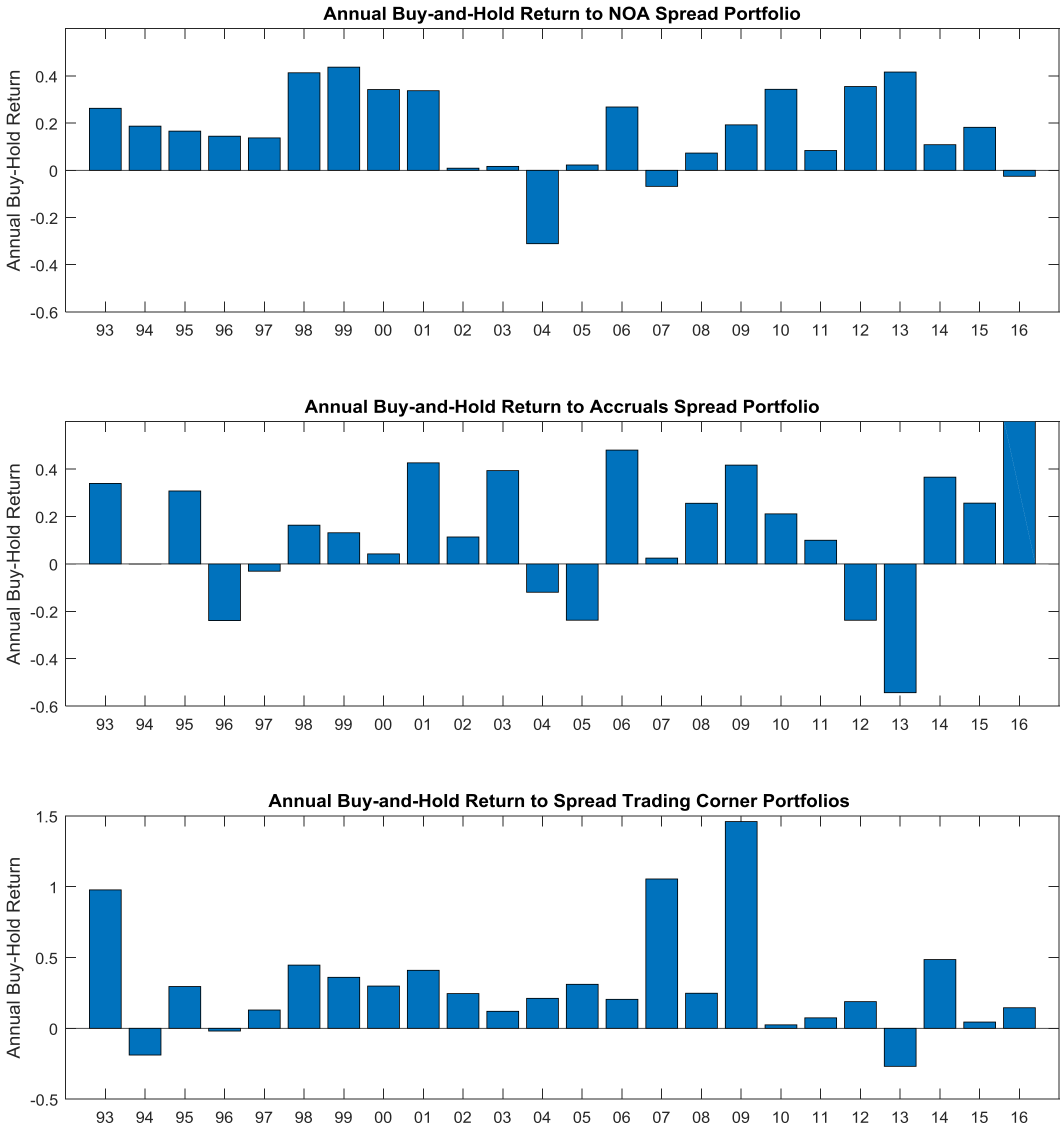
This table reports robustness analysis for KLW mispricing tests from model (4). In Panel A, the full sample is partitioned into profit and loss-making firms, according to year *t* earnings. In Panel B, the full sample is partitioned into resource and non-resource stocks. The dependent variable is firm *i*'s buy-and-hold return over the subsequent 12 months. The key test variables are accruals, cashflow and net operating assets. A positive (negative) slope on a test variable indicates under (over) pricing. Each model also controls for firm size, book-to-market and prior 12-month momentum using (for each of these three variables) dummy variables representing the firm's membership in a quintile portfolio as at December each year. Model (4) is estimated after pooling firm-year observations across the period 1992-2015. Standard errors of regression slopes and their corresponding *p*-values are estimated in two ways. First, "vanilla" OLS assumptions assuming that standard errors are distributed iid are estimated and *p*-values are reported in (round) parentheses. Second, a panel regression with standard errors double clustered on year and firm are estimated as per Petersen (2009) and Thompson (2011), with and *p*-values reported in <angle> brackets.

Partition		**ACC**	**CFO**	**NOA**
		Panel A: Comparison of loss- and profit-making firms		
Loss-making firms	slope	-0.0517	0.0587	-0.1669
(*n* = 12,501)	vanilla	(0.2333)	(0.1249)	(0.0001)
	clustered	<0.6053>	<0.6569>	<0.0001>
Profit-making firms	slope	-0.3995	-0.0001	-0.0640
(*n* = 9,252)	vanilla	(0.0001)	(0.9982)	(0.0001)
	clustered	<0.1462>	<0.9995>	<0.0013>
		Panel B: Comparison of resource and non-resource firms		
Non-resource firms	slope	-0.0884	0.2430	-0.1167
(*n* = 10,663)	vanilla	(0.0760)	(0.0001)	(0.0001)
	clustered	<0.3986>	<0.0002>	<0.0001>
Resource firms	slope	-0.0366	0.0633	-0.1626
(*n* = 11,090)	Vanilla	(0.4207)	(0.1323)	(0.0001)
	clustered	<0.7062>	<0.6801>	<0.0001>
		Panel C: Comparison of big and small firms		
Big firms	slope	0.0397	0.2541	-0.0648
(*n* = 4,800)	vanilla	(0.6659)	(0.0001)	(0.0001)
	clustered	<0.7808>	<0.0003>	<0.0161>
Small firms	slope	-0.0914	0.0713	-0.1720
(*n* = 16,953)	vanilla	(0.0123)	(0.0127)	(0.0001)
	clustered	<0.3319>	<0.5037>	<0.0001>

Figure 1

Annual Buy-and-Hold Returns on NOA and Accruals Spread Trading

Panel A depicts the annualised buy-and-hold return to a spread portfolio that enters long positions in stocks with low NOA and short positions in stocks with high NOA. Panel B depicts the annualised buy-and-hold return to a spread portfolio that enters long positions in stocks with low Accruals and short positions in stocks with high Accruals. Panel C is the annualised buy-and-hold return to a strategy that enters long positions in stocks with low NOA and low accruals and short positions in stocks with high NOA and high accruals.



Highlights

Future stock returns are negatively related to accruals and net operating assets (NOA).

NOA appears to have an important moderating influence on the accrual effect.

An accrual effect only exists for stocks with high NOA.

Accounting for cross-sectional and time-series dependence, there is no evidence of accrual mispricing.

There is robust evidence that NOA are overpriced.